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Meaning-Making in Machine Learning Predictions: Lived Experiences of Financial Professionals

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ABSTRACT

As machine learning (ML) technologies increasingly shape decision-making in finance there is growing concern about how professionals interpret and engage with algorithmi predictions. While prior research has focused on model accuracy and systen performance, little is known about the lived experiences of users who interact witl predictive systems in high-stakes financial contexts. The subjective and interpretiv dimensions of this engagement remain underexplored, prompting the question: how d financial professionals experience, interpret, and respond to ML-generated predictions i their daily decision-making processes? This study applies an interpretativ phenomenological approach to explore the meanings users construct when working witl predictive systems. Using in-depth semi-structured interviews with ten financ professionals and an Interpretative Phenomenological Analysis (IPA) framework, th research identified key themes such as navigating ambiguity, balancing trust and control emotional reactions to algorithmic uncertainty, and adaptive meaning-making strategies The findings demonstrate that users interpret ML predictions not merely as data point but as ambiguous and emotionally charged cues that require subjective negotiatio within organizational and ethical constraints. These insights provide a deepe understanding of how decision-making is shaped by both the technical nature o algorithms and the human need for meaning and accountability. This study highlights th need for more human-centered AI systems and suggests that future research shoul investigate interpretive experiences across different professional settings to inform ethical and user-sensitive design practices. Nevertheless, the study is limited by its smal sample size and focus on a single professional domain, which may restrict th generalizability of findings. In practical terms, the results emphasize the importance o training programs, organizational guidelines, and transparent system design to bette support financial professionals in interpreting and responsibly applying ML predictions.

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INTRODUCTION

In recent years, the integration of machine learning (ML) systems into financial decision-making processes has become increasingly prevalent, driven by advancements in data science and artificial intelligence. Financial institutions now rely heavily on predictive analytics to assess risk, guide investment strategies, and optimize operational efficiency (Iqbal et al., 2025; Rocha et al., 2022a). This technological shift has not only transformed the landscape of financial practice but has also redefined how decisions are made in high-stakes environments. Within this dynamic context, the use of algorithmic predictions introduces a new layer of complexity to human judgment, prompting individuals to interpret, validate, or even challenge the outputs generated by opaque computational models.

The relevance of this phenomenon extends beyond the technical performance of ML systems (Mukhlis, 2025a; Mukhlis & Saidah, 2025). It touches upon deeply human concerns such as trust, responsibility, and control—particularly when individuals must act upon recommendations they may

not fully understand. The experience of engaging with algorithmic predictions is inherently subjective; it is shaped by personal intuition, professional identity, emotional response, and contextual pressures. As such, the interaction between human users and machine-generated intelligence becomes not merely a procedural matter but a profound experiential encounter. In financial settings where decisions can carry significant implications, these experiences can influence not only outcomes but also perceptions of credibility, risk, and accountability.

Despite the growing presence of ML systems in professional domains, little is known about how individuals make sense of the predictions they encounter (Luo et al., 2023; Nivedita et al., 2025a). While technical evaluations and performance metrics offer valuable insights into system accuracy, they often overlook the nuanced ways in which users internalize, interpret, and respond to predictive outputs. This gap in understanding highlights the need for an exploration that prioritizes the lived experiences of those directly involved in decision-making with AI support. Phenomenological inquiry, with its focus on subjective meaning and context-bound experience, offers a compelling framework for uncovering the underlying structures of sense-making in these technologically mediated environments.

The exploration of individuals' experiences in engaging with predictive technologies has emerged as a critical area of inquiry, particularly within professional domains where decision-making is intertwined with complex algorithmic systems. In finance, the growing reliance on machine-generated predictions has led to an increasing interest in understanding how users interpret, internalize, and apply these outputs in real-world contexts. Studies such as those by Ghimire et al., (2025) and Devaraji & Sivaraman, (2024) have emphasized the importance of user-centered perspectives, highlighting the cognitive and emotional dimensions that accompany the use of AI in decision support systems. These works underscore the centrality of subjective experience as a lens through which the impact and utility of predictive technologies can be meaningfully assessed.

However, significant methodological challenges persist in capturing the depth and richness of these experiences. Quantitative approaches, while effective in measuring performance metrics or user satisfaction, often fall short in revealing the complex interpretative processes users undergo when engaging with opaque, data-driven systems. As noted by Shi & Guo, (2022), standard survey methods tend to flatten the diversity of user experiences into generalized trends, thereby obscuring the nuanced ways individuals make sense of algorithmic outputs in uncertain or high-stakes environments. These limitations suggest that much of the current empirical research fails to fully grasp the lived reality of users—what it feels like, for instance, to make critical decisions based on predictions that may be accurate, but not explainable.

This methodological gap underscores a broader issue in the field: the inadequacy of traditional research designs to account for the existential and interpretive dimensions of human-technology interaction (Mukhlis, Janwari, et al., 2023; Mukhlis & Abdullah, 2025). When the essence of a phenomenon lies in the interplay between cognition, emotion, and social context—as it does in the case of users responding to ML predictions—only a method capable of accessing experiential meaning can offer a comprehensive understanding. It is this recognition that affirms the value of a phenomenological approach, particularly interpretative phenomenological analysis (IPA), in addressing the limitations of prior studies and illuminating the deeply human side of algorithmic decision-making.

In the current landscape of financial technology, most institutional responses to the challenges posed by machine learning predictions have emphasized technical improvements, such as enhancing model explainability, increasing algorithmic transparency, or implementing user training modules (Borsah et al., 2025; Gupta et al., 2022). These practical interventions aim to improve user trust and alignment with system outputs. However, while valuable, such approaches are primarily rooted in functionalist assumptions and tend to address the surface-level interaction between users and predictive systems. They often neglect the deeper experiential layers—how users actually live through and make meaning of their encounters with algorithmic outputs under pressure, uncertainty, or organizational constraints.

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Empirical research has largely adopted quantitative or system-centric designs to evaluate the effectiveness of predictive models, focusing on metrics such as accuracy, efficiency, or user satisfaction. These studies, as seen in the works of Hu et al., (2025), provide useful benchmarks but offer limited insight into how professionals interpret, negotiate, and respond to predictions in emotionally and cognitively complex contexts. As a result, the richness of users' lived experiences—especially their sense-making processes, affective responses, and ethical reflections—remains underexplored and poorly understood.

A more suitable alternative for addressing this gap lies in adopting a phenomenological approach that prioritizes the subjective dimension of experience (Zhao & Zhao, 2021). Interpretative Phenomenological Analysis (IPA), in particular, allows researchers to investigate how individuals construct meaning from their engagement with predictive technologies, not merely in terms of utility or outcome, but as a deeply human process embedded in social, emotional, and professional realities. This methodological shift is essential for moving beyond descriptive evaluations and toward a holistic understanding of the essence of human interaction with machine learning in decision-making contexts.

Previous research has explored how professionals engage with artificial intelligence in decision-making, particularly in fields such as healthcare, finance, and public policy. Studies by Nivedita et al., (2025) have highlighted user struggles in understanding and trusting algorithmic outputs, but these works often emphasize technical or behavioral outcomes. While some studies acknowledge emotional responses and ethical concerns, they rarely examine the lived experience of decision-makers facing algorithmic ambiguity. Theoretical frameworks such as human-computer interaction or cognitive load theory offer useful insights, but they tend to overlook how people feel, interpret, and give meaning to these moments of uncertainty. There remains a need to understand these phenomena from the inside, through the lens of the user's own experience.

This study uses an interpretative phenomenological approach to explore how financial professionals experience machine learning predictions in real-time decision-making (Mukhlis, Maryam, et al., 2023; Mukhlis et al., 2024). This method was selected for its ability to reveal how individuals construct meaning through reflection and interpretation within their specific contexts. Unlike quantitative surveys or system-based assessments, phenomenology centers the user's voice and perspective. By applying Interpretative Phenomenological Analysis (IPA), the study captures not only what users do, but how they think and feel when interacting with predictive technologies. This approach directly addresses the knowledge gap by offering a deeper, more human understanding of algorithm-supported decision-making.

The article is structured as follows. The introduction outlines the broader context and the significance of studying this phenomenon (Mukhlis, Arifin, Ridwan, & Zulbaidah, 2025; Mukhlis, Arifin, Ridwan, Zulbaidah, et al., 2025). The methods section describes the phenomenological design, participant selection, data collection through in-depth interviews, and analysis using IPA. The results section presents themes derived from user experiences, supported by direct quotations and narrative interpretation. Finally, the discussion reflects on these findings in light of existing literature, and the conclusion highlights the implications for both theory and practice in data-driven decision-making.

RESEARCH METHODS

Study Design

This study adopted an interpretative phenomenological approach to explore the lived experiences of users interacting with machine learning (ML) prediction systems in financial decision-making environments. Phenomenology was selected for its emphasis on understanding the subjective meanings constructed by individuals in response to specific phenomena. The interpretative variant of phenomenology, rooted in Heideggerian philosophy, focuses on how individuals interpret their experiences within their sociocultural and professional contexts. This design was particularly suited to investigate how users engage with and assign meaning to the outputs of predictive systems that are

often perceived as opaque or abstract. By embracing this approach, the study enabled a deep, context-rich exploration of users' experiential narratives beyond surface-level behaviors or perceptions.

Participants

Participants were professionals working in financial institutions who had regular interaction with ML-based predictive systems as part of their decision-making processes. A purposive sampling strategy was used to identify individuals with direct, sustained experience using predictive technologies in real-world financial contexts (Daly, 2007; Longhofer et al., 2012). Inclusion criteria consisted of professionals aged 30–55 years with a minimum of two years of experience in roles involving data-driven decisions supported by ML tools. Individuals were excluded if they had only occasional exposure to such systems or lacked autonomous decision-making authority in their roles. A total of ten participants were involved in the study, comprising six males and four females, with an average age of 42. All participants held mid- to senior-level positions, such as risk analysts, financial consultants, and decision support managers.

Data Collection

Data were collected through in-depth, semi-structured interviews guided by an interview protocol designed to elicit reflections on participants' experiences with ML outputs (Carreiras & Castro, 2012; Iosifides, 2016). The interviews were conducted face-to-face in quiet, private meeting rooms at the participants' workplaces to ensure a comfortable and distraction-free environment. Each interview lasted between 45 and 70 minutes and was audio-recorded with the participants' consent. The interview protocol was adapted from existing phenomenological instruments and included prompts such as, "Can you describe a time when a system prediction contradicted your expectation?" and "How do you usually respond to automated risk scores?" The protocol was pilot-tested and revised for clarity and relevance prior to the main data collection.

Data Analysis

The collected data were analyzed using Interpretative Phenomenological Analysis (IPA), a qualitative technique designed to capture the essence of lived experiences and the meaning-making processes of individuals (Migdal, 2018). The analysis began with verbatim transcription of all interviews, followed by multiple readings to ensure immersion in the data. Meaning units were identified and coded manually, then grouped into emergent themes through a systematic process of thematic clustering. NVivo software was used to assist in organizing the data and maintaining an audit trail. Reductive techniques were applied to isolate essential structures of the experience while maintaining contextual integrity. Through iterative interpretation, the final themes were developed to reflect both shared and unique aspects of participant experiences with ML predictions.

Ethical Considerations

Ethical approval was obtained from the appropriate institutional research ethics committee prior to the commencement of the study. Written informed consent was secured from all participants, who were briefed on the purpose of the research, their right to withdraw at any time, and the measures taken to ensure confidentiality. Anonymity was preserved by replacing identifiable information with pseudonyms, and data were securely stored in compliance with international research ethics standards, including the Declaration of Helsinki.

RESULTS

This study explored how users experience and interpret the outputs of machine learning (ML) predictive systems in financial decision-making contexts. Through in-depth interviews with professionals who regularly interact with predictive technologies, several essential themes emerged, each reflecting distinct yet interrelated dimensions of user experience. The results are structured around four major themes that were inductively derived from the participants' narratives.

Navigating Ambiguity—Interpreting the 'Black Box'

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Participants consistently described a sense of uncertainty and ambiguity when engaging with ML system outputs, particularly due to the lack of transparency and explainability.

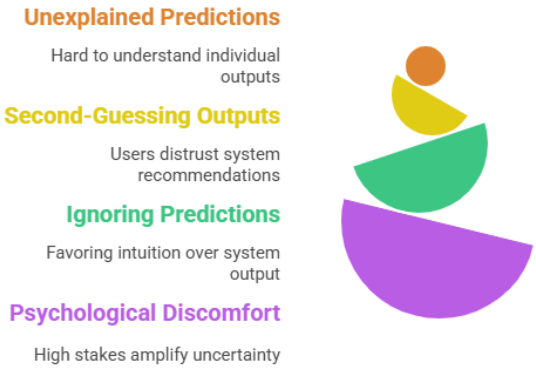
"The system told me the risk score was high, but it never explained why. I had to guess based on patterns I've seen before, but it felt like I was making decisions in the dark." (P3)

Many users reported that while they trusted the overall performance of the ML system, they struggled with understanding individual predictions. This led to a cautious approach where outputs were either second-guessed or ignored entirely in favor of intuition.

"Sometimes I just disregard the prediction if it contradicts my gut feeling or what I see from the market. You can't rely on something you don't fully understand." (P7)

The opacity of ML models created not only interpretive challenges but also psychological discomfort, especially in high-stakes scenarios.

ML Interpretability Hinders User Trust



Tension Between Trust and Control

A prominent theme across interviews was the tension between trust in algorithmic outputs and the desire to retain control over decision-making.

"I'm supposed to trust the system—it's smarter than me in theory—but if something goes wrong, it's my name on the report." (P5)

This tension was often manifested in a pattern of selective trust: participants would use the ML output as a reference but rarely allow it to override their professional judgment. The feeling of being held accountable for decisions made with partial understanding of the technology heightened anxiety and fostered a sense of professional vulnerability.

"It's a double-edged sword. You want to leverage the data power of AI, but at the end of the day, it doesn't take responsibility—you do." (P2)

Emotional Responses to Algorithmic Uncertainty

Participants expressed a range of emotional reactions when dealing with ML predictions, particularly when those predictions contradicted their expectations.

"When the model gives a prediction that doesn't match my analysis, I feel confused—sometimes even frustrated. It makes me question if I'm missing something or if the system is." (P1)

This emotional turbulence was intensified when decisions carried financial consequences or organizational risks. Some participants described experiencing decision fatigue, citing the cognitive load of constantly interpreting outputs that lacked contextual grounding.

"It's mentally exhausting to always have to interpret these results. There's no context, no story—just a number and a risk flag." (P8)

Such emotional strain highlighted the human cost of interacting with advanced analytical tools that prioritize technical precision over human interpretability.

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Adaptation Strategies—Bridging Intuition and Machine Logic

Despite challenges, participants demonstrated adaptability by developing strategies to integrate machine output with their domain knowledge. Many described building mental models over time to "decode" predictions and align them with familiar decision-making frameworks.

"After a while, I started to recognize what the system meant when it flagged certain things. It's like learning a new language—it's frustrating at first, but then you develop a feel for it." (P6)

Others resorted to heuristic filters, comparing outputs with their own calculations or historical trends before making final decisions.

"I never take it at face value. I match it against my own data sets and instinct. It becomes one of many inputs, not the only one." (P9)

These adaptation strategies reveal a dynamic process of learning and negotiation between human intuition and machine-generated knowledge.

The essence of the phenomenon lies in the users' ongoing struggle to reconcile the promise of algorithmic intelligence with the limitations of interpretability and emotional acceptance. Users do not passively consume predictions; instead, they actively engage, question, reframe, and sometimes resist them—constructing meaning not just from what the model says, but also from how they feel and think in response to it. Their experience is shaped by a constant interplay between technological opacity and human judgment, ultimately revealing the profoundly interpretive nature of decision-making in the age of machine learning.

DISCUSSION

The findings of this study reveal the complex and often conflicted nature of user experiences when interacting with machine learning predictions in financial decision-making (Pliakos & Vens, 2020a; Rocha et al., 2022b). At the core of these experiences lies a tension between trust and ambiguity, as users attempt to interpret algorithmic outputs without full transparency, while remaining accountable for the decisions they make. These insights directly address the central research question posed in the introduction—how do users experience, interpret, and respond to ML-generated predictions within their professional contexts?

This study offers a unique contribution by uncovering how users construct meaning when confronted with opaque, yet authoritative, algorithmic outputs. Rather than treating predictions as objective data points, participants described their interactions as interpretive encounters shaped by personal judgment, organizational norms, and emotional responses. These interpretive efforts were not incidental; they formed the foundation of how decisions were justified, resisted, or adapted. By capturing these lived experiences through an interpretative phenomenological lens, the study highlights a crucial aspect often overlooked in AI and financial decision-making research—the subjective negotiation between human agency and machine output. In doing so, it demonstrates that trust in ML systems is not merely a technical challenge but a deeply human process informed by emotion, uncertainty, and context.

These findings resonate with, and expand upon, prior research in related domains. For example, Mohammadi et al., (2024) found that clinicians struggled with the "black box" nature of AI decision tools, echoing similar themes of interpretive labor and discomfort observed in this study. Similarly, Ribeiro et al., (2025) emphasized the need for human-centered design in predictive technologies, particularly in domains involving high cognitive and emotional stakes. However, while earlier studies have largely focused on interface design or model transparency, the present research adds depth by illuminating the personal, internalized experiences of users engaging with predictive systems. It bridges the gap between functional usability and phenomenological meaning-making, offering empirical evidence that algorithmic trust and understanding are formed not through instruction alone, but through lived negotiation in daily practice.

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The implications of these findings are both scientific and practical, particularly in the development and implementation of machine learning systems in high-stakes environments (Mukhlis, 2025b; Mukhlis, Suradi, et al., 2023). From a professional standpoint, the study suggests that effective adoption of predictive technologies cannot rely solely on technical training or algorithmic transparency. It must also consider the affective and interpretive dimensions of user experience, especially in fields such as finance where decisions carry ethical, reputational, and emotional weight. On a broader cultural level, the findings reflect a growing discomfort with automated authority and the persistent human need for meaning-making in technological systems. This research thus calls for a more integrative design philosophy that centers the user's lived experience—not just as a point of data interaction, but as a meaningful site of human interpretation and responsibility.

Like all qualitative inquiries rooted in phenomenology, this study has limitations that constrain the scope of its generalization (Morshed et al., 2024; Schwendicke et al., 2020). The sample was composed of a small number of mid- to senior-level financial professionals within specific organizational settings, which may not represent broader industry practices or user profiles. Additionally, the interpretative nature of the analysis means that findings are contextually grounded and may not apply uniformly across cultures or technological domains. However, these limitations do not detract from the study's value; rather, they point to the richness of subjective experience and the importance of context when examining human-technology interactions. Recognizing these boundaries provides a foundation for further inquiry, rather than a restriction on interpretive depth.

Future research could expand on these insights by exploring similar user experiences across different sectors, such as healthcare, education, or public administration, where predictive systems are increasingly integrated (Jeong et al., 2025; Pliakos & Vens, 2020b). Comparative phenomenological studies could illuminate how different professional cultures mediate algorithmic trust and resistance. Additionally, longitudinal research may reveal how users' interpretations evolve over time as familiarity with predictive systems increases. By continuing to investigate these experiential dimensions, scholars and practitioners can contribute to the design of more humane, context-sensitive AI systems that respect the complexity of human judgment and responsibility.

CONCLUSION

This study explored how financial professionals experience and interpret machine learning predictions within high-stakes decision-making contexts. The findings revealed that users engage with algorithmic outputs not as passive recipients but as active interpreters who must navigate ambiguity, negotiate trust, and reconcile predictive data with personal and professional judgment. These experiences often involve emotional tension, cognitive adaptation, and reflective meaning-making, highlighting the deeply human dimensions of algorithm-supported decisions. By applying an interpretative phenomenological approach, the study filled a critical gap in existing literature that has largely overlooked the lived realities of users in data-driven environments. The insights gained here contribute to a more nuanced understanding of how professionals integrate technology into their decision-making processes. Future research may expand on this work by examining similar phenomena across different sectors or cultural contexts to better inform the design of ethically responsible and human-centered AI systems.

CONFLICT OF INTEREST

The authors declare no conflict of interest. All stages of the research, including the design, data collection, analysis, interpretation, and manuscript preparation, were conducted independently and free from any commercial or financial relationships that could be construed as a potential conflict of interest.

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