From Impulsive Investment to Mindful Decisions: Exploring Design Opportunities of AI-Mediated Interventions for Emotionally Biased Investors

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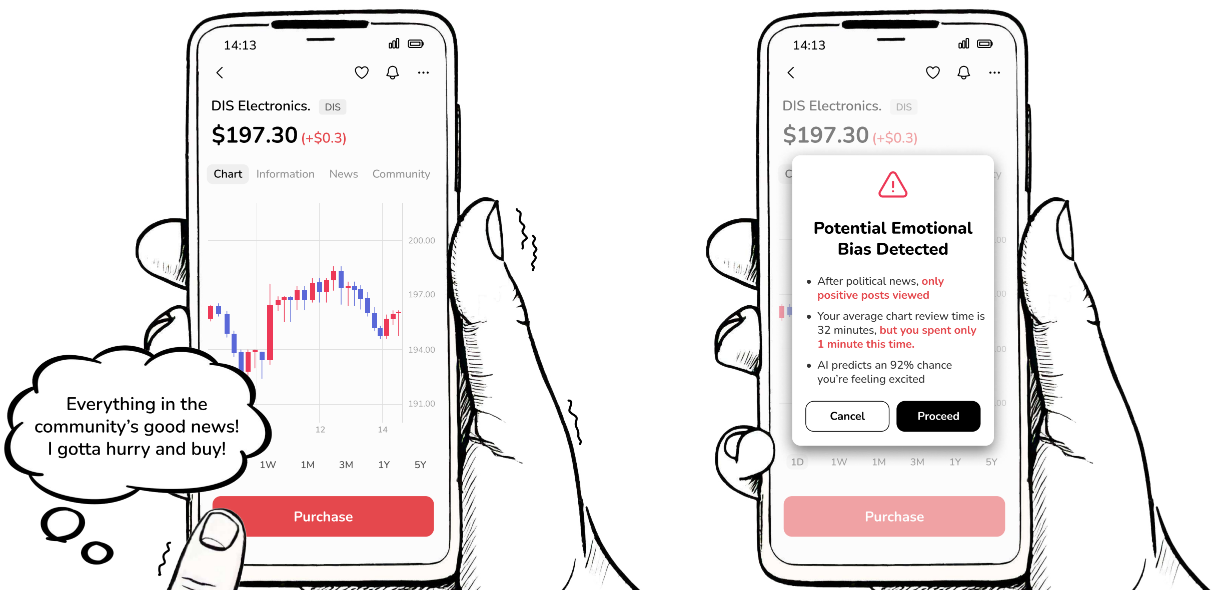

Figure 1: A scenario illustrating the proposed design suggestion. When users deviate from their usual investment routines—such as relying solely on positive community posts or significantly reducing their typical chart review time—the system presents a brief prompt highlighting potential emotional biases. Users can then reconsider their decision or proceed, preserving autonomy while supporting reflection.

ABSTRACT

While providing convenient market access, mobile investment applications often amplify emotional trading through features such as real-time market data and news updates. Our study explored design opportunities for AI-mediated interventions that help investors recognize their emotional biases. Through interviews with 13 investors, we examined how emotions emerge throughout the investment process, how they are reflected in investment behavior, and whether emotion-based interventions can be effective. Our findings revealed that participants experienced recurring cycles of impulsive decisions driven by anxiety, overconfidence, and immediate reward-seeking, which persisted due to intermittent successes and platform convenience. They preferred objective data over directive interventions and valued real-time support that preserves autonomy and retrospective analysis capabilities for long-term improvement. Drawing on these insights, we propose a design concept featuring data-driven reflection mechanisms that help users recognize deviations from established investment patterns. Our work highlights opportunities for adaptive, reflection-oriented AI interventions explicitly tailored to investors' emotional awareness.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in HCI.**

KEYWORDS

Financial Interaction Design; Behavioral Design; Mobile Investment Applications; Just-In-Time Adaptive Intervention

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1 INTRODUCTION

Investment decisions are critical processes that significantly shape an individual's financial future. The recent proliferation of mobile investment applications provides real-time market data and news updates, enabling rapid decision-making [11]. However, recent studies have raised the concern that these convenient features also facilitate irrational and impulsive decisions [2, 8, 16, 17]. Specifically, small screens and automated recommendation algorithms amplify ranking biases, causing investors to focus on a few popular stocks overly [16]. Additionally, the ease of one-click trading weakens investors' self-control, resulting in excessive trading sensitive to short-term market fluctuations [2]. Real-time notifications and news further heighten emotional arousal, prompting impulsive investment decisions driven by anxiety or excitement [17]. Consequently, investors accustomed to such environments increasingly rely on impulsive judgment rather than long-term strategies, prioritizing high-risk assets or immediate gains [8].

Since these issues are deeply intertwined with the design and user experience of digital investment platforms, the HCI community has also explored various approaches, including improved user interface design, AI-based investment advisory systems, and behaviorally oriented interventions [3, 4, 9]. For instance, Chaudhry and Kulkarni [3] systematically analyzed how smartphone investing app interfaces influence investor behaviors and proposed UI design guidelines to mitigate emotional biases and promote more rational, sustainable investment decisions. Similarly, Kawai et al. [9] showed how gamified leaderboards bias investor choices, recommending UI improvements such as composite risk-duration metrics and educational warnings. In addition, Chaudhry and Kulkarni [4] developed a game-based visualization of investment portfolios to reduce impulsive trading and encourage long-term investment habits.

However, existing interventions have primarily focused on asynchronous support or preventing future issues, which may not adequately address the real-time dynamics of rapidly changing market conditions and the associated emotional fluctuations. To overcome this limitation, Just-In-Time Adaptive Intervention (JITAI)—an approach providing timely, adaptive support based on real-time tracking—has gained increasing attention [13]. For example, healthcare research has used smartphone and wearable sensor data to detect depression and anxiety, enabling personalized interventions [12]. In education, real-time emotion recognition using physiological signals has effectively improved student performance by dynamically adjusting learning environments [10]. Also, in finance, Singh et al. [15] identified significant relationships between traders' psychophysiological activation (e.g., excitement, stress) and their trading behaviors, underscoring the importance of investors' real-time emotional states. Grounded in these insights, this study aims to explore the design space of AI interventions that help individual investors recognize their psychological states in real-time to make more informed decisions.

This study investigates specific contexts where individual investors experience emotional biases and explores effective AI interventions to address them. We conducted in-depth interviews with 13 individual investors who trade via mobile applications. Our findings revealed investors frequently made impulsive decisions driven by anxiety, overconfidence, and immediate reward-seeking, creating a vicious cycle amplified by unexpected market events or convenient platforms. Participants suggested that AI interventions prompting emotional reflection before trades or retrospective analysis afterward could help mitigate these impulsive decisions, provided interventions respect user autonomy. Based on these findings, we propose a gradual, autonomy-supportive AI intervention approach designed to detect moments when investors deviate from their habitual trading patterns and to help them recognize and break recurring emotional bias cycles.

This study makes the following key contributions. First, we provide empirical insights into how emotional biases drive behavioral cycles in mobile investment environments based on interviews. Second, we explore appropriate timing and methods for AI interventions that respect investor autonomy within emotional trading contexts. Third, we propose a novel design concept utilizing data-driven reflection mechanisms to help investors recognize deviations from their established investment routines.

2 METHOD

This study aims to comprehensively explore how emotions emerge throughout the investment process and how they are reflected in investment behavior while examining whether emotion-based interventions can be effective. Rather than presenting a finalized user study or guidelines in this exploratory phase, the focus was on proposing new possibilities and eliciting diverse opinions and discussion points. In this section, we provide a detailed account of how the interviews were designed. This study was approved by the university's institutional review board (IRB).

2.1 Participant Recruitment

We recruited 13 individual investors (9 female, 4 male) who had consistently engaged in stock trading via mobile trading applications over the past six months, with at least one trade in the month before the interview. Participants' ages ranged from 20 to 29 (M = 24.77, SD = 2.68). On average, participants had 34.08 months (SD = 20.03) of trading experience through mobile applications. Table 1 provides detailed demographic information for each participant. Recruitment was conducted by posting an announcement on social media and through snowball sampling [7]. A preliminary online survey confirmed participants' length of trading via mobile applications and whether they had experienced emotion-driven investments. The interviews lasted approximately 60 minutes, and each participant received an honorarium of 30,000 KRW (approximately 20 USD).

2.2 Procedure

The interviews were conducted in person (3 participants) or via Zoom (10 participants), each lasting approximately 60 minutes. All

ID	Age	Gender	Mobile Investing Exp.	Self-rated Financial Knowledge
P1	28	Male	8 months	Low
P2	24	Female	9 months	Low
P3	20	Female	6 months	Low
P4	23	Female	4 years	Low
P5	25	Female	4 years	Mid-High
P6	29	Male	4 years	Medium
P7	25	Female	6 years	Low
P8	24	Female	4 years	Mid-Low
P9	29	Female	3 years	Medium
P10	26	Male	3 years	Medium
P11	23	Female	3 years	High
P12	24	Female	1 years	High
P13	22	Male	3 years	High

Table 1: Demographic Profile of Study Participants (N=13).

interviews were recorded and transcribed with the participants' consent. The interview protocol was structured into five main sections designed to explore participants' emotional experiences during investment decision-making systematically. (1) First, participants were asked about their general emotional self-regulation abilities to provide baseline emotional awareness. (2) Next, we explored participants' investment habits, typical decision-making processes, preferred platforms, and information sources. (3) The core of the interview focused on participants' emotional experiences during specific investment situations. We used prompts such as *"What was the immediate trigger for your recent stock purchase/sale?"* followed by *"What emotions did you feel first when encountering that trigger?"*, guiding participants through detailed recountings of their emotional states at each decision-making stage. (4) We then explored participants' awareness of emotional influences by asking questions like *"Have you ever regretted an investment? Do you think it was due to emotional impulses?"* This helped us understand participants' metacognitive awareness of their emotional states during investment. (5) Finally, participants selected one irrational investment case they had shared to discuss how an AI system capable of sensing emotional states in real-time might have impacted their decision. Using prompts such as *"If AI had intervened at that moment, how would you have felt?"* and *"When would receiving such assistance have been most effective?"*, participants considered various intervention formats, wording preferences, and their potential effectiveness. Participants considered different intervention formats and whether these would realistically influence their behavior.

2.3 Data Analysis

This study gathered qualitative data from 13 audio-recorded interviews. The recordings were transcribed after removing all personally identifiable information to protect participants' anonymity. The primary focus of the analysis was on emotional factors arising during the investment process, the influence of these emotions on decision-making, and participants' expectations and concerns regarding real-time emotion detection by AI. Following the Thematic Analysis approach [1], we performed repeated open coding of the interview transcripts to refine the initial codebook in alignment with the study's objectives and focal points. We then employed affinity diagramming [5] to cluster related codes and synthesize the key themes, ultimately achieving a deeper understanding of the relationship between emotion and investment decisions and potential strategies for AI intervention.

3 FINDINGS

In this section, we present our findings in two parts. First, we describe how emotions trigger impulsive trading behaviors and why investors struggle to break this cycle. Second, we outline participants' expectations for AI interventions, highlighting their desire for real-time emotional support, balanced autonomy, and retrospective analysis.

3.1 How Participants Fall into the Emotional Trading Trap

3.1.1 Emotions as Investment Signals. Most of our participants highlighted anxiety, overconfidence, and desire for immediate gratification as key emotional biases affecting investment decisions. They often felt a greater fear of losses than satisfaction from gains, significantly impairing their rational judgment. Overconfidence from familiarity also posed risks; as P8 stated, *"Since I work in this industry, I was convinced the company's stock would inevitably rise, so I invested without further verification"*. Additionally, participants impulsively traded due to excitement or the desire for short-term emotional rewards. Some participants interpreted collective anxiety within the market community as meaningful investment cues. For example, P10 noted, *"When negative comments flooded the community, I thought everyone was fearful, meaning it must be the right time to buy"*. These emotional influences consistently undermined the rational decision-making of the participants.

3.1.2 Investment Principles Broken by Emotional Moments. Participants typically had clear principles that guided their investment decisions, but specific emotional moments repeatedly disrupted these principles, causing impulsive trades and subsequent regrets. Unexpected market events often triggered emotional reactions, disrupting participants' original strategies. For instance, P12 explained, *"I usually buy small amounts to observe trends, but when a sudden political issue arose, I impulsively made a large purchase"*. Additionally, mental overload or sudden busyness triggered impulsive decisions without proper reflection; as P4 recounted, *"Even for a carefully considered stock, I suddenly became too busy and didn't want to think anymore, so I just bought it—and immediately regretted it"*. Meanwhile, P3 and P6 struggled with investing more readily in losing stocks than in profitable ones. Overall, these emotionally charged moments consistently led to impulsive decisions that participants soon regretted.

3.1.3 Self-Justification Reinforcing Emotional Cycles. Participants struggled to escape the emotional trading cycle due to illusions created by intermittent successes and tendencies toward rationalization, despite repeated losses and regrets. In particular, occasional profitable trades reinforced participants' illusions of competence, leading them to repeat impulsive decisions even though they clearly recognized the risks. For example, P2 remarked, *"I made profits three times this way, so even though it's gambling, I thought I might* *succeed once more"*, highlighting how occasional successes easily overshadow consistent losses. Some participants also rationalized poor decisions by attributing failures to external circumstances or bad luck. For instance, P1 stated, *"Every time I buy, the stock immediately drops"*. This shows how P1 blamed uncontrollable market movements or unfortunate timing instead of examining their own decision-making process. Thus, these illusions and rationalization tendencies among participants were the primary reasons for the continued repetition of emotional trading.

3.2 User Expectations and Concerns for AI Interventions

3.2.1 AI as an Emotional Safety Net. Participants clearly articulated their expectations for AI systems to support investment decisions by providing traditional financial data and real-time emotional support. Several participants directly requested that AI provide active guidance during trading. For instance, P13 suggested that AI could present information opposing immediate impulses, such as reasons to sell when buying. Similarly, P2 desired explicit AI warnings, stating, *"It would be helpful if AI issued a warning when I am making a trade solely based on subjective feelings"*. Interestingly, beyond direct trading advice, participants showed significant interest in receiving feedback about their emotional states. For example, P10 described canceling a planned purchase after noticing elevated excitement through real-time heart rate data displayed on a smartwatch, explaining, *"I once canceled a purchase after noticing my heart rate on my smartwatch, realizing I was excited"*, and adding, *"AI does not need to process heart rate data; just displaying it as-is would be sufficient"*. Overall, participants were positive toward AI interventions that address their emotional vulnerabilities.

3.2.2 Balancing Real-Time AI Intervention and User Autonomy. Although participants desired specific real-time support from AI, they did not want to lose their sense of autonomy. To mitigate emotional biases, many participants found it helpful to have an opportunity to reassess their decisions just before executing a trade. P8 noted, *"Even if just a simple message appears asking if this price is truly appropriate, I think I would calm down and reconsider"*. Similarly, P4 stated, *"If a chatbot prompts me to summarize why I want to buy this stock, even briefly, it would be beneficial"*. However, P1 pointed out that *"random pop-ups covering the screen would seriously undermine user autonomy and be more annoying than helpful"*, indicating that excessively intrusive interventions could backfire. Similarly, P6 questioned whether *"if AI forcibly prevents an emotional trade and the stock later surges, would users not blame the AI?"* This underscores that unilateral AI interventions or prescriptive trading directives could engender negative user perceptions when outcomes deviate from expectations.

3.2.3 Retrospective Analysis for Long-term Improvement. Participants also expressed that real-time interventions alone might not fully break the emotional cycle; instead, they emphasized the importance of retrospective reflection for sustained behavioral changes. Several participants showed strong interest in a system that allows them to examine their trading behaviors retrospectively. P12 stated, *"If AI could store my trading data and later show me when I was most emotionally unstable, I would try to avoid similar situations in the future"*. This suggests that quantifying investors' psychological states through data can enhance the effects of long-term learning. Similarly, P13 proposed *"Just like journaling or keeping a financial ledger, tracking my decisions could help me combat emotional trading. It would be beneficial if AI prompts me to reflect on 'why I acted this way' after a trade"*. Participants wanted to continuously improve their investment habits by analyzing emotional patterns and decision-making processes alongside their profit-and-loss records.

3.3 Balancing Timely Intervention with Reflection Opportunities

Participants described emotional biases as being especially pronounced at specific moments during their investment decision-making process. They expressed preferences for support systems that could provide assistance precisely when these emotional vulnerabilities occur, without being overly intrusive. This aligns with the concept of Just-In-Time Adaptive Interventions (JITAI), which deliver timely support exactly when users most need it.

Participants expressed clear preferences for AI support that respects their autonomy, preferring objective feedback rather than prescriptive guidance. They valued opportunities for emotional reflection, both before executing trades and retrospectively afterward, viewing this as essential for sustainable behavioral change. However, our findings also highlight that interventions perceived as intrusive or overly controlling could result in user resistance. This is consistent with prior research indicating that excessive nudges or manipulative interventions can undermine user autonomy [14].

Considering these insights, we suggest a key design implication: AI interventions should leverage real-time detection of emotional deviations from established investment routines, providing timely but non-intrusive opportunities for reflection. One concrete example illustrating this implication is a data-driven reflection feature that visually compares each trade to the user's habitual trading patterns, enabling investors to quickly recognize emotionally driven deviations (see Figure 1). Initially, this feature serves as a subtle, non-intrusive prompt, helping users identify impulsive trades after the fact, thereby gradually building awareness of their emotional vulnerabilities [6]. Over time, as users develop trust in the system, they might opt to activate additional, user-initiated pre-trade interventions—such as checklists or real-time alerts—at moments the system identifies as emotionally charged. This gradual and autonomy-supportive approach aligns closely with established JITAI principles emphasizing user-initiated interaction as particularly effective [13].

4 LIMITATIONS

While this study offers preliminary insights into emotional biases within mobile investment environments, several limitations warrant consideration. Our sample comprised 13 individual investors, predominantly in their twenties, and with an average trading experience of 34.08 months. This demographic may not fully represent the breadth of experiences found across different age groups, investment backgrounds, or varying levels of trading expertise. Furthermore, our data collection relied on participants' retrospective accounts of their emotional states during investment decisions. Although this approach provided rich contextual information, future research could benefit from complementary real-time measurement techniques. Finally, the proposed AI-based intervention framework is an initial conceptualization that requires further development and empirical validation to ascertain its effectiveness and applicability across diverse investment contexts.

5 CONCLUSION AND FUTURE WORK

This study explored individual investors' emotional biases and the role AI interventions can play in mitigating these biases within mobile investment environments. We found that emotional biases such as loss aversion, overconfidence, and the disposition effect significantly impacted investor decisions, particularly under rapid market fluctuations or personal time pressures. Participants frequently reported anxiety-driven impulsive trades, decisions influenced by overconfidence from past successes, and struggles to escape repeated patterns of selling profitable stocks prematurely while holding onto losing ones. Participants favored objective, autonomy-supportive AI feedback over prescriptive interventions and valued opportunities for reflection during and after trades. Based on these findings, we propose a reflection approach that enables real-time interventions in response to changes in user behavior, allowing users to recognize emotionally driven deviations from their habitual investment behaviors. This approach may help investors reduce impulsive trading and build sustainable, long-term investment habits. Future work will focus on exploring, developing and analyzing the effectiveness of implementations that learn each user's typical investment patterns and intervene in real-time when detecting deviations that may signal emotional biases. We aim to diversify our data collection channels to gather as much contextual information as possible. We plan to recruit participants with varying levels of investment experience to ensure our findings generalize across different investor profiles, addressing a limitation of our current study. Through this work, we aim to better understand how AI systems might effectively support human decision-making in emotionally charged contexts while respecting user autonomy and fostering sustainable behavioral change—extending our research beyond investment applications to broader questions of AI-mediated behavioral interventions.

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REFERENCES

[1] Virginia Braun and Victoria Clarke. 2006. Using thematic analysis in psychology. *Qualitative research in psychology* 3, 2 (2006), 77–101.

[2] Xiao Cen. 2024. Smartphone trading technology, investor behavior, and mutual fund performance. *Management Science* 70, 10 (2024), 6897–6916.

[3] Sayan Chaudhry and Chinmay Kulkarni. 2021. Design patterns of investing apps and their effects on investing behaviors. In *Proceedings of the 2021 ACM Designing Interactive Systems Conference*. 777–788.

[4] Sayan Chaudhry and Chinmay Kulkarni. 2022. Robinhood's forest: A persuasive idle game to improve investing behavior. In *Proceedings of the 27th International Conference on Intelligent User Interfaces*. 594–603.

[5] Juliet M Corbin and Anselm Strauss. 1990. Grounded theory research: Procedures, canons, and evaluative criteria. *Qualitative sociology* 13, 1 (1990), 3–21.

[6] Anna L Cox, Sandy JJ Gould, Marta E Cecchinato, Ioanna Iacovides, and Ian Renfree. 2016. Design frictions for mindful interactions: The case for microboundaries. In *Proceedings of the 2016 CHI conference extended abstracts on human factors in computing systems*. 1389–1397.

[7] Leo A Goodman. 1961. Snowball sampling. *The annals of mathematical statistics* (1961), 148–170.

[8] Ankit Kalda, Benjamin Loos, Alessandro Previtero, and Andreas Hackethal. 2021. *Smart (Phone) Investing? A within Investor-time Analysis of New Technologies and Trading Behavior.* Technical Report. National Bureau of Economic Research.

[9] Daisuke Kawai, Kyle Soska, Bryan Routledge, Ariel Zetlin-Jones, and Nicolas Christin. 2024. Stranger Danger? Investor Behavior and Incentives on Cryptocurrency Copy-Trading Platforms. In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems*. 1–20.

[10] Cèlia Llurba and Ramon Palau. 2024. Real-Time Emotion Recognition for Improving the Teaching–Learning Process: A Scoping Review. *Journal of Imaging* 10, 12 (2024), 313.

[11] Suzanee Malhotra. 2020. Study of features of mobile trading apps: A silver lining of pandemic. *Malhotra, S.(2020). Study of features of Mobile Trading Apps: A silver lining of pandemic. Journal of Global Information & Business Strategy (JGIBS)* 12, 1 (2020), 75–80.

[12] Isaac Moshe, Yannik Terhorst, Kennedy Opoku Asare, Lasse Bosse Sander, Denzil Ferreira, Harald Baumeister, David C Mohr, and Laura Pulkki-Råback. 2021. Predicting symptoms of depression and anxiety using smartphone and wearable data. *Frontiers in psychiatry* 12 (2021), 625247.

[13] Inbal Nahum-Shani, Shawna N Smith, Bonnie J Spring, Linda M Collins, Katie Witkiewitz, Ambuj Tewari, and Susan A Murphy. 2018. Just-in-time adaptive interventions (JITAIs) in mobile health: key components and design principles for ongoing health behavior support. *Annals of behavioral medicine* (2018), 1–17.

[14] Nicole Neuss and Verena Zielke. 2022. Nudging the Private Investor - A Systematic Literature Review. In *Pacific Asia Conference on Information Systems*.

[15] Manish Singh, Qingyang Xu, Sarah J Wang, Tinah Hong, Mohammad M Ghassemi, and Andrew W Lo. 2022. Real-time extended psychophysiological analysis of financial risk processing. *Plos one* 17, 7 (2022), e0269752.

[16] Haibo Wu and Chongfeng Wu. 2024. Mobile device use and the ranking effect on trading behavior: Evidence from natural experiments. *Pacific-Basin Finance Journal* 85 (2024), 102317.

[17] Jinjoo Yoon and Gabjin Oh. 2022. Investor herding behavior in social media sentiment. *Frontiers in Physics* 10 (2022), 1023071.