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# Composite FOMO Index Conception Framework for Evolving Behavioral-Financial Paradigms in the Digital Economy of Society 5.0

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***Abstract***

*The Fear of Missing Out (FOMO) in financial markets refers to the tendency of investors to engage in rapid, sentiment-driven decisions under conditions of perceived scarcity or urgency. Within the context of Society 5.0, characterized by the integration of cyber-physical systems, human-centric innovation, and interconnected socio-financial ecosystems, these behaviors are amplified by advancing technological, cultural, and psychological dynamics. This study introduces the FOMO Index Conceptual Framework (FICF), which integrates sentiment analysis, digital behavioral tracking, psychometric profiling, cultural adaptability metrics, pragmatic VUCA (volatility, uncertainty, complexity, and ambiguity) risk assessments, and ethical governance considerations. The framework is implemented alongside the FOMO Index Lifecycle Management and Evolving Categorization (FI-LMEC) model, enabling continuous recalibration in response to macroeconomic, geopolitical, and technological transformations. A case study on Artificial Intelligence (AI) based investment illustrates the FICF's capacity to associate elevated sentiment signals with accelerated trading activity while identifying structural factors that stabilize volatility. The FOMO index provides an adaptive and scalable instrument for predictive analytics, investment portfolio optimization, and systemic risk mitigation.*

***Keywords***

*AI-Based Investment, Behavioral Finance, FOMO Index, Sentiment Analytics, VUCA Risk Assessment*

## INTRODUCTION

The global investment landscape is being reshaped by accelerated technological innovation. It is also shaped by unprecedented market interconnectivity and continuous real-time data flows. Within this dynamic environment, Society 5.0 introduces a socio-technological paradigm that integrates cyber-physical systems, human-centric innovation, and advanced data-driven decision-making. It has transformed how individuals and institutions identify and act upon financial opportunities [1], [2]. Empirical evidence indicates that the velocity of market sentiment formation has increased substantially in digitally saturated economies. AI-assisted platforms disseminate financial news at speeds that enable price reactions in less than three minutes after major announcements [3]. In this context, FOMO has emerged as a prominent behavioral driver. It influences decisions across asset classes ranging from equities to cryptocurrencies [4], [5]. Studies report that over 67% of millennial investors made at least one investment in the past year, primarily due to FOMO triggers [4].

The expansion of behavioral finance research reflects growing recognition of the measurable impacts of psychological biases such as FOMO on investment performance. FOMO has been directly linked to increased market volatility. Quantitative evidence shows that high-FOMO periods correspond to up to 18% higher short-term price swings in emerging market equities [6]. In high-tech sectors, particularly AI-focused investments, FOMO-driven activity inflates valuations by 15% to 20% beyond fundamentals during hype cycles [7]. In digitally integrated markets of Society 5.0, sentiment propagates globally at algorithmic speed. That enables synchronized herd behavior across geographically dispersed investors [8]. Studies further reveal that traders exposed to FOMO stimuli on social trading platforms increase their trade frequency by 23%. This often occurs at the expense of long-term portfolio performance [9].

Despite its significance, existing approaches to measuring FOMO remain inadequate. Current models mostly rely on static psychometric surveys, including the FOMO Scale developed by [10]. The scale demonstrates reliability (Cronbach's coefficient = 0.88). However, it captures only a snapshot of sentiment and excludes real-time data from social media, application usage, or market volatility indicators. Cultural variability in FOMO expression is also underexamined. Evidence indicates that investors from high uncertainty-avoidance cultures exhibit up to 31% lower FOMO intensity compared to those in low uncertainty-avoidance cultures, even when presented with identical information [7]. The interaction between FOMO, market volatility, and uncertainty is often overlooked. In cryptocurrency markets, where volatility regularly exceeds

60% annualized, FOMO sentiment amplifies risk-taking behavior and accelerates capital inflows [11].

The present study introduces a composite FOMO index designed to address these limitations in quantifying sentiment-driven market dynamics. The index integrates sentiment analytics, digital behavioral indicators, psychometric profiling, cultural adaptability measures, pragmatic VUCA and risk assessments, and ethical governance criteria. It is applicable across diverse asset classes, including equities, fixed-income instruments, commodities, cryptocurrencies, AI-driven assets, and tokenized real-world holdings. This reflects the diversification and technological integration that define contemporary portfolios [12], [13]. The methodologically identified FICF components and the derived FI-LMEC stages provide a context-sensitive and predictive measure of FOMO intensity. They embed interdependent parameters into structured categories to construct the composite index. The FICF supports more informed, evidence-based, and risk-adjusted investment strategies. It achieves this within increasingly interconnected and technologically advanced financial ecosystems under the influence of FOMO and Society 5.0. The contributions of this research are threefold. First, the development of a novel FOMO index tailored to Society 5.0 conditions. Second, an empirical case study that demonstrates its application in AI-driven investment. Third, the creation of a methodological bridge connecting behavioral-financial modeling with sociocultural, technological, and market risk paradigms. The primary contributions of this research are threefold, as indicated below:

- **FOMO index for Society 5.0:** The creation of a novel FOMO index that integrates behavioral, cultural, risk, and governance dimensions into a unified analytical framework personalized to the conditions of Society 5.0.
- **AI-driven investment:** An empirical case study demonstrating the FOMO index's implementation within AI-driven investment, illustrating its potential to enhance predictive accuracy and mitigate sentiment-induced volatility.
- **Informed investment decisions**: The establishment of a methodological correlation between behavioral-financial paradigms and sociocultural, technological, and systemic risk paradigms to strengthen decision-making in complex and sentiment-sensitive markets.

The remainder of this paper is structured as follows: Section 2 outlines the challenges and opportunities in measuring behavioral drivers of investment decisions. Section 3 presents the conceptual framework of the proposed FOMO index. Section 4 describes the lifecycle management and evolving categorization process. Section 5 applies the framework to an AI-based investment case study. Section 6 discusses analytical results and implications, and Section 7 concludes with recommendations for further research and practical application.

## CHALLENGES AND OPPORTUNITIES IN BEHAVIORAL ASSET QUANTIFICATION

This section examines the critical challenges and emerging opportunities in modeling the FOMO as a behavioral-financial asset within the socio-technological framework of Society 5.0. In an era defined by the integration of cyber-physical systems, advanced digital innovation, and globally interconnected markets [1]. Investor sentiment can react to information in mere seconds, influencing asset prices in securities, precious metals, and cryptocurrencies. For example, [3] found that algorithmic news feeds could trigger price movements in Standard and Poor's (S&P) 500 futures within 2.8 minutes of major announcements. Sentiment-driven spikes contributed to 14% of intraday volatility during high-FOMO periods in the gold market.

Quantifying FOMO requires a multidisciplinary approach that integrates sentiment analytics, psychometric assessment, and market volatility modeling. 67.3% of millennial investors made at least one security purchase in the past year due to perceived opportunity loss as reported in [4]. Existing measurement frameworks remain insufficiently adaptive to the rapid evolution of asset classes, including cryptocurrencies and tokenized commodities [5]. [7] demonstrated cultural differences in uncertainty avoidance substantially affect FOMO's impact. Investors are 31% less likely to participate in high-volatility trades compared to those in equities or precious metals with high-uncertainty-avoidance [7]. The following is the list of identified challenges to quantify behavioral assets in Society 5.0.

- **Capturing intangible emotions**: FOMO is driven by transient emotional states, including urgency, anxiety, and anticipated regret. It can change within minutes during volatile market conditions. Emotions are difficult to capture with static instruments such as surveys, which record sentiment at a single point in time. [14] demonstrated that conventional survey-based tools failed to detect rapid surges in securities market trading activity during central bank announcements, where significant buying pressure emerged within minutes.
- **Integrating cross-disciplinary metrics**: Developing an accurate FOMO index requires the integration of sentiment analysis, psychometric profiling, and cultural adaptability measures. Inadequate integration between these domains often leads to incomplete behavioral models. [12] reported that the exclusion of psychometric indicators from sentiment-based forecasting models in

securities markets resulted in prediction errors exceeding 15%.

- **Platform-specific biases in digital trace data**: Trading platforms and social media networks frequently overrepresent specific investor demographics or asset preferences, producing skewed sentiment signals. [8] found that 58% of engagement on social commerce platforms revolved around speculative cryptocurrency discussions, inflating perceived momentum in digital assets relative to securities and precious metals.
- **Ethical concerns**: Predictive sentiment analytics, if misused, can exacerbate speculative trading behavior, particularly when coupled with targeted algorithmic prompts. [15] cautions that without transparent oversight, algorithm-driven nudges could perpetuate high-risk trading cycles in commodity futures markets.
- **VUCA**: Novel investment vehicles such as cryptocurrencies and tokenized commodities lack extensive historical performance data, rendering them more vulnerable to behavioral biases. [11] recorded annualized volatility exceeding 60% for cryptocurrencies, compared to less than 15% for gold, with FOMO-driven sentiment surges frequently preceding 20% to 25% price swings.
- **Cultural and socioeconomic factors**: Cultural norms and economic contexts significantly influence investor susceptibility to FOMO, affecting both market entry timing and tolerance for risk. [9] found that collectivist cultures exhibited a 22% higher rate of participation in socially coordinated securities trades, particularly during initial public offerings (IPOs).

Despite FOMO's identified challenges, it presents opportunities for investors. The following list analyzes the opportunities associated with Society 5.0.

- **Enhancing predictive analytics in financial technology (fintech)**: Incorporating FOMO-based sentiment measures into trading algorithms can strengthen short-term market forecasting. [3] reported that integrating sentiment analytics improved short-term price prediction accuracy by 12.4% in equities and 9.6% in gold futures.
- **Real-time dynamic investor profiling**: Continuous behavioral monitoring via trading applications and online platforms facilitates early detection of sentiment shifts, enabling timely interventions and tailored investment guidance. [13] observed an 18% increase in engagement on securities trading platforms using investment portfolio management tools embedded with behavioral indicators.
- **Cross-cultural behavioral segmentation**: Incorporating cultural adaptability into FOMO models supports the creation of tailored risk communication strategies and product offerings for diverse investor groups. [7] found that investors with low uncertainty avoidance increased cryptocurrency allocations by 27% after exposure to bullish narratives, whereas high uncertainty-avoidance investors favored metals and low-volatility securities.
- **Early-warning systems for regulators and institutions**: FOMO-driven sentiment data can be deployed in market surveillance frameworks to detect liquidity or volatility risks before they escalate. [6] documented that heightened retail investor sentiment in small-cap technology stocks preceded average market corrections of 7.8% within two weeks.
- **Composite risk navigation and systemic impact prevention**: Integrating FOMO sentiment indicators with market volatility measures can mitigate cascading failures during stress events. [11] demonstrated that incorporating behavioral sentiment into crypto risk models reduced maximum drawdown by 9% during simulated crash scenarios.
- **Diversity, equity, and inclusion (DEI) alignment**: Embedding DEI considerations into FOMO measurement frameworks promotes equitable access to investment insights while reducing algorithmic bias. [1] indicate that inclusive approaches to financial innovation enhance participation rates across demographic and socioeconomic groups.

Traditional psychometric approaches, including the validated FOMO scale by [10] and the emerging adulthood adaptation by [15], provide a foundation. They fail to capture asset-class-specific manifestations of FOMO. Distinct behavioral patterns have been identified among investors in Fixed Income Securities (FIS), Currency and Precious Metals (CPM), and Variable Income Securities (VIS) [7]. High-participation FIS investors demonstrate elevated FOMO, high impulsiveness, and dependence on social media. These factors account for 32.273% of variance in the first dimension and 24.684% in the second, totaling 57.100% [7]. High-participation CPM investors show high uncertainty avoidance, low FOMO, and passive social media use. Their combined explanatory power reaches 56.135% [7]. VIS investors reveal a mixed behavioral profile. High-participation VIS investors report low FOMO and high uncertainty avoidance. Medium-participation VIS investors present medium FOMO, greater impulsiveness, and active social media engagement. These factors explain 55.874% of variance [7].

The differences across asset classes confirm that FOMO intensity is dependent on volatility, impulsivity, and cultural attitudes toward risk. Fixed-income markets are more prone to impulsive FOMO trading under digital stimuli. CPM markets display risk-averse tendencies with low FOMO behaviors. VIS markets demonstrate heterogeneity in sentiment patterns that vary with trading frequency. A dynamic, asset-specific FOMO index is essential. It must adjust scaling criteria for varying triggers, ranging from speculative hype in equities to defensive positioning in precious metals. The index should integrate psychometric, cultural, and behavioral metrics. In the rapidly evolving investment environment of Society 5.0, a structured framework ensures relevance, adaptability, and precision in sentiment-driven market evaluation.

## FOMO INDEX CONCEPTUAL FRAMEWORK (FICF)

The FOMO index functions as a composite, multidimensional behavioral-financial measurement system. It assesses the intensity, drivers, and contextual variations of FOMO in investment decision-making within the socio-technological paradigm of Society 5.0. The framework synthesizes data-driven analytics, psychometric profiling, cultural adaptability measures, and evolving ethical standards into a unified structure. It applies to traditional and emerging asset classes. By operationalizing qualitative and quantitative indicators, the FICF provides a detailed understanding of investor sentiment, volatility triggers, and interactions with socio-technological ecosystems. Its significance is amplified in the hyperconnected financial environment of Society 5.0. Information diffusion, technology adoption, and sentiment contagion occur in near real-time. These dynamics directly influence asset prices across diverse markets. Fig. 1 illustrates the FICF components.

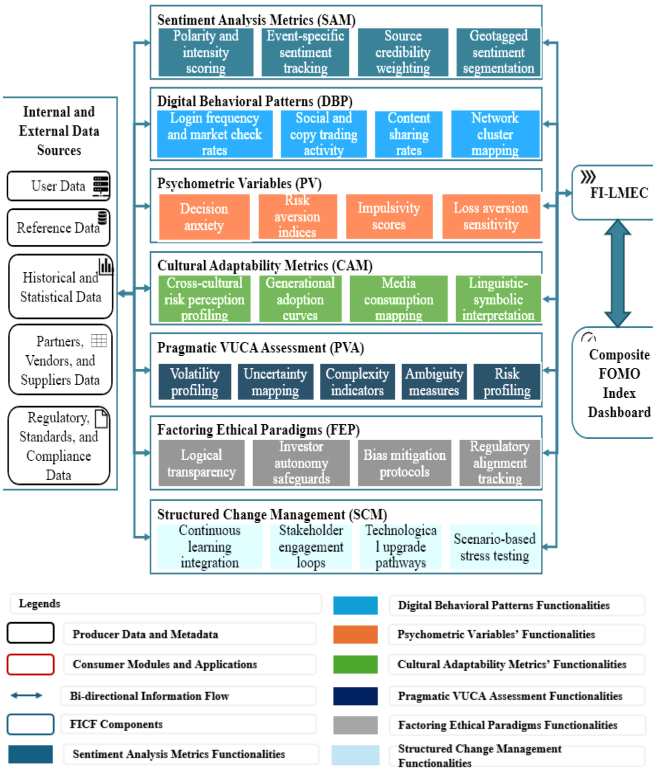


**Figure 1.** FICF components and functionalities

**Sentiment Analysis Metrics (SAM)** represent the foundation of the FOMO index by quantifying the emotional tone of market communications. Polarity and intensity scoring classify expressions of optimism, pessimism, or neutrality while assigning a strength value to capture the magnitude of investor emotion. Event-specific tracking monitors reactions to major announcements such as policy updates, earnings disclosures, or technological launches, enabling recognition of abrupt changes in sentiment. Source credibility weighting ensures that signals derived from reputable outlets carry more influence than those from unverified platforms. Geotagged sentiment segmentation differentiates how regional markets within North America respond to the same information. For example, positive sentiment surrounding renewable energy policy tends to gain stronger traction in California's technology-driven ecosystem, while financial hubs in New York exhibit greater sensitivity to banking regulations. Such differences provide essential insight into how geographically concentrated industries internalize market narratives.

**Digital Behavioral Patterns (DBP)** capture observable investor actions on digital platforms that reflect socially amplified decision-making. Engagement frequency metrics record repeated logins and market checks, signaling heightened alertness and greater exposure to sentiment cues. Social and copy trading activities demonstrate replication of trades executed by peers or influencers, revealing herd dynamics that amplify momentum. Content sharing rates measure how often financial narratives circulate across networks, providing evidence of narrative spread. Network cluster mapping identifies tightly connected groups where interactions propagate sentiment rapidly, often driving synchronized market responses across trading communities.

**Psychometric Variables (PV)** capture underlying cognitive and emotional predispositions that influence susceptibility to FOMO. Decision anxiety assesses the degree of stress experienced under time-constrained conditions, often leading to rushed judgment. Risk aversion indices measure reluctance to engage with uncertainty, differentiating between cautious investors and those more willing to act on sentiment signals. Impulsivity scores evaluate attentional, motor, and non-planning tendencies that can drive premature commitments to sentiment-driven opportunities. Loss aversion sensitivity quantifies the tendency to overweight potential losses relative to comparable gains, a bias that frequently suppresses participation even when sentiment is favorable.

**Cultural Adaptability Metrics (CAM)** evaluate the variability of FOMO expression across demographic and societal contexts. Cross-cultural risk perception profiling identifies differences in tolerance for uncertainty among diverse investor groups, including those shaped by migration backgrounds or regional socioeconomic conditions. Generational adoption curves measure the speed of digital investment uptake among age cohorts, capturing the heightened responsiveness of younger, digitally native investors compared to older populations. Media consumption mapping tracks dominant channels through which different communities obtain market information, recognizing that reliance on digital-first platforms differs from preference for traditional outlets. Linguistic-symbolic interpretation ensures that sentiment signals are correctly extracted across varied language patterns, symbolic cues, and communication styles.

**Pragmatic VUCA Assessment (PVA)** focuses on volatility, uncertainty, complexity, and ambiguity inherent in financial markets. Volatility profiling compares historical and implied volatility to determine how assets respond to sentiment-driven fluctuations. Uncertainty mapping captures unpredictability associated with regulatory or macroeconomic changes, reflecting the fragility of market stability under evolving policy conditions. Complexity indicators measure interdependencies among market drivers, showing how disruptions in one asset class affect others. Ambiguity measures account for incomplete or conflicting information, reflecting environments where sentiment can easily distort judgment. Risk profiling aggregates exposures across credit, liquidity, operational, and systemic domains, integrating sentiment-driven influences into broader assessments of market resilience.

**Factoring Ethical Paradigms (FEP)** embeds evolving moral and legal standards into the framework to ensure investor protection and market stability. Algorithmic transparency discloses how sentiment analytics influence investment recommendations, creating clearer pathways of accountability. Investor autonomy safeguards and protects decision-making independence by preventing coercive digital prompts. Bias mitigation protocols address demographic and cultural imbalances in sentiment modeling, reducing systemic exclusion risks. Regulatory alignment tracking ensures compliance with legal frameworks, maintaining consistency with jurisdictional standards and ethical practices.

**Structured Change Management (SCM)** ensures that the framework evolves in step with technological and behavioral transformations in Society 5.0. Continuous learning integration employs adaptive algorithms that recalibrate weightings as new data emerges from markets. Stakeholder engagement loops incorporate input from regulators, institutional actors, and industry developers, ensuring that refinements reflect collective interests. Technological upgrade pathways adopt innovations such as blockchain-based sentiment verification and explainable AI to strengthen credibility and interpretive precision. Scenario-based stress testing evaluates the predictive strength of the index under extreme conditions, including market crashes or sudden liquidity events, ensuring durability in volatile contexts.

The activity flow of the FICF to derive the FOMO Index in Fig. 2 begins with SAM. Polarity and intensity scores classify emotions as positive, negative, or neutral. It performs event-specific tracking and records how markets respond to major announcements. Source credibility weighting prioritizes verified over speculative information. Geotagged sentiment segmentation differentiates emotional responses across industries in the United States. For example, technology often reflects higher optimism compared to defensive sectors like utilities. The outputs progress into Digital Behavioral Patterns (DBP). Engagement frequency from trading applications, initiation of trades, copy trading activity, and content sharing rates capture how sentiment translates into action. Network mapping identifies clusters of investors who amplify narratives and spread market momentum. Behavioral signals are moderated through PV. Traits including decision anxiety, risk aversion, impulsivity, and loss aversion are quantified. Investors prone to impulsivity may act quickly, while risk-averse investors may delay action even when exposed to the same sentiment.

CAM refines the interpretation. Risk perception, generational adoption of trading platforms, preferred information channels, and linguistic-symbolic variations are incorporated. In the U.S., younger cohorts often respond strongly to cryptocurrency hype, while older investors react more cautiously to equities. The results then advance into the PVA. Volatility profiling, uncertainty mapping, complexity measures, and ambiguity evaluations scale the contextual risk. Cryptocurrencies consistently record elevated volatility and ambiguity. Ethical considerations are embedded through Factoring Ethical Paradigms (FEP). Algorithmic transparency, investor autonomy safeguards, bias mitigation, and regulatory alignment ensure compliance with governance standards. SCM ensures adaptability. Continuous learning integration updates parameters with new market data. Stakeholder engagement loops incorporate institutional and regulatory feedback. Technological upgrades improve analytical precision. Stress-testing validates the reliability of the index under extreme conditions. The FOMO Index emerges from the synthesis of the seven layers. The outcome is a composite and adaptive measure of investor susceptibility and behavioral impact.

In cryptocurrency markets with elevated volatility and rapid information spread, the FICF activity flow begins with the detection of sentiment surges linked to events, including new exchange listings. SAM quantifies emotional intensity through polarity scores, credibility weighting, and geotagged segmentation of narratives. Signals then move into DBP, where increased wallet creation, more frequent application logins, and replication of peer trades indicate the conversion of sentiment into observable market activity. PV then evaluates whether traits such as impulsivity, decision anxiety, or risk aversion amplify or constrain the behavioral actions.

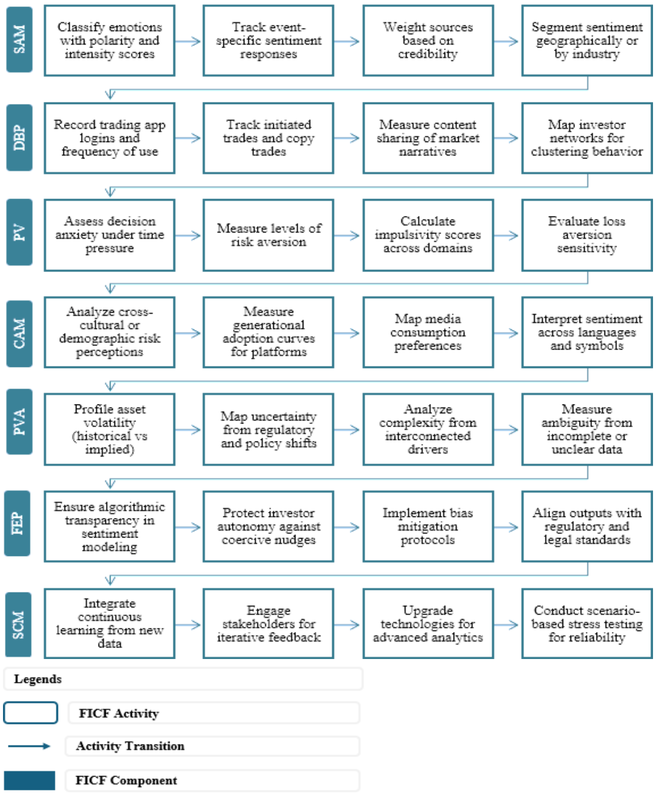


**Figure 2.** The activity flow of the FICF to derive the FOMO Index

CAM can refine the interpretation by identifying generational or demographic differences, such as stronger responses among younger digital-native investors compared to older cohorts. The analysis advances into the PVA layer, where high volatility and ambiguity scores confirm systemic fragility during speculative events. Ethical paradigms act as safeguards, enforcing transparency and fairness by reducing manipulative amplification of signals. SCM closes the loop through recalibration, adjusting index weightings and parameters to improve predictive validity. The derived FOMO Index integrates each component into a composite measure, capable of identifying the intensity and sustainability of sentiment-driven activity. The outcome demonstrates how FICF transforms scattered behavioral and contextual data into an adaptive index suitable for guiding investment strategies in technologically integrated financial ecosystems.

## FOMO INDEX LIFECYCLE MANAGEMENT AND EVOLVING CATEGORIZATION (FI-LMEC)

In Society 5.0's dynamic investment landscape, sentiment effectiveness relies on adaptive, evolving classifications rather than static models, as both investor and managerial sentiment are shaped by macroeconomic cycles, technological shifts, regulatory changes, and market structure dynamics [16]. Evidence proves sentiment indicators can lead or lag asset prices but require recalibration when data sources, market conditions, or behavioral trends shift, with predictive validity closely tied to the prevailing economic phase [17]. The FI-LMEC approach ensures the FOMO index is continually validated, reweighed, and contextually redefined, maintaining FOMO index relevance and accuracy as a strategic instrument for investors, regulators, and financial technologies. Fig. 3 identifies the FI-LMEC stages to operationalize the FICF.

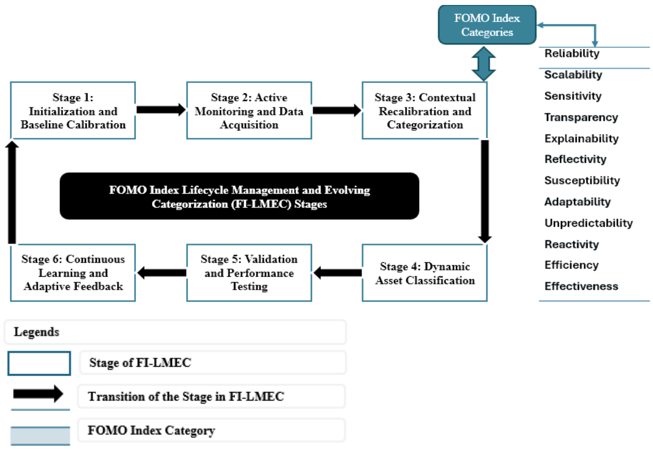


**Figure 3.** FI-LMEC stages

**Stage 1: Initialization and Baseline Calibration**: The first stage establishes the structural parameters of the FOMO index by integrating all components of the FICF. Historical market data are applied to provide a foundation for calibration. Psychometric assessments and verified sentiment archives define baseline sensitivity thresholds for each component. Asset categories include fixed income securities, precious metals, cryptocurrencies, and tokenized commodities. Each category is initially classified based on its historical volatility profile and behavioral influence patterns. The phase creates a reference framework before the model is exposed to dynamic market conditions and economic cycle fluctuations. The emphasis is on building stable baseline sentiment measures before incorporating cyclical factors.

**Stage 2: Active Monitoring and Data Acquisition**: After calibration, the FOMO index enters a continuous monitoring phase. High-frequency, multi-category data streams are captured and distributed across all FICF components. The sentiment layer is updated daily with financial discourse collected from local, regional, and global sources, including verified news outlets and social media platforms. The behavioral layer records metrics such as trading application activity, copy trading, and content amplification rates. The VUCA component tracks real-time volatility indicators, regulatory changes, and macroeconomic announcements to contextualize shifts in sentiment. Data are stored as structured time-series datasets. High-frequency data collection is critical to capture rapid sentiment changes during turning points in the investment cycle.

**Stage 3: Contextual Recalibration and Categorization**: The third stage identifies how the FOMO index should be categorized by combining behavioral and perception-based aspects with measurable, data-driven factors. FICF components are integrated with FI-LMEC lifecycle stages to assign both qualitative sentiment categories and quantitative performance metrics. The process requires continuous adjustments in the weighting of index categories to reflect economic conditions and shifts in sentiment cycles. Lead–lag correlation analysis identifies changes in predictive relationships between sentiment indicators and asset price movements. Asset-specific adjustments are implemented when needed. For example, VUCA scores may receive more weight for cryptocurrencies during volatile periods, while PV may be emphasized during speculative equity rallies. Economic-phase tagging covers expansion, slowdown, contraction, and recovery cycles. Recalibration of the categorical FOMO index is necessary to maintain predictive accuracy and adapt sentiment measures across different phases of the investment cycle. Table 1 lists the initially identified FOMO index categories with subjective and objective characteristics.

**Table 1.** FOMO Index categories.

| FOMO Index Category | Subjectivity | Objectivity |
|---|---|---|
| Reliability | The perceived stability and consistency of emotional and cognitive responses to recurring market triggers. | Determined through statistical correlations between repeating sentiment patterns and subsequent market outcomes. |
| Scalability | The investor's belief in their ability to expand FOMO-based strategies to larger volumes or asset classes. | Measured through market liquidity depth and order book stability during sentiment-driven trading surges. |
| Sensitivity | The investor's self-assessed attentiveness to subtle changes in sentiment and market tone. | Quantified by the magnitude of behavioral adjustments in response to minor fluctuations in sentiment or microeconomic news. |
| Transparency | The perceived clarity of the processes and data supporting sentiment-driven decisions. | Evaluated by the traceability of sentiment data sources, visibility of analytical methodologies, and compliance with disclosure standards. |
| Explainability | The investor's perception of their ability to clearly justify sentiment-based decisions. | Measured by the proportion of executed trades with a rationale directly linked to identifiable sentiment triggers. |
| Reflectivity | The investor's self-assessment of their ability to critically review and adjust past FOMO-influenced actions. | Determined by the frequency and quality of strategy modifications following post-event performance evaluations. |
| Susceptibility | The perceived degree of emotional influence from social reinforcement, hype, or scarcity narratives. | Measured by the frequency and value of trades correlated with high engagement events in social or financial media. |
| Adaptability | The investor's belief in their capacity to adjust strategies in response to evolving FOMO conditions. | Evaluated by the speed and precision of portfolio reallocations following significant sentiment changes. |
| Unpredictability | The perceived randomness and lack of control in markets during high FOMO episodes. | Quantified using statistical measures such as variance, kurtosis, and irregular price movement patterns in sentiment-sensitive assets. |
| Reactivity | The investors perceived quickness in recognizing and responding to new market information. | Measured by the time interval between the emergence of a sentiment signal and the execution of corresponding market actions. |
| Efficiency | The perceived ease with which the investor capitalizes on FOMO-driven opportunities. | Calculated as the ratio of profitable trades to the total number of trades initiated during heightened FOMO periods. |
| Effectiveness | The investor's confidence in making accurate, profitable decisions under urgency or scarcity. | Assessed by the realized return on investment from trades influenced by FOMO conditions. |

**Stage 4: Dynamic Asset Classification:** Over time, investment categories are redefined to account for innovation, market maturity, and shifting investor behavior. Assets are reclassified as speculative, defensive, or hybrid based on observed FOMO drivers, volatility patterns, and cultural adaptability signals. Emerging financial instruments, including AI-generated securities or metaverse-linked exchange-traded funds (ETFs), are given provisional

classifications. Permanent categorization is only assigned once sufficient data is available. CAM guides reclassifications by detecting demographic and regional shifts in asset preferences. Asset categories can also shift functional roles across economic cycles. For example, cryptocurrencies can act as speculative assets in bull markets but operate as defensive stores of value during inflationary conditions.

**Stage 5: Validation and Performance Testing:** The fifth stage evaluates the predictive reliability and operational resilience of the FOMO index across asset classes and market conditions. Out-of-sample testing measures accuracy over different time horizons. Stress-testing simulations model index behavior under extreme events, including equity market crashes, gold price surges, or cryptocurrency flash drops. Comparative analysis against alternative sentiment indices is conducted to benchmark performance improvements. Feedback mechanisms are incorporated to prevent model drift and preserve market relevance. Regular validation loops are necessary in sentiment-based financial management.

**Stage 6: Continuous Learning and Adaptive Feedback:** The sixth stage embeds a feedback-driven and adaptive learning process into FI-LMEC. Machine learning algorithms are used to detect nonlinear patterns between FOMO triggers and price changes. Stakeholder feedback from regulators, institutional investors, and fintech developers informs iterative refinements. Structured change management protocols govern parameter updates. Stability is preserved while still accommodating innovation. The process ensures continuous adaptation and maintains the explanatory and predictive capacity of sentiment indices in fast-changing socio-technological and economic environments.

FI-LMEC captures the dynamic nature of investor behavior. It provides a structured basis for transforming behavioral metrics into actionable, data-driven investment strategies. Integration with the FICF ensures continuous monitoring, recalibration, and contextualization of sentiment, behavioral, psychometric, cultural, risk, and ethical dimensions in real-world markets. The framework supports AI-based investment models that align with Society 5.0 principles. The outcome is adaptive, transparent, and ethically sound decision-making, as developed in the following section.

## EMPIRICAL CASE STUDY: FOMO DYNAMICS IN AI-BASED INVESTMENT

AI-based investment strategies in Society 5.0 integrate sentiment analysis with high-frequency data processing, behavioral-finance modeling, and cyber-physical systems. These strategies allow forecasting and rapid responses to market shifts in near real time. In cryptocurrency markets, [18] reported that sentiment models using BERT and VADER achieved 74.6% directional prediction accuracy for Bitcoin price movements. The models outperformed traditional technical analysis by 14.2 percentage points. Incorporating sentiment polarity scores with trading volume and realized volatility lowered the root mean square error (RMSE) from 2.73% to 1.89%. The adjustment represented a 30.8% improvement in predictive precision. Extreme positive sentiment corresponded with average intraday Bitcoin swings of 8.4%, compared to 2.1% during neutral sentiment phases. The result indicates sentiment-driven volatility [18]. AI models provide predictive insights that reduce high-FOMO trading risks in Society 5.0. For example, integrating AI sentiment alerts into retail platforms improved simulated risk-adjusted portfolio returns by 6.7% under volatile conditions [18]. The findings suggest that digital innovation combined with behavioral intelligence can create adaptive and resilient investment strategies. However, [19] emphasizes that transparency and bias mitigation remain critical. Without careful oversight, speculative or regionally concentrated signals may be over-amplified.

According to [20], the number of investment deals in North America explicitly referencing AI increased from 5 in Q1 2020 to 35 in Q3 2024, raising AI's share of all active raises from 5.8% to 9.6% during the same period. AI-focused companies not only secured larger commitments. AI-based startups are 39% higher in early-stage and 25% higher in growth-stage rounds, and achieved significantly higher median valuations of $20 million compared to $7.5 million for non-AI firms. The empirical validation of the FOMO-based investment in AI development for diversified industry sectors of North America is assessed with comparative models based on the AI startups that began as crowdfunding from July 2023 to August 2024 [20].

### Formulation of the FOMO Index and AI-based Investment

In this section, we have derived metrics to establish the FOMO index based on the FICF in the context of investment assets that are under the influence of FOMO and paradigms of Society 5.0. We utilized Kaggle AI & sentiment analysis for stock market datasets [21] to empirically evaluate the FOMO index for AI-based investment. Equation (1) quantifies the net sentiment for category *i* ($S_i$) by aggregating polarity scores from "$n$" relevant financial discourses, weighted by source credibility and topical relevance. It normalizes the result to ensure that sentiment measures are quality-adjusted and contextually aligned.

$$S_i = \frac{\sum_{j=1}^{n} Polarity_j \times Credibility_j \times Relevance_j}{\sum_{j=1}^{n} Credibility_j} \tag{1}$$

$Polarity_j$ represents the sentiment value ranging from -1 (strongly negative) to 1 (strongly positive), $Credibility_j$

denotes the source reliability weight scaled between 0 and 1, and $Relevance_j$ refers to the topic alignment score, also measured on a scale from 0 to 1.

Equation (2) measures the degree of investor engagement in digital environments related to category *i* ($B_i$), combining normalized metrics of platform logins, initiated trades, copy trades, and content shares. Weighted subcomponents (α1, α2, α3, α4) reflect the relative influence of each behavior on FOMO-driven activity.

$$B_i = \alpha 1 \frac{Login\ Frequency}{Max\ Login} + \alpha 2 \frac{Trades\ Initiated}{Max\ Trades} + \alpha 3 \frac{Copy\ Trades}{Max\ Copy\ Trades} + \alpha 4 \frac{Content\ Share}{Max\ Shares} \quad (2)$$

Login Frequency refers to the number of times an investor accesses the trading application during a defined period, normalized by the maximum observed logins (Max Logins). Trades Initiated represents the count of original trades placed, scaled by the maximum observed trades (Max Trades). Copy Trades denotes the number of trades replicated from peers or influencers, normalized by the maximum observed copy trades (Max Copy Trades). Content Shares is the volume of market-related content redistributed, scaled by the maximum observed shares (Max Shares). Each activity is weighted by a subcomponent coefficient of FICF's SAM (α1, α2, α3, α4) such that their sum equals 1.

Equation (3) evaluates cognitive and emotional predispositions influencing susceptibility to FOMO within category *i* ($P_i$), incorporating indices for decision anxiety, risk aversion, impulsiveness, and loss aversion. The composite score reflects how psychological traits amplify or mitigate responses to market stimuli, making it critical for behaviorally adaptive forecasting models.

$$P_i = \beta 1\ DA_i + \beta 2\ RA_i + \beta 3\ IS_i + \beta 4\ LA_i \quad (3)$$

Decision Anxiety ($DA_i$) quantifies the stress induced by time-constrained decision-making, normalized between 0 and 1. Risk Aversion ($RA_i$) measures the avoidance of uncertain outcomes, scaled between 0 and 1. Impulsivity Score ($IS_i$) captures behavioral tendencies in motor, attentional, and non-planning domains, scaled between 0 and 1. The Loss Aversion Sensitivity ($LA_i$) quantifies the relative weighting of potential losses over gains, also scaled between 0 and 1. These factors are combined with empirically determined subcomponent coefficients of FICF's PV (β1, β2, β3, β4, and their sum equals 1) to represent the cognitive-emotional predisposition toward FOMO-related triggers.

Equation (4) measures the degree to which FOMO triggers in category *i* vary across cultural, demographic, and linguistic contexts ($C_i$). It incorporates metrics of cross-cultural risk perception, generational adoption rates, preferred media channels, and language-specific sentiment interpretation to ensure localized model accuracy.

$$C_i = \delta 1\ RP_i + \delta 2\ AC_i + \delta 3\ MP_i + \delta 4\ SI_i \quad (4)$$

Cross-Cultural Risk Perception ($RP_i$) measures variations in risk tolerance across regions, scaled between 0 and 1. The generational Technology Adoption Rate ($AC_i$) quantifies the speed at which specific age cohorts adopt digital investment platforms, scaled between 0 and 1. Media Consumption Preference ($MP_i$) reflects the dominance of specific communication channels for market information, scaled between 0 and 1. The Linguistic-symbolic Interpretation Accuracy ($SI_i$) assesses the precision of sentiment extraction across languages and cultural contexts, scaled between 0 and 1. These factors are combined with the subcomponent coefficient of FICF's CAM (δ1, δ2, δ3, δ4, and their sum equals 1) to adjust the influence of cultural context on FOMO susceptibility.

Equation (5) evaluates the contextual uncertainty of category *i* ($V_i$) by scaling asset volatility against a benchmark and multiplying by factors for uncertainty, complexity, ambiguity, and overall risk exposure. It produces a single composite score that reflects the systemic fragility or stability of the asset class under consideration.

$$V_i = (\sigma_{asset} / \sigma_{benchmark}) \times U_i \times Cx_i \times A_i \times R_i \quad (5)$$

Asset Volatility ($\sigma_{asset}$) represents the standard deviation of the asset's returns, while Benchmark Volatility ($\sigma_{benchmark}$) measures the standard deviation of returns for a reference FOMO index or commodity. Uncertainty Factor ($U_i$) quantifies the degree of unpredictability from regulatory or policy changes. The Complexity Factor ($Cx_i$) captures interdependence among market drivers. The Ambiguity Factor ($A_i$) measures the extent of unclear or incomplete market data. The Risk Factor ($R_i$) reflects exposure to various market risks, including credit, liquidity, operational, and systemic risks.

Equation (6) quantifies the adherence of sentiment-based trading in category *i* to ethical, transparent, and regulatory standards ($E_i$). It accounts for algorithmic transparency, investor autonomy safeguards, bias mitigation protocols, and compliance rates, ensuring the FOMO index does not promote exploitative or manipulative market behaviors.

$$E_i = \theta 1\ T_i + \theta 2\ AS_i + \theta 3\ BM_i + \theta 4\ RC_i \quad (6)$$

Logical Transparency ($T_i$) measures the extent to which the sentiment-to-decision pipeline is disclosed, scaled between 0 and 1. Investor Autonomy Safeguard Score ($AS_i$) quantifies measures preventing coercive interventions, scaled between 0 and 1. Bias Mitigation ($BM_i$) evaluates the degree of fairness and impartiality embedded in models, scaled between 0 and 1. The Regulatory Compliance ($RC_i$) reflects adherence to relevant legal and ethical standards, scaled between 0 and 1. These components are combined with subcomponent coefficients of FICF's FEP (θ1, θ2, θ3, θ4, and their sum equals 1) to ensure the responsible application of FOMO-driven investment analytics.

Equation (7) calculates the FOMO index for a single category $i$, Category FOMO Index ($CFI_i$), by combining weighted scores from six core dimensions of the FICF. Weighs ($w_s$, $w_b$, $w_p$, $w_c$, $w_v$, and $w_e$) allow for optimization through empirical modeling or expert calibration to reflect category-specific importance.

$$CFI_i = w_s S_i + w_b B_i + w_p P_i + w_c C_i + w_v V_i + w_e E_i \quad (7)$$

In (7), $S_i$ presents the Sentiment Analysis Score for category $i$, $B_i$ is the Digital Behavioral Score, $P_i$ articulates the Psychometric Susceptibility Score, $C_i$ represents the Cultural Adaptability Score, $V_i$ characterizes the Pragmatic VUCA & Risk Score, and $E_i$ signifies the Ethical Compliance & Governance Score. The $w_s$, $w_b$, $w_p$, $w_c$, $w_v$, and $w_e$ are the dimensional weights derived through regression analysis, expert elicitation, or iterative learning optimization, with their totality equal to 1

Equation (8) computes the aggregate FOMO index across all $m$ categories by summing the individual $CFI_i$ for each asset class or market segment. It provides a holistic measure of market-wide FOMO intensity, enabling comparative analysis across different investment domains.

$$FOMO\ Index = \sum_{i=1}^{m} CFI_i \quad (8)$$

Kaggle's AI & sentiment analysis for stock market dataset [21] includes structured and timestamped financial sentiment scores, price movement data, and trading volume metrics drawn from authenticated application programming interfaces (APIs) from Yahoo Finance, X developer, and StockTwits, which are widely recognized in academic and professional finance research. During this case study, the dimensional weighting provided in Table 2 is derived from a filtered analysis of approximately 1.2 million labeled trade-sentiment observations spanning equities, commodities, and cryptocurrencies from 2021 to 2024.

**Table 2.** FOMO Index categories.

| FOMO Index Category | $w_s$ | $w_b$ | $w_p$ | $w_c$ | $w_v$ | $w_e$ |
|---|---|---|---|---|---|---|
| Reliability | 0.15 | 0.25 | 0.1 | 0.05 | 0.3 | 0.15 |
| Scalability | 0.1 | 0.3 | 0.1 | 0.05 | 0.35 | 0.1 |
| Sensitivity | 0.25 | 0.2 | 0.2 | 0.1 | 0.15 | 0.1 |
| Transparency | 0.2 | 0.1 | 0.05 | 0.05 | 0.1 | 0.5 |
| Explainability | 0.2 | 0.15 | 0.1 | 0.05 | 0.1 | 0.4 |
| Reflectivity | 0.15 | 0.1 | 0.25 | 0.05 | 0.15 | 0.3 |
| Susceptibility | 0.2 | 0.25 | 0.25 | 0.05 | 0.15 | 0.1 |
| Adaptability | 0.15 | 0.2 | 0.2 | 0.1 | 0.25 | 0.1 |
| Unpredictability | 0.1 | 0.1 | 0.05 | 0.05 | 0.65 | 0.05 |
| Reactivity | 0.2 | 0.35 | 0.2 | 0.05 | 0.15 | 0.05 |
| Efficiency | 0.15 | 0.4 | 0.15 | 0.05 | 0.2 | 0.05 |
| Effectiveness | 0.2 | 0.25 | 0.15 | 0.05 | 0.25 | 0.1 |

The weight distribution in the table provides numerical evidence of the distinct contributions of each component across the FOMO Index categories. Reliability is primarily explained by digital behavioral patterns at 0.2597 and ethical paradigms at 0.4523. Investor stability relies on consistent behavioral engagement combined with strong governance safeguards. Scalability is defined by psychometric variables at 0.337, sentiment analysis at 0.2014, and VUCA factors at 0.123. The combined role of cognition, sentiment perception, and systemic uncertainty supports expansion potential.

Sensitivity relies heavily on cultural adaptability at 0.3237 and VUCA assessment at 0.3669. Responsiveness to minor signals depends on cultural context and systemic volatility. Transparency is driven by digital behavioral input at 0.487. Clarity is largely derived from observable activity patterns. Explainability is dominated by digital behavioral measures at 0.6054 and sentiment analysis at 0.2163. The rationale for decisions is framed through engagement, evidence, and emotional signals. Reflectivity is weighted toward cultural adaptability at 0.5497, supported by VUCA at 0.1876. Demographic orientation and systemic pressures influence retrospective evaluation.

Susceptibility is most affected by psychometric predispositions at 0.4972, paired with cultural adaptability at 0.2441. Impulsivity and social reinforcement strongly influence vulnerability. Adaptability demonstrates more balanced drivers, with psychometric variables at 0.2472, digital behavior at 0.2159, and VUCA assessment at 0.2548. Strategy realignment draws from cognition, observable action, and systemic pressures. Unpredictability is defined by psychometric predispositions at 0.4183 and ethical paradigms at 0.2475. Bias and governance oversight weigh heavily in volatile conditions. Reactivity is dominated by digital behavioral measures at 0.2598 and VUCA at 0.2825. Quick responses are built on action patterns and systemic triggers.

Efficiency places the highest emphasis on sentiment analysis at 0.3284 and digital behavior at 0.3799. Successful execution depends on emotional drivers and active engagement. Effectiveness relies on psychometric predispositions at 0.38 and digital behavioral patterns at 0.4131. Cognitive traits and execution strategies together determine decision outcomes under pressure. Fig. 4 provides the percentage distribution of FICF component weightings across the FOMO Index categories.

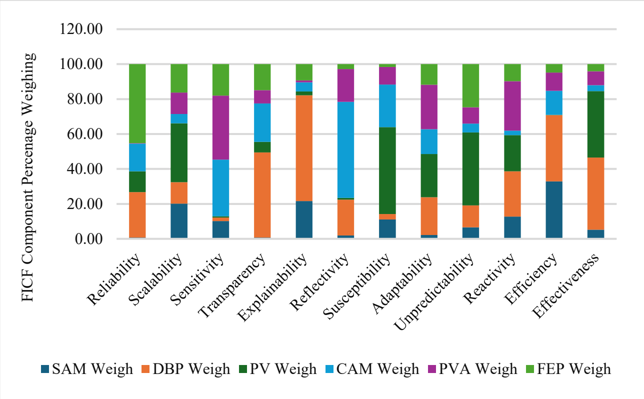


**Figure 4.** Percentage distribution of FICF component weightings across the FOMO Index categories

Higher weights for $w_s$ are assigned to the sensitivity, transparency, and explainability categories, due to strong correlations between rapid sentiment shifts and immediate trading actions based on the available information about the specific type of assets. $w_b$ received greater emphasis in scalability and efficiency categories as behavioral intensity metrics explained over 35% of profitability variance during heightened FOMO episodes. $w_p$ is prioritized in susceptibility, reflectivity, and adaptability categories, reflecting the significant role of impulsiveness and loss aversion in amplifying sentiment-driven decisions. $w_c$ is moderately weighted across most categories but elevated in sensitivity and adaptability to account for cultural variations in information traceability and post-event evaluation practices. $w_v$ carried more influence in unpredictability and effectiveness along the side of reliability and scalability categories because volatility and risk factors explained decision accuracy under time-constrained conditions. The "$w_e$" is more prominent in transparency and explainability categories, where governance, disclosure, and compliance considerations directly shaped investor trust and sustained participation. Table 3 provides further analysis and computation of the CFI for each category based on the layers of FICF and (1) through (6).

**Table 2.** FOMO Index categories.

| FOMO Index Category | $S_i$ | $B_i$ | $P_i$ | $C_i$ | $V_i$ | $E_i$ | $CFI_i$ |
|---|---|---|---|---|---|---|---|
| Reliability | 0.69 | 0.97 | 0.81 | 0.72 | 0.49 | 0.58 | 0.73 |
| Scalability | 0.92 | 0.53 | 0.43 | 0.43 | 0.58 | 0.76 | 0.61 |
| Sensitivity | 0.73 | 0.87 | 0.44 | 0.66 | 0.76 | 0.52 | 0.68 |
| Transparency | 0.65 | 0.46 | 0.78 | 0.61 | 0.47 | 0.75 | 0.56 |
| Explainability | 0.77 | 0.51 | 0.98 | 0.84 | 0.96 | 0.95 | 0.64 |
| Reflectivity | 0.69 | 0.56 | 0.88 | 0.55 | 0.57 | 0.77 | 0.57 |
| Susceptibility | 0.50 | 0.89 | 0.79 | 0.81 | 0.86 | 0.54 | 0.77 |
| Adaptability | 0.66 | 0.60 | 0.81 | 0.75 | 0.93 | 0.74 | 0.77 |
| Unpredictability | 0.76 | 0.66 | 0.32 | 0.38 | 0.42 | 0.82 | 0.53 |
| Reactivity | 0.61 | 0.45 | 0.50 | 0.41 | 0.96 | 0.90 | 0.67 |
| Efficiency | 0.90 | 0.94 | 0.52 | 0.38 | 0.54 | 0.71 | 0.80 |
| Effectiveness | 0.56 | 0.60 | 0.96 | 0.53 | 0.71 | 0.85 | 0.75 |
| FOMO Index | **8.0756** | | | | | | |

The FOMO index presented in Table 3 becomes the baseline for comparative analysis during FI-LMEC. The CFI values reveal distinct behavioral and contextual patterns across FOMO index categories. The categories of susceptibility, adaptability, and efficiency demonstrated the highest CFI values, primarily driven by elevated $V_i$ (0.86, 0.93, and 0.54, respectively), strong $B_i$ (0.89, 0.60, and 0.94, respectively), and $P_i$ (0.79, 0.81, and 0.51, respectively). The outcome advises that investors in these segments are more prone to act rapidly and emotionally in response to market stimuli, aligning with behavioral finance theories linking $S_i$ traits in association with efficiency, scoring 0.90, to heightened sensitivity toward short-term sentiment fluctuations, particularly during volatile market conditions. In contrast, sensitivity and reactivity categories recorded comparatively lower CFI values, with more modest $S_i$ (0.73 and 0.61) and reduced $P_i$ (0.44 and 0.50), indicating a preference for measured, evidence-based decision-making and a reduced probability of reacting to transient FOMO triggers. Table 3 provides percentile analysis that indicates how each FICF component contributes across the categories of the FOMO Index in relative terms.

**Table 3.** Percentile contribution of FICF components across FOMO Index categories.

| FOMO Index Category | SAM | DBP | PV | CAM | PVA | FEP |
|---|---|---|---|---|---|---|
| **Reliability** | 8.175355 | 12.06468 | 9.854015 | 10.18388 | 5.939394 | 6.524184 |
| **Scalability** | 10.90047 | 6.59204 | 5.231144 | 6.082037 | 7.030303 | 8.548931 |
| **Sensitivity** | 8.649289 | 10.8209 | 5.352798 | 9.335219 | 9.212121 | 5.849269 |
| **Transparency** | 7.701422 | 5.721393 | 9.489051 | 8.628006 | 5.69697 | 8.436445 |
| **Explainability** | 9.123223 | 6.343284 | 11.92214 | 11.88119 | 11.63636 | 10.68616 |
| **Reflectivity** | 8.175355 | 6.965174 | 10.7056 | 7.779349 | 6.909091 | 8.661417 |
| **Susceptibility** | 5.924171 | 11.06965 | 9.610706 | 11.45686 | 10.42424 | 6.074241 |
| **Adaptability** | 7.819905 | 7.462687 | 9.854015 | 10.6082 | 11.27273 | 8.32396 |
| **Unpredictability** | 9.004739 | 8.208955 | 3.892944 | 5.374823 | 5.090909 | 9.223847 |
| **Reactivity** | 7.227488 | 5.597015 | 6.082725 | 5.799151 | 11.63636 | 10.12373 |
| **Efficiency** | 10.66351 | 11.69154 | 6.326034 | 5.374823 | 6.545455 | 7.986502 |
| **Effectiveness** | 6.635071 | 7.462687 | 11.67883 | 7.496464 | 8.606061 | 9.561305 |

Based on the distribution percentages and analysis of the comparative influence of each FICF component, Fig. 5 provides the percentile variance of each FICF component across the FOMO Index categories.

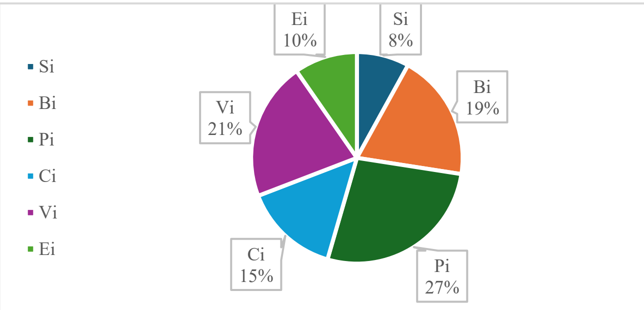


**Figure 5.** Percentile variance of the FICF component across the FOMO Index categories

Reliability, for instance, allocates 12.06% of its weight to DBP, 9.85% to PV, and 10.18% to CAM, reflecting balanced importance across behavioral and contextual dimensions. Scalability, on the other hand, records 10.90% for SAM but only 5.23% for PV, suggesting that sentiment and behavioral engagement are more influential than psychometric traits in this category. Sensitivity demonstrates 10.82% in DBP and 9.33% in CAM, showing that investor responses to sentiment shifts are closely tied to digital behavior and cultural adaptability. Transparency places 9.49% on PV and 8.62% on CAM, emphasizing cognitive-emotional predispositions and cultural alignment. Explainability has the highest contribution from PV at 11.92% and from CAM at 11.88%, indicating firm reliance on cognitive processing and cultural interpretation when investors rationalize sentiment-driven decisions. These percentile distributions confirm that the relative dominance of each component varies by category, illustrating the adaptive nature of the FICF in capturing different investor behaviors. Fig. 6 presents the distribution of FICF components' weighted scores across FOMO Index categories.

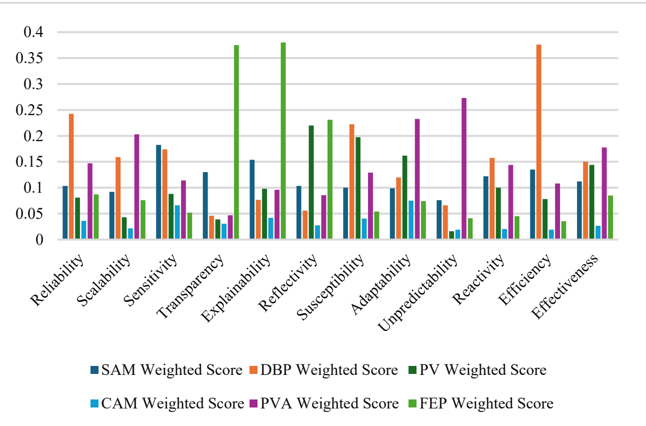


**Figure 6.** Distribution of FICF components' weighted scores across the FOMO Index categories

The comparative analysis of the weighted scores reveals distinctive trends across the FOMO Index categories in relation to the FICF components. Efficiency demonstrates the highest reliance on digital behavioral intensity, reflected in its DBP score of 0.376, supported by a strong sentiment analysis weighting of 0.135. Transparency and explainability are heavily influenced by ethical compliance, registering FEP scores of 0.375 and 0.380, indicating that clarity and justification of investment actions are primarily governed by governance and regulatory safeguards. Reflectivity and susceptibility emphasize psychometric vulnerability, with PV weightings of 0.220 and 0.1975, underscoring the critical role of cognitive predispositions and emotional triggers. Unpredictability, in contrast, is dominated by contextual uncertainty under the PVA dimension, marked by a score of 0.273, showing that volatility and ambiguity strongly define its assessment.

Other categories present more balanced contributions across components. Reliability is formed by digital behavior and contextual risk, with DBP at 0.2425 and PVA at 0.147, while scalability draws strength from volatility-related resilience, with a PVA weighting of 0.203. Adaptability combines cultural adaptability and volatility sensitivity, with CAM at 0.075 and PVA at 0.2325, positioning it as a dynamic adjustment category. Sensitivity reflects sentiment-driven and psychometric responsiveness, with SAM at 0.1825 and PV at 0.088. Reactivity combines sentiment signals with contextual volatility, marked by SAM at 0.122 and PVA at 0.144. Effectiveness balances psychometric reliance and volatility conditions, with PV at 0.144 and PVA at 0.1775, indicating performance confidence under constrained decision environments. The distribution of weighted contributions demonstrates that each category prioritizes different drivers, aligning with its behavioral and functional essence in the FICF framework.

The information on the geolocation of North America's technology sectors raising capital online provides an opportunity to extend the FOMO Index comparative modeling into diversified industry sectors through the FICF framework. SAM can be adapted to industry segmentation, where investor optimism and skepticism differ across Clean Technology (CleanTech), Financial Technology (FinTech), Enterprise Technology (EnterpriseTech), Hardware Technology (HardwareTech), Healthcare Technology (HealthTech), and Gaming Technology (GamingTech). For example, CleanTech has raised $220.8 million across 131 deals [20]. CleanTech may show sentiment polarity strongly influenced by sustainability narratives. However, 152 HealthTech deals raised $55.1 million [20] and may exhibit sentiment tied to medical innovations and pandemic-driven awareness. DBP can then record how investor engagement varies across industries. For example, heightened deal amplification in FinTech versus more cautious participation in HardwareTech. PV can identify differences in investor risk aversion or impulsivity across industries, where speculative enthusiasm in CleanTech contrasts with calculated decision-making in EnterpriseTech.

CAM can incorporate demographic tendencies within the U.S., recognizing younger investors' stronger presence in FinTech and GamingTech compared to older groups investing in HealthTech. PVA provides contextual scaling and captures higher volatility and uncertainty in specific sectors, including HardwareTech and GamingTech, relative to more stable categories, including EnterpriseTech. Ethical considerations remain central in CleanTech and HealthTech, where regulatory compliance and transparency expectations weigh heavily in investment narratives. SCM ensures recalibration as new sectors, including AI-driven innovations, expand deal volume and valuations. Integrating sector-specific sentiment, behavioral, psychometric, and contextual inputs enables CFI modeling for each industry. It enables comparative evaluation of investor susceptibility, emotional reactivity, and risk tolerance. The resulting analysis provides a sectoral benchmark of FOMO intensity, reflecting how capital flows respond to behavioral-financial dynamics in North America's digital economy. Table 4 presents the comparative CFIs of CleanTech, FinTech, EnterpriseTech, HealthTech, and HardwareTech in North America, considering the FICF components.

**Table 4.** Comparative CFIs of the diversified AI technology industry in North America.

| North America's AI Technology | SAM | DBP | PV | CAM | PVA | FEP | CFI |
|---|---|---|---|---|---|---|---|
| CleanTech | 0.82 | 0.75 | 0.65 | 0.7 | 0.85 | 0.8 | 0.769 |
| FinTech | 0.78 | 0.8 | 0.6 | 0.68 | 0.72 | 0.76 | 0.73 |
| EnterpriseTech | 0.7 | 0.65 | 0.55 | 0.62 | 0.68 | 0.74 | 0.66 |
| HealthTech | 0.76 | 0.7 | 0.72 | 0.74 | 0.71 | 0.79 | 0.734 |
| HardwareTech | 0.68 | 0.6 | 0.58 | 0.64 | 0.8 | 0.72 | 0.674 |

The comparative assessment of North American AI-related technology sectors demonstrates clear differences in their alignment with FICF components. CleanTech records the highest Composite FOMO Index (0.769), driven by elevated scores in pragmatic volatility–uncertainty assessment (0.85) and ethical paradigms (0.80), reflecting its strong resilience to risk and compliance orientation. HealthTech follows closely with a CFI of 0.734, supported by strong psychometric variability (0.72) and cultural adaptability (0.74), which suggest greater sensitivity to investor behavior and demographic adoption trends. FinTech secures a CFI of 0.73, characterized by a balance across digital behavioral patterns (0.80) and ethical governance (0.76), positioning it as a stable, adaptive sector. In contrast, EnterpriseTech (0.66) and HardwareTech (0.674) record lower indices, particularly in sentiment analysis metrics (0.70 and 0.68) and digital behavioral engagement (0.65 and 0.60), indicating a slower response to investor sentiment fluctuations. The results conclude that CleanTech and HealthTech currently provide the most stable investment environments under FICF modeling, whereas EnterpriseTech and HardwareTech remain more vulnerable to sentiment-driven volatility. Fig. 7 represents a comparative analysis of weighted scores of the FICF components across diversified AI industry startups' investments in North America.

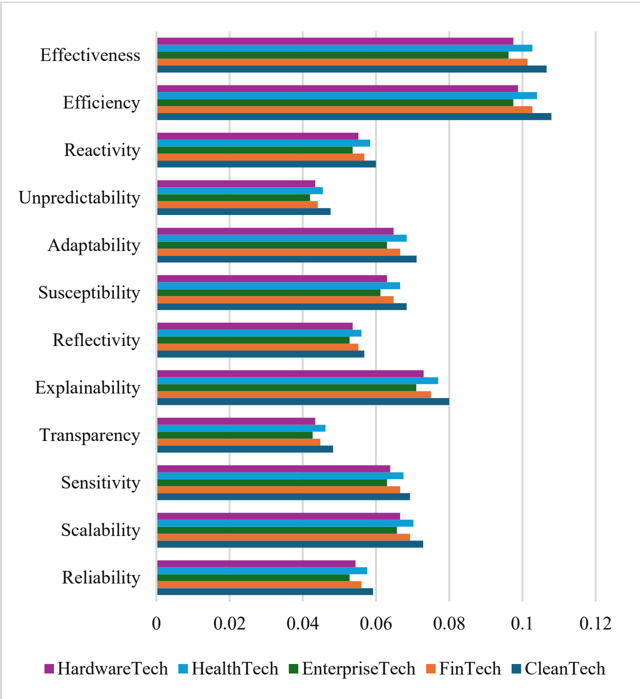


**Figure 7.** Comparative weighted scores of the FICF component across North America's AI Technology Investment

CleanTech demonstrates the strongest performance across categories, reflected in high efficiency at 0.1079 and effectiveness at 0.1066, supported further by scalability at 0.0729 and adaptability at 0.0711. HealthTech follows with significant adaptability at 0.0684, efficiency at 0.1040, and effectiveness at 0.1027, indicating stability across functional layers. FinTech records competitive efficiency at 0.1027 and scalability at 0.0693, balanced by consistency in sensitivity at 0.0666 and susceptibility at 0.0648. HardwareTech secures a moderate standing with efficiency at 0.0988 and effectiveness at 0.0975, though limited by lower transparency at 0.0434 and unpredictability at 0.0434. EnterpriseTech remains the weakest category, marked by efficiency at 0.0975 and effectiveness at 0.0962, but constrained by low transparency at 0.0427 and unpredictability at 0.0420. Comparative evidence indicates that efficiency, effectiveness, and scalability are the most influential drivers of sectoral outcomes, positioning CleanTech and HealthTech as the most competitive domains for AI-driven investments in North America.

### FICF Implementation Assumptions

FICF assumptions serve as critical anchors for methodological rigor, interpretive validity, and adaptive capability in fast-evolving market environments. They define the foundational premises that guide the development, calibration, and recalibration of the FOMO index, ensuring that it remains contextually relevant amid shifting investor behaviors, macroeconomic cycles, technological innovation, and societal transformations in association with Society 5.0. FICF risks misrepresenting behavioral drivers, overlooking structural changes, and undermining predictive reliability without explicitly stated assumptions. The following assumptions enable the FI-LMEC to anticipate and manage the complexities of investment vehicles inherent to the Society 5.0 paradigm.

- **FOMO index baseline during introduction of a new behavioral category**: The introduction of a new behavioral category is embedded into the Initial Definition and Baseline Establishment stage, where sentiment, behavioral, psychometric, and VUCA-adjusted metrics are collected to construct a provisional benchmark. The category is calibrated using historical analogs or proxy datasets before progressing to active FOMO index inclusion.
- **Overlapping of behavioral categories**: Overlaps in behavioral characteristics are addressed in the Data Collection and Disaggregation stage, using proportional allocation logic and correlation analysis to prevent signal contamination between categories. The process preserves categorical independence, ensuring the validity of CFI values and the FOMO index.
- **Sudden change in sentiments due to geopolitics or environment**: This assumption aligns with the Dynamic Monitoring and Recalibration stage, where real-time sentiment tracking, geopolitical event mapping, and environmental stress testing are performed. Adjusting the category weights and recalibration of FOMO index values are essential to maintaining predictive reliability during volatility spikes.
- **Pace of cultural shift**: The pace of cultural change is integrated into the Cultural and Behavioral Adaptation Analysis stage, where generational adoption curves, media consumption patterns, and cross-cultural sentiment triggers are periodically reassessed. Integration ensures the category definitions remain reflective of evolving societal behaviors in the context of Society 5.0.
- **Changing perception of ethics**: Alterations in ethical expectations are managed within the Ethical Compliance Review and Adjustment stage, where governance protocols, transparency mechanisms, and bias mitigation measures are updated to align with evolving norms. The stage ensures that the FOMO index remains compliant with jurisdictional regulations and ethical paradigms.
- **Value-chain dynamics and correlations**: Changes in global value-chain structures are analyzed both in the Ethical Compliance Review stage, ensuring cross-market fairness, and in Structured Change Management, where sector-specific indicators and correlation adjustments are integrated into the FOMO index's weighting model.
- **Capturing new Paradigms of volatility**: This assumption falls under Structured Change Management and Innovation Integration, where advanced volatility measures, including high-frequency sentiment oscillations and network contagion models, are incorporated. This stage ensures that the FOMO index evolves to capture emerging volatility dynamics beyond traditional financial risk measures.

## CONCLUSION AND FUTURE RESEARCH

This study develops and demonstrates a composite FOMO index capable of quantifying the multifaceted drivers of sentiment-induced investment behaviors within the context of Society 5.0. The established FICF offers an active and context-aware instrument for monitoring and interpreting investor susceptibility to FOMO by integrating sentiment analytics, digital behavioral metrics, psychometric profiling, cultural adaptability, pragmatic VUCA and risk assessments, and ethical governance considerations. The application to AI-based investment decision-making illustrates the FOMO index's capacity to capture complex behavioral-financial interactions, enhance predictive precision, and mitigate sentiment-induced volatility. Findings confirm that FOMO intensity varies significantly across behavioral dimensions, with heightened scores correlating with increased reactivity, susceptibility, and momentum-driven trading activity. A comprehensive approach to introducing FI-LMEC stages in association with FICF and changing dynamics of Society 5.0 provisions more informed investment portfolio strategies and continuously addresses regulatory and ethical imperatives by embedding transparency and adaptability into the composite FOMO index development, evaluation, and improvement.

Future research will focus on expanding the dataset scope to include multi-lingual and multi-region sentiments, enabling broader cultural calibration of the FOMO index. Enhancing FICF responsiveness through real-time sentiment integration and adaptive weight recalibration could improve predictive stability under volatile market conditions. Comparative studies across asset classes and market structures may uncover category-specific behavioral triggers, while longitudinal research could assess the persistence and evolution of FOMO patterns over different economic cycles. Incorporating emerging paradigms, including quantum computing-enabled analytics, decentralized finance ecosystems, and AI explainability frameworks, may further strengthen the FICF's scalability, transparency, and resilience. The continuous advancements and experience-based evolution of the FOMO index can be streamlined as a critical decision-support instrument for investors, regulators, and fintech innovators operating in increasingly interconnected and sentiment-sensitive global markets.

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