GNA Journal of
Management & Technology

ISSN-0974-572
Vol. 16 No. 2, July-December, 2025

EMOTIONAL FINANCE MEETS FINTECH: AI APPLICATIONS IN BEHAVIOURAL ASSET PRICING

Malkeet Singh

Assistant Professor, Pyramid college, Phagwara

Email:malkeetsingh9919@gmail.com

Abstract

The integration of Emotional Finance and Financial Technology (FinTech) is reshaping how financial markets interpret and respond to investor behaviour. While traditional asset pricing models assume rational decision-making, behavioural finance has demonstrated the influence of psychological biases. Emotional Finance advances this perspective by focusing on unconscious processes, narratives, and collective sentiments that shape financial choices. At the same time, AI-enabled FinTech platforms offer unprecedented capabilities to capture and analyse emotional signals embedded in financial news, social media, and investor communications.

This paper examines how artificial intelligence facilitates the incorporation of emotional and behavioural signals into asset pricing frameworks. Through a conceptual review, we analyse applications such as natural language processing for sentiment extraction, emotion detection in investor discourse, and adaptive trading models using reinforcement learning. Building on these insights, the study proposes an expanded behavioural asset pricing paradigm that systematically integrates affective and unconscious investor dynamics.

The analysis highlights both the opportunities and challenges of this convergence. AI-driven emotional analytics can enhance market efficiency, broaden access to behavioural insights, and support more informed financial decision-making. However, it also raises ethical concerns related to data surveillance, algorithmic bias, and the amplification of herd behaviour. Overall, the proposed framework offers a novel perspective on asset pricing that better reflects the complexity of human behaviour and provides a foundation for future empirical research, regulatory discourse, and innovation in financial services.

Keywords: *Emotional Finance, Behavioural Asset Pricing, Artificial Intelligence, FinTech, Sentiment Analysis*

1. INTRODUCTION

Asset pricing has traditionally been grounded in rationalist frameworks such as the Efficient Market Hypothesis (Fama, 1970) and the Capital Asset Pricing Model (Sharpe, 1964), which assume that investors process information objectively and make decisions based on risk–return optimisation.

However, repeated empirical anomalies—ranging from speculative bubbles such as the dot-com boom to systemic crises like the 2008 global financial collapse—have exposed the limitations of these assumptions. In response, Behavioural Finance (Kahneman & Tversky, 1979; Shiller, 2000) introduced psychological realism into financial theory, demonstrating how heuristics, cognitive biases, and bounded rationality shape investor behaviour and market outcomes.

Emotional Finance advances this behavioural perspective by shifting attention from conscious biases to unconscious emotional processes, narratives, and collective fantasies that underpin financial decision-making (Tuckett & Taffler, 2008). Rather than treating emotions as residual noise around rational valuation, Emotional Finance conceptualises them as structural forces that influence market sentiment, risk perception, and herd dynamics. This approach provides a deeper explanation for phenomena such as extreme volatility, contagion, and panic-driven market movements that remain difficult to reconcile within standard pricing models.

At the same time, the rapid expansion of Financial Technology (FinTech), supported by advances in Artificial Intelligence (AI), has fundamentally altered how financial markets operate. FinTech innovations span trading, asset management, payments, and lending, while AI techniques enable the analysis of vast volumes of structured and unstructured data in real time (Arner, Barberis, & Buckley, 2016). Methods such as natural language processing (NLP), machine learning, and reinforcement learning allow the extraction of emotional cues from sources including financial news, earnings calls, analyst reports, and social media discourse. These developments create new possibilities for systematically integrating emotional signals into asset pricing mechanisms.

The motivation for this study arises from three interrelated gaps in the literature. First, Behavioural Finance largely concentrates on conscious heuristics and biases, offering limited insight into unconscious emotional drivers of investment behaviour. Second, while Emotional Finance provides a rich psychoanalytic interpretation of market dynamics, it has historically lacked scalable empirical tools for operationalisation. Third, although AI-driven FinTech applications are increasingly embedded in trading and investment practices, their potential role in capturing and pricing unconscious emotional dynamics remains insufficiently theorised. Addressing these gaps requires an integrative framework that connects emotional theory with computational capability.

The integration of Emotional Finance and AI-enabled FinTech is particularly relevant for explaining market phenomena characterised by sudden shifts in sentiment, fear, or euphoria. AI tools—especially NLP-based sentiment and emotion analysis—can identify linguistic and narrative indicators of such emotions in real time (Tetlock, 2007; Nyman et al., 2021). When incorporated into adaptive pricing and trading models, these signals offer the potential to enhance both explanatory power and predictive accuracy. Consequently, AI may function as a critical bridge between

unconscious investor dynamics and observable market behaviour.

This perspective also aligns with contemporary concerns in finance research and policy. Regulators increasingly focus on systemic risks associated with algorithmic trading, sentiment contagion, and herd behaviour, while asset managers seek strategies that anticipate market psychology rather than merely react to fundamentals. By positioning Emotional Finance within the technological infrastructure of modern FinTech, this paper situates emotional dynamics at the core of ongoing innovation in asset pricing.

2. METHODOLOGY

This study adopts a conceptual research design aimed at theory development rather than empirical testing. The paper does not employ primary or secondary datasets, nor does it involve statistical modelling, econometric estimation, or hypothesis testing. Instead, the objective is to advance behavioural asset pricing theory by integrating insights from Emotional Finance with recent developments in AI-enabled Financial Technology (FinTech).

The proposed framework is developed through a systematic synthesis of existing literature spanning four key domains: traditional asset pricing models, behavioural finance, emotional finance, and artificial intelligence applications in finance. Seminal and contemporary studies in each domain are critically reviewed to identify their core assumptions, theoretical contributions, and limitations. Particular attention is given to how investor behaviour is conceptualised across these approaches and to the extent to which emotional and unconscious dynamics are incorporated into pricing models.

Building on this integrative review, the study analytically connects psychoanalytic insights from Emotional Finance with computational capabilities offered by AI-driven FinTech, such as natural language processing, machine learning, and reinforcement learning. These tools are examined not as empirical instruments but as **conceptual enablers** that demonstrate how emotional narratives and affective signals can be translated into measurable inputs within asset pricing frameworks.

Accordingly, the contribution of this paper is **theoretical and conceptual in nature.** The framework presented is intended to guide future empirical research, inform methodological design for quantitative studies, and support policy and practice-oriented discussions. Empirical validation and statistical testing are deliberately left for subsequent research that can operationalise and test the propositions emerging from this conceptual model.

Research Aim and Objectives

The primary aim of this paper is to develop a conceptual framework that integrates Emotional Finance with AI-enabled FinTech to advance behavioural asset pricing theory.

To achieve this aim, the study pursues the following objectives:

1. To critically examine the limitations of traditional and behavioural asset pricing models in capturing unconscious and emotional investor dynamics.
2. To synthesise insights from Emotional Finance and FinTech literature, highlighting the role of AI in detecting and quantifying emotional signals.
3. To propose a conceptual framework of AI-enhanced Emotional Finance for behavioural asset pricing.
4. To identify key applications, opportunities, and ethical challenges associated with embedding emotional analytics into AI-driven financial systems.

The remainder of the paper is structured as follows. The next section reviews the relevant literature on asset pricing, Emotional Finance, and FinTech. This is followed by the development of the proposed conceptual framework, a discussion of practical applications and ethical considerations, and implications for future research, policy, and financial practice.

3. LITERATURE REVIEW

1. Traditional Asset Pricing Models

The foundations of asset pricing theory are grounded in assumptions of rational expectations and market efficiency. Classical frameworks such as the Capital Asset Pricing Model (CAPM) (Sharpe, 1964; Lintner, 1965) and the Efficient Market Hypothesis (EMH) (Fama, 1970) conceptualise investors as rational agents who evaluate assets based on objective risk–return trade-offs. CAPM formalises expected returns as a linear function of systematic market risk (beta), while EMH posits that asset prices fully and instantaneously reflect all available information, thereby precluding the possibility of consistent abnormal returns.

Despite their theoretical appeal, these models have been repeatedly challenged by empirical anomalies, including momentum, size, and value effects (Jegadeesh & Titman, 1993; Fama & French, 1992). The Arbitrage Pricing Theory (APT) (Ross, 1976) relaxed the single-factor structure of CAPM by allowing multiple sources of systematic risk, yet it retained the core assumptions of rationality and equilibrium. As a result, traditional asset pricing models provide an important benchmark but struggle to explain speculative bubbles, market crashes, and persistent mispricing driven by investor sentiment and collective behaviour.

2. Behavioural Finance

Behavioural Finance emerged in response to the limitations of rationalist models by incorporating insights from cognitive psychology into financial decision-making. Building on Prospect Theory (Kahneman & Tversky, 1979), this literature demonstrates that investors systematically deviate from rationality due to heuristics, biases, and bounded rationality.

Key behavioural mechanisms identified in the literature include loss aversion, whereby investors

exhibit asymmetric preferences toward gains and losses; overconfidence and representativeness, which lead to excessive trading and misjudged expectations; and herding and feedback trading, through which individual biases aggregate into market-wide phenomena such as bubbles and crashes (Shiller, 2000). By embedding psychological realism into asset pricing, Behavioural Finance significantly enhanced explanatory power relative to traditional models.

However, much of behavioural research focuses on conscious and observable decision-making errors, often measured through laboratory experiments, surveys, or stylised trading data. While effective in explaining deviations from rational benchmarks, this approach offers limited insight into the unconscious emotional processes and shared narratives that influence market dynamics, particularly during periods of heightened uncertainty.

3. Emotional Finance

Emotional Finance represents a further extension of behavioural approaches by explicitly examining unconscious emotional processes in financial markets. Drawing on psychoanalytic theory, Tuckett and Taffler (2008, 2011) argue that investment decisions are not solely cognitive but are also affective and imaginative. Investors unconsciously project hopes, fears, and fantasies onto financial assets, treating them as objects of emotional attachment rather than neutral instruments.

From this perspective, speculative bubbles can be interpreted as collective fantasies of unlimited growth, while market crashes reflect the breakdown of shared illusions. Emotional Finance also emphasises the role of narratives—stories that investors construct to manage anxiety and uncertainty about the future (Tuckett, 2011). Unlike Behavioural Finance, which often treats biases as errors to be corrected, Emotional Finance conceptualises emotions and narratives as constitutive elements of market behaviour.

Despite its strong explanatory depth, Emotional Finance faces significant challenges in empirical operationalisation. Psychoanalytic concepts are inherently difficult to quantify, limiting their direct incorporation into formal asset pricing models. This gap between rich theory and measurable application has constrained the broader adoption of Emotional Finance within mainstream financial economics.

4. FinTech and Artificial Intelligence in Finance

The past two decades have witnessed rapid growth in Financial Technology (FinTech), encompassing innovations in payments, lending, trading, robo-advisory services, and blockchain-based systems (Arner, Barberis, & Buckley, 2016). Central to this transformation is the application of Artificial Intelligence (AI), which enables the processing of large-scale structured and unstructured financial data.

Key AI applications in finance include natural language processing (NLP) for sentiment and tone

analysis of financial news, earnings calls, and social media (Tetlock, 2007; Loughran & McDonald, 2016); machine learning models that capture nonlinear relationships in asset returns (Gu, Kelly, & Xiu, 2020); reinforcement learning for adaptive trading strategies; and computer vision techniques for analysing visual and behavioural cues in investor communications. These tools extend the informational foundation of asset pricing beyond fundamentals, incorporating real-time behavioural and sentiment indicators.

5. Convergence: AI as a Bridge for Emotional Finance

The convergence of Emotional Finance and AI-enabled FinTech offers a pathway to operationalise unconscious emotional dynamics in asset pricing. NLP techniques can extract emotional tone, anxiety, optimism, or denial embedded in financial narratives, while machine learning models can quantify the relationship between these emotional signals and asset returns. Reinforcement learning further enables the modelling of how collective emotional states evolve into market trends through feedback mechanisms. In this way, AI transforms affective and narrative elements—previously treated as intangible—into measurable pricing inputs.

6. Synthesis and Research Gap

Taken together, the literature reflects a progressive evolution in asset pricing theory. Traditional finance assumes rational investors operating in efficient markets; Behavioural Finance relaxes this assumption by introducing conscious cognitive biases and heuristics; and Emotional Finance advances further by emphasising unconscious emotions, fantasies, and narratives as foundational drivers of market behaviour. However, while theoretical depth increases across these approaches, their integration into formal pricing models remains incomplete.

AI-enabled FinTech provides the missing methodological link. By translating emotional narratives and unconscious affect into quantifiable signals, AI bridges the gap between Emotional Finance theory and empirical asset pricing. This synthesis clarifies how the proposed framework builds on and extends existing theories: it retains the structural insights of traditional models, incorporates behavioural deviations, and systematically embeds emotional dynamics through computational tools. The present study positions itself at this intersection, proposing a conceptual model in which AI functions as the conduit through which unconscious investor emotions are integrated into behavioural asset pricing.

Conceptual Framework

1. Rationale for a New Framework

Traditional asset pricing rests on rational expectations, while Behavioural Finance highlights cognitive biases. Emotional Finance goes further by emphasising unconscious emotions, fantasies, and narratives. However, its concepts have remained largely theoretical because of the difficulty in

quantifying unconscious processes.

FinTech, empowered by Artificial Intelligence, provides precisely the tools needed to operationalise these processes. AI can analyse language, images, and behavioural traces to detect emotional signals. When integrated with Emotional Finance theory, this enables the construction of a framework where affective dynamics can systematically feed into pricing models.

Thus, the proposed framework consists of three interconnected pillars:

1. Detection of Emotional Signals (investor narratives, unconscious anxieties, collective fantasies).

2. **Translation into Behavioural Pricing Adjustments** (via AI algorithms embedded in FinTech platforms).

3. **Feedback Loops** (between market prices, narratives, and investor emotions).

2. Pillar One: Detection of Emotional Signals

Investor behaviour is shaped by both conscious reasoning and unconscious drivers. Emotional Finance argues that emotions like anxiety, hope, denial, and fantasy underpin investment choices (Tuckett & Taffler, 2008). These signals are often embedded in:

- Narratives and discourse: analyst reports, media coverage, earnings calls.
- Investor communications: social media posts, blogs, forums.
- Non-verbal cues: facial expressions, tone of voice in interviews.

AI tools — especially **Natural Language Processing (NLP)** — can capture sentiment, tone, and even subtle markers of anxiety or confidence in textual data (Loughran & McDonald, 2016). **Computer vision** and **speech analysis** extend this to audiovisual signals. These methods provide quantifiable proxies for unconscious investor dynamics.

3. Pillar Two: Translation into Behavioural Pricing Adjustments

Once detected, emotional signals must be integrated into pricing models. AI offers methods for this translation:

- **Machine Learning models** can correlate emotional signals with asset returns, volatility, or liquidity.
- **Reinforcement Learning systems** allow adaptive trading strategies that learn from shifting emotional states.
- **Hybrid behavioural models** can combine fundamentals (earnings, cash flows) with emotional indicators (sentiment, anxiety indices).

In this way, Emotional Finance becomes operational, not just conceptual. Instead of treating emotions as "noise," they are formalised as **pricing factors** alongside traditional fundamentals.

4. Pillar Three: Feedback Loops

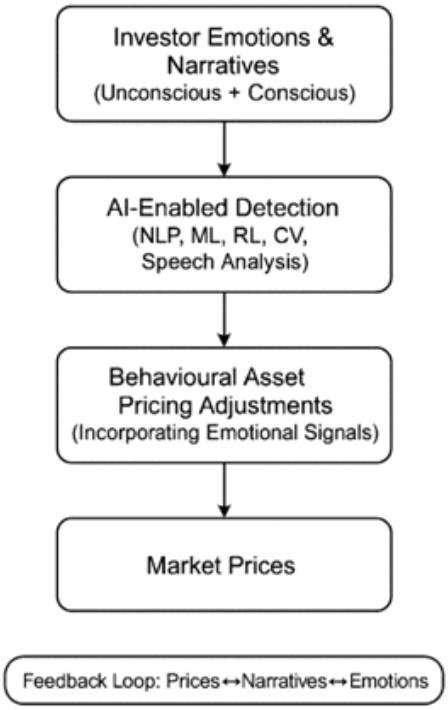
Markets are reflexive: prices influence narratives, which in turn shape emotions and future prices

(Soros, 1987). The framework incorporates feedback loops where:

1. Emotional signals are detected (e.g., rising anxiety in media).
2. AI models adjust pricing (e.g., volatility premiums increase).
3. Price changes alter investor narratives (e.g., panic selling fuels further anxiety).
4. New emotional signals emerge, continuing the cycle.

This recursive process explains how small emotional shifts can escalate into bubbles or crashes — phenomena poorly captured by rationalist models.

5. Conceptual Framework



(Source: Developed by Author)

6. Theoretical Contribution

This framework contributes to the literature by:

- Extending Behavioural Asset Pricing to include unconscious affective processes.
- Offering a methodological bridge: AI operationalises psychoanalytic insights.
- Highlighting the recursive dynamics of markets through feedback loops.

It addresses the three gaps identified earlier:

1. Behavioural Finance's neglect of unconscious dynamics.
2. Emotional Finance's lack of empirical operationalisation.
3. FinTech/AI's limited engagement with behavioural theory.

AI Applications in Behavioural Asset Pricing

1. Natural Language Processing (NLP) and Sentiment Analysis

Language is central to Emotional Finance because investor emotions are embedded in narratives and discourse. **NLP** provides computational methods to analyse vast amounts of textual data such as financial news, earnings call transcripts, analyst reports, and social media.

- **Sentiment detection:** Algorithms classify text as positive, negative, or neutral. Advanced models identify nuanced emotions such as anxiety, confidence, or denial (Loughran & McDonald, 2016).
- **Topic modelling:** Tools like Latent Dirichlet Allocation (LDA) extract themes from market conversations, revealing shifting collective narratives.
- **Event detection:** NLP can capture sudden narrative shifts that precede market movements, e.g., rising mentions of "liquidity crisis" before sell-offs.

Application to asset pricing: NLP-generated sentiment indices can be incorporated into behavioural asset pricing models as additional factors predicting returns and volatility (Tetlock, 2007; Nyman et al., 2021).

2. Machine Learning (ML) for Predictive Modelling

Traditional linear models struggle with the complexity of human emotions. **Machine Learning (ML)** captures nonlinear relationships between emotional signals and market outcomes.

- **Supervised learning:** Models are trained on historical data linking sentiment indicators with returns, allowing predictions of future pricing anomalies.
- **Unsupervised learning:** Clustering algorithms identify hidden patterns in investor behaviour, such as groups prone to panic selling.
- **Deep learning:** Neural networks extract subtle signals from high-dimensional datasets, including text, voice, and images.
- **Application to asset pricing:** ML enhances factor models by adding sentiment and emotion-related predictors. For example, volatility forecasting improves when anxiety-related language from earnings calls is included.

3. Reinforcement Learning (RL) for Adaptive Trading

Markets are dynamic, with emotions shifting rapidly. Reinforcement Learning (RL) offers adaptive trading strategies that update based on real-time emotional signals.

- **Agent–environment interaction:** RL agents "learn" from price movements and sentiment data, adjusting trading strategies dynamically.
- **Reward functions:** Strategies incorporate both financial returns and emotional-risk indicators, e.g., penalising trades during panic-driven volatility.
- **Market simulations:** RL can simulate how collective emotions evolve into bubbles or crashes, offering insights into systemic risk.

Application to asset pricing: RL introduces adaptive mechanisms, embedding emotional dynamics into real-time pricing.

4. Computer Vision (CV) and Speech Analysis

Emotions are not only in text but also in **voice and facial expressions**. Advances in **computer vision** and **speech analysis** allow detection of non-verbal cues:

- **Facial recognition:** Identifying anxiety, confidence, or uncertainty in executives during televised earnings calls.
- **Speech tone analysis:** Detecting stress or hesitation in the voices of CEOs or analysts.
- **Multimodal fusion:** Combining textual sentiment, vocal tone, and facial expression for richer emotional profiling.

Application to asset pricing: These signals can be quantified into indices of market confidence or anxiety, serving as behavioural factors in pricing models.

5. Integration into FinTech Platforms

AI applications are increasingly embedded into FinTech platforms used by asset managers, traders, and retail investors.

- **Robo-advisors:** Personalised investment advice now incorporates behavioural profiling, adjusting portfolios based on emotional risk tolerance.
- **Trading platforms:** Real-time sentiment dashboards allow traders to anticipate emotional contagion in markets.
- **Risk management tools:** Institutions monitor systemic emotional risk (e.g., herd panic) to anticipate volatility spikes.

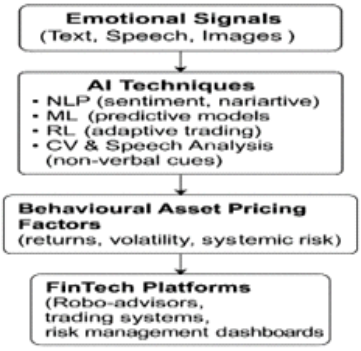
This integration operationalises Emotional Finance, moving from theory to practice.

6. Opportunities and Risks

While promising, AI applications in Emotional Finance raise new challenges:

- **Opportunities:**
- Better prediction of volatility and anomalies.
- Inclusion of investor psychology in pricing models.
- Democratization of behavioural insights through FinTech tools.
- **Risks:**
- Over-reliance on algorithms may amplify herd behaviour.
- Misinterpretation of emotional signals may create false signals.
- Ethical concerns of surveillance and privacy.

7. Thus, AI is both a bridge and a disruptor in behavioural asset pricing.



(Source: Developed by Author)

Ethical and Policy Considerations

1. Privacy and Surveillance Risks

AI tools in FinTech often rely on extensive data collection, including **text, voice, and visual signals.** When applied to Emotional Finance, these methods may involve monitoring investor communications, facial expressions, or speech patterns. While this enhances predictive capacity, it also raises profound **privacy concerns.**

- **Investor consent:** Many users may be unaware that their emotional expressions are being harvested as data points.
- **Surveillance creep:** Continuous monitoring risks creating financial ecosystems where personal emotions are commodified for trading advantages.
- **Regulatory gaps:** Current financial regulations often address market manipulation but rarely account for emotional surveillance.

Thus, policymakers must balance innovation with privacy protections.

2. Algorithmic Bias and Fairness

AI models are only as reliable as the data used to train them. Biases embedded in training datasets can distort emotional detection:

- **Cultural bias:** Emotional expressions vary across cultures; what signals anxiety in one context may be neutral in another.
- **Gender and linguistic bias:** NLP systems may misinterpret sentiment based on gendered language patterns.
- **Market bias:** Overrepresentation of data from developed markets may limit the applicability of models to emerging economies.

If unchecked, these biases can lead to **unfair pricing dynamics,** amplifying inequalities in access to financial opportunities.

3. Amplification of Herd Behaviour

One of the paradoxes of AI-enhanced Emotional Finance is its potential to both **mitigate and amplify systemic risks.**

- **Mitigation:** AI can alert institutions to rising collective anxiety, enabling preventive measures.
- **Amplification:** If many actors rely on similar sentiment-based algorithms, herd behaviour may intensify, triggering **self-fulfilling crises.**

For example, widespread algorithmic recognition of "panic" in financial news may lead to synchronised sell-offs, destabilising markets. This raises questions about the collective consequences of algorithmic decision-making.

4. Transparency and Explainability

Financial regulators emphasise **explainability** in algorithmic decision-making. Yet, many AI systems, particularly deep learning models, function as "black boxes."

- **Investor accountability:** When algorithms misinterpret emotions, leading to mispriced assets, accountability becomes unclear.
- **Regulatory oversight:** Supervisors face challenges in auditing opaque AI-driven trading systems.
- **Ethical governance:** Without transparency, trust in financial markets could erode, undermining stability.

Therefore, developing explainable AI (XAI) systems is critical for embedding Emotional Finance responsibly into asset pricing.

5. Policy Responses and Global Perspectives

Several regulatory frameworks are beginning to address AI and FinTech ethics:

- **European Union AI Act (2021)** categorises financial AI systems as "high risk," requiring transparency and fairness checks.
- **U.S. Securities and Exchange Commission (SEC)** has raised concerns about robo-advisors' reliance on opaque models.
- **Financial Conduct Authority (FCA) in the UK** emphasises consumer protection and algorithmic accountability.

However, few explicitly consider emotional data. Future policies must tackle:

1. Standards for collecting and processing emotional signals.
2. Rules on disclosure when emotional analytics inform pricing.

6. Ethical Balance: Innovation vs. Human Dignity

At its core, Emotional Finance reflects the human side of markets — anxiety, hope, and fantasy. Using AI to quantify these dimensions risks reducing deeply personal emotions into mere data points. While

innovation enhances predictive power, ethical practice demands respect for **human dignity and autonomy.**

Thus, the challenge is to foster **responsible innovation:** enabling AI-driven behavioural pricing without creating exploitative or destabilising systems.

Conceptual Framework and Insights

1. Implications for Practice

2. Asset Managers and Traders

For asset managers, the integration of Emotional Finance and AI opens up new sources of alpha. Traditional quantitative strategies rely on fundamentals or technical patterns, but AI-enhanced models incorporate **emotional sentiment indices**, allowing managers to anticipate shifts in volatility before they materialise in prices. For example, sentiment analysis of earnings calls can provide early warning signals of declining investor confidence, enabling portfolio adjustments.

Traders, particularly those in high-frequency environments, can benefit from real-time **emotional monitoring.** Dashboards that track market anxiety or optimism allow more nuanced risk management. However, this advantage may erode as more actors adopt similar tools, increasing systemic interdependence.

Policymakers and Regulators

For regulators, the implications are twofold. First, AI-based Emotional Finance tools can help **monitor systemic risk** by identifying patterns of collective anxiety or euphoria. Second, regulators must develop **ethical and governance frameworks** to address surveillance, algorithmic bias, and herd amplification risks. These tools could be incorporated into macroprudential oversight, providing early warnings for crises.

FinTech Innovators

FinTech firms stand at the forefront of this transformation. Integrating Emotional Finance into robo-advisory platforms or trading applications can **personalise financial advice** by aligning recommendations with an investor's emotional risk tolerance. At the same time, innovators face the challenge of ensuring **responsible use,** balancing user benefits with privacy and transparency obligations.

2. Interdisciplinary Collaboration

Future research requires collaboration across finance, psychology, computer science, and ethics. Emotional Finance provides psychoanalytic depth, while AI provides computational capacity. Joint efforts can bridge theory and practice, advancing both methodological innovation and conceptual clarity.

Ethical Finance Studies

The integration of AI and Emotional Finance raises ethical questions that demand scholarly attention. Research must explore how to design systems that respect **privacy, fairness, and dignity** while maintaining predictive accuracy. This calls for interdisciplinary contributions from law, philosophy, and sociology alongside finance.

3. Summary

In practice, the convergence of Emotional Finance and AI enables **more responsive, psychology-informed asset pricing models,** while in research, it invites **new methodologies and interdisciplinary inquiry.** Together, they mark a paradigm shift in how financial markets are understood, regulated, and navigated.

Conclusion

This paper advances asset pricing theory by proposing a **conceptual framework that integrates Emotional Finance with AI-enabled FinTech,** thereby extending traditional and behavioural models of market behaviour. While conventional asset pricing frameworks emphasise rational expectations and Behavioural Finance focuses on conscious cognitive biases, the present study highlights the role of u**nconscious emotions, narratives, and collective affect** as structural drivers of financial markets. The central contribution of this paper lies in demonstrating how artificial intelligence can serve as a methodological bridge, translating these emotional dynamics into **measurable and actionable pricing signals.** In doing so, the study offers a theoretically grounded pathway for incorporating affective forces into behavioural asset pricing.

The framework contributes conceptually by repositioning emotions not as residual noise but as integral components of market dynamics, and methodologically by identifying AI tools—such as natural language processing, machine learning, and reinforcement learning—as enablers of this integration. This perspective provides enhanced explanatory insight into market phenomena including speculative bubbles, sudden crashes, and volatility clustering that remain difficult to explain using rational or cognitive models alone. At the same time, the analysis underscores the ethical and systemic implications of embedding emotional analytics within AI-driven financial systems, particularly with respect to data privacy, algorithmic bias, sentiment amplification, and regulatory oversight.

Notwithstanding its contributions, this study has several limitations. First, the paper is conceptual in nature and does not provide empirical validation of the proposed framework. Second, the discussion of emotional dynamics relies primarily on theoretical and qualitative interpretations rather than measurable constructs. Third, the analysis abstracts from institutional and market-specific variations that may condition how emotional signals are generated and processed across different financial

contexts.

These limitations point to several avenues for future research. Empirical studies could test the predictive power of emotion-based indicators extracted through AI techniques across asset classes and market regimes. Methodological research may focus on developing robust metrics for unconscious emotional signals and examining their interaction with traditional risk factors. Further work is also needed to explore regulatory and ethical frameworks that govern the use of emotional data in financial decision-making, particularly in relation to transparency, accountability, and systemic risk. Finally, interdisciplinary research combining finance, psychology, data science, and ethics can deepen understanding of how human emotions and technology jointly shape modern financial markets.

In conclusion, the convergence of Emotional Finance and AI-enabled FinTech represents a meaningful step toward a more psychologically realistic and technologically sophisticated understanding of asset pricing. By integrating emotional dynamics into computational frameworks, this study contributes to the ongoing rethinking of finance in a digital era—one that recognises markets as both economic and emotional systems shaped by human behaviour and algorithmic mediation.

References

Arner, D. W., Barberis, J., & Buckley, R. P. (2016). The evolution of Fintech: A new post-crisis paradigm? *Georgetown Journal of International Law, 47*(4), 1271–1319.

Barberis, N., & Thaler, R. (2003). A survey of behavioral finance. In G. M. Constantinides, M. Harris, & R. Stulz (Eds.), *Handbook of the Economics of Finance* (pp. 1053–1123). Elsevier.

Bollerslev, T., Tauchen, G., & Zhou, H. (2009). Expected stock returns and variance risk premia. *Review of Financial Studies, 22*(11), 4463–4492.

Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor psychology and security market under- and overreactions. *Journal of Finance, 53*(6), 1839–1885.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *Journal of Finance, 25*(2), 383–417.

Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *Journal of Finance, 47*(2), 427–465.

Gu, S., Kelly, B., & Xiu, D. (2020). Empirical asset pricing via machine learning. *Review of Financial Studies, 33*(5), 2223–2273.

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. J*ournal of Finance, 48*(1), 65–91.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk.

Econometrica, 47(2), 263–291.

Lintner, J. (1965). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *Review of Economics and Statistics, 47*(1), 13–37.

Loughran, T., & McDonald, B. (2016). Textual analysis in accounting and finance: A survey. *Journal of Accounting Research, 54*(4), 1187–1230.

Nyman, R., Kapadia, S., Tuckett, D., Gregory, D., Ormerod, P., & Smith, R. (2021). News and narratives in financial systems: Exploiting big data for systemic risk assessment. *Journal of Economic Dynamics and Control, 127*, 104134.

Ross, S. A. (1976). The arbitrage theory of capital asset pricing. *Journal of Economic Theory, 13*(3), 341–360.

Shiller, R. J. (2000). *Irrational exuberance.* Princeton University Press.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *Journal of Finance, 19*(3), 425–442.

Soros, G. (1987). *The alchemy of finance.* Wiley.

Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. *Journal of Finance, 62*(3), 1139–1168.

Tuckett, D. (2011). *Minding the markets: An emotional finance view of financial instability.* Palgrave Macmillan.

Tuckett, D., & Taffler, R. J. (2008). Phantastic objects and the financial market's sense of reality: A psychoanalytic contribution to the understanding of stock market instability. *International Journal of Psychoanalysis, 89*(2), 389–412.

Tuckett, D., Smith, R. E., & Nyman, R. (2014). Tracking phantastic objects: A computer algorithmic investigation of narrative evolution in unstructured data sources. *Social Networks, 38*, 121–133.

Varian, H. R. (2014). Big data: New tricks for econometrics. J*ournal of Economic Perspectives, 28*(2), 3–28.

Wermers, R. (1999). Mutual fund herding and the impact on stock prices. *Journal of Finance, 54*(2), 581–622.

Zhang, Y. J., & Xiong, W. (2019). Sentiment and speculative bubbles. *Journal of Financial Economics, 134*(3), 564–590.

Yoshida, N., & Nakamura, A. (2020). Reinforcement learning in financial markets: A survey. *Finance Research Letters, 32,* 101211.

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

Lo, A. W. (2005). Reconciling efficient markets with behavioral finance: The adaptive markets hypothesis. *Journal of Investment Consulting, 7*(2), 21–44.

Baker, M., & Wurgler, J. (2007). Investor sentiment in the stock market. *Journal of Economic Perspectives, 21*(2), 129–152.

Barberis, N., Shleifer, A., & Vishny, R. (1998). A model of investor sentiment. *Journal of Financial Economics, 49*(3), 307–343.

Schiller, D., & Crew, B. (2019). Artificial intelligence in finance: Ethical and regulatory challenges. *AI & Society, 34*(2), 411–423.

Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning.* MIT Press.