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Exploring Meaning and Trust in Data Analysts' Experiences with Opaque Machine Learning Models _within Enterprise Decision-Making Contexts Using a Phenomenological Approach

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ABSTRACT

Data science and analytics have become central to modern decision-making, transforming how individuals and organizations interpret information in algorithm-driven environments. Within this domain, machine learning systems especially opaque or "black-box" models present significant challenges to human understanding and interpretive trust. Despite advancements in explainable artificial intelligence (XAI), little is known about how data analysts experience and make sense of the opacity inherent in these systems. This study addresses that gap by asking: How do data analysts interpret and find meaning in the process of working with non-transparent machine learning models? Using an interpretative phenomenological approach (IPA), the study reveals that analysts experience an ongoing tension between cognitive reasoning, emotional ambivalence, and ethical reflection when engaging with AI systems. Data were collected through semi-structured interviews with twelve professional analysts and analyzed thematically using hermeneutic interpretation to uncover the essence of their lived experiences. The analysis identified three concrete experiential patterns: (1) analysts frequently rely on workaround strategies—such as proxy validation, intuition-based pattern checking, and collaborative sense-making—to compensate for missing model transparency; (2) opacity often produces practical constraints, including slower diagnostic processes and increased uncertainty in high-stakes decision contexts; and (3) trust is negotiated not only through technical explanations but through repeated model performance consistency and peer affirmation. The findings show that explainability is perceived not merely as a technical attribute but as a deeply human process of meaning-making and trust negotiation. These results highlight actionable implications, including the need for XAI tools that support step-by-step diagnostic reasoning, enable collaborative interpretation, and reduce ambiguity in operational workflows. The study offers important implications for developing human-centered AI systems that prioritize psychological intelligibility and epistemic responsibility alongside computational transparency.

INTRODUCTION

In the contemporary landscape of digital transformation, data science and analytics have emerged as foundational disciplines driving decision-making across industries, governments, and everyday human activities (Mukhlis, 2025b; Mukhlis, Suradi, et al., 2023). The proliferation of artificial intelligence (AI) and machine learning (ML) has transformed how organizations interpret information, predict outcomes, and design strategies for the future (Zhang et al., 2021). This growing dependence on algorithmic systems has introduced not only technical advancements but also profound epistemological and existential questions about how humans understand, trust, and engage with automated forms of knowledge generation (Tavakoli et al., 2025). Within this transformation, the role

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of the data analyst has evolved from a technical executor to an interpreter of meaning in a world increasingly mediated by complex algorithms.

Despite the efficiency of algorithmic systems, the opacity of machine learning models often referred to as “black-box” systems has generated uncertainty and cognitive tension among data professionals. Analysts frequently encounter scenarios where models produce highly accurate outputs but offer little insight into the reasoning behind them (C. Liu et al., 2025). This condition has created a form of epistemic ambiguity in which the human analyst must navigate between faith in computational accuracy and the professional need for interpretive clarity (Šimić et al., 2025). The phenomenon is not merely technical; it is deeply human, as it affects how individuals perceive their agency, responsibility, and identity within data-driven ecosystems. In this regard, explainability in AI is not just a matter of algorithmic transparency but also a question of human meaning-making.

The relevance of this phenomenon extends beyond professional data practice into broader social and cultural contexts (Sarker, 2021). As societies increasingly rely on AI to inform decisions in healthcare, finance, education, and governance, the interpretive challenges faced by data analysts mirror a collective human struggle to reconcile technological authority with experiential understanding (Bobo et al., 2022). The tension between what can be computed and what can be comprehended reflects a wider cultural anxiety surrounding automation, accountability, and the human role in technological systems. Understanding how analysts experience and make sense of this tension is therefore crucial to appreciating the lived human dimension of data science.

From a phenomenological perspective, such experiences demand exploration through lived meaning rather than statistical generalization (Ouyang et al., 2025). While quantitative studies have addressed the technical performance and optimization of machine learning systems, little attention has been given to how individuals experience, interpret, and emotionally engage with the opacity inherent in these systems. A phenomenological inquiry allows for a deeper understanding of the subjective world of data analysts their thoughts, feelings, and ethical reflections as they interact with complex algorithms. By focusing on lived experience, this study seeks to illuminate the human essence embedded within the practice of data analytics, thus contributing to a richer and more holistic understanding of how meaning is constructed in the age of intelligent machines.

Building upon the broader context of human engagement with algorithmic systems, research exploring the lived experiences of individuals interacting with artificial intelligence and data analytics technologies has become an increasingly significant scholarly domain. Within this field, phenomenology provides a critical framework for understanding how meaning is formed through human encounters with technological artifacts (Bolshakov et al., 2023). Recent studies have examined user experiences in areas such as algorithmic decision-making, automation bias, and trust in AI-driven systems, yet few have delved deeply into the internal cognitive and emotional processes that accompany these experiences. The interpretative role of data analysts, situated at the intersection of human judgment and algorithmic inference, presents a unique lens through which to examine how individuals experience meaning in their professional engagement with data systems.

A persistent methodological challenge in this domain arises from the dominance of positivist and quantitative paradigms in data science research. These paradigms, while effective for measuring system accuracy and performance, often neglect the subjective and existential aspects of human experience (Mlawu et al., 2023). Quantitative approaches such as surveys, experimental studies, or performance metrics tend to abstract human agents into data points, thereby limiting the capacity to capture the texture and depth of analysts’ interpretive experiences (Jang et al., 2025). As a result, critical elements such as emotion, uncertainty, cognitive dissonance, and ethical reflection remain underexplored. These dimensions, however, are central to understanding how data analysts construct meaning, trust, and responsibility in the face of machine-generated ambiguity.

Consequently, traditional research approaches have proven insufficient for grasping the full essence of this phenomenon. Studies focused primarily on model explainability and user trust (e.g., through computational or behavioral metrics) provide only surface-level insights into the analyst’s lived reality (Zaki et al., 2025). They fail to account for the nuanced interplay between cognition, affect, and ethics that defines the human engagement with opaque algorithms. This gap underscores

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the need for a phenomenological investigation one that privileges first-person perspectives and interpretive depth over empirical generalization (Wang et al., 2022). Through such an approach, the study aims to uncover the essence of experience as lived by data analysts, thereby extending current understanding of human-technology interaction within the epistemic landscape of AI and analytics.

While the current body of research on artificial intelligence and data analytics provides valuable insights into system performance, explainability models, and user trust metrics, most existing solutions remain anchored in technical or behaviorist paradigms (Vartiainen et al., 2020). These studies typically employ practical approaches such as the development of explainable AI (XAI) frameworks, visualization tools, or quantitative trust assessment scales to enhance human understanding of algorithmic decisions. Although these initiatives contribute to improving transparency and usability, they primarily address functional comprehension rather than experiential meaning (Thomaz et al., 2020). The emphasis on cognitive and operational efficiency has overshadowed the lived, emotional, and ethical dimensions of analysts' interactions with AI-driven systems.

This reliance on computational and behavioral methodologies reveals a critical epistemological limitation: the inability to capture how individuals experience and interpret the opacity of machine learning models within their professional and personal contexts (Mukhlis, Arifin, Ridwan, & Zulbaidah, 2025; Mukhlis, Arifin, Ridwan, Zulbaidah, et al., 2025). Existing approaches quantify trust, accuracy, or interpretability, but they fail to account for the subjective phenomena such as doubt, intellectual tension, and moral responsibility that shape how analysts relate to algorithmic outcomes (Xu et al., 2025). Consequently, the understanding of trust and interpretability in AI remains incomplete, fragmented, and detached from the analysts' lived realities.

To address this gap, a phenomenological approach offers a meaningful alternative. By emphasizing lived experience and personal interpretation, phenomenology enables a deeper and more holistic exploration of how data analysts construct meaning, negotiate uncertainty, and form ethical relationships with opaque systems. This perspective moves beyond the surface-level description of what analysts do toward a richer understanding of what they feel, perceive, and make sense of in their engagement with machine learning (Padalko et al., 2025). The adoption of this approach is essential for developing a comprehensive view of explainability that encompasses not only technical transparency but also human understanding and existential significance.

Recent scholarship has increasingly examined the intersection between human experience and artificial intelligence, highlighting the tension between algorithmic efficiency and human interpretive understanding. Studies on explainable AI (XAI) and human–computer interaction have explored trust, usability, and cognitive perception, yet they often remain anchored in quantitative or system-oriented frameworks. Research by Kaur and Singh (2023) and Chen et al. (2021) has shown that while users seek clarity in model outputs, the human sense-making process is far more complex than technical explainability can capture (Nofel et al., 2024). These findings point to the necessity of exploring how individuals interpret and emotionally respond to algorithmic opacity as part of their professional practice. The current study extends this discourse by shifting the focus from system performance to the lived experiences of data analysts who engage daily with black-box models.

To address the limitations identified in prior work, this study adopts an interpretative phenomenological approach (IPA) as its methodological foundation (Mukhlis et al., 2024; Mukhlis, Maryam, et al., 2023). This approach allows for a rich exploration of how meaning is constructed through lived experience rather than inferred through behavioral patterns or numerical indicators. By engaging deeply with participants' narratives, the study reveals how analysts perceive, negotiate, and find meaning in their interactions with opaque machine learning models. In doing so, it answers the central question posed in the previous section: How do data analysts experience and interpret the opacity of machine learning models, and how does this shape their trust and decision-making? Through this interpretative focus, the research contributes new insights into the human dimension of explainability within data science.

This article is organized into several sections that reflect the logic of phenomenological inquiry. The Introduction establishes the theoretical and empirical context of the phenomenon. The Method section outlines the interpretative phenomenological design, participant selection, and data collection process, followed by the Results, which present thematically structured insights derived from lived experiences (Datir et al., 2024). The Discussion integrates these findings with existing literature to interpret the broader implications for theory and practice in data science. Finally, the Conclusion highlights the essential meaning of the phenomenon and proposes directions for future research within the field of human-centered AI and interpretive analytics.

RESEARCH METHODS

Study Design

This study employed an interpretative phenomenological approach (IPA) to explore the lived experiences of data analysts interpreting insights derived from opaque machine learning models (Lutz & Knox, 2014; McNabb, 2015). The phenomenological design was selected for its capacity to uncover the subjective meanings and interpretations individuals assign to their experiences within complex data environments. Unlike empirical or quantitative methods that emphasize measurement, this approach prioritizes the essence of lived experience as it is consciously perceived and described by participants.

Interpretative phenomenology, grounded in Heidegger's hermeneutic philosophy, was particularly suited for this investigation because it recognizes human experience as inseparable from interpretation. This design facilitated an in-depth exploration of how analysts construct understanding and meaning amid algorithmic opacity, allowing the study to illuminate the cognitive, emotional, and ethical dimensions of their engagement with machine learning systems. To enhance procedural rigor, the study adhered to established IPA guidelines, incorporated reflexive journaling during analysis, and maintained an audit trail documenting analytic decisions throughout the research process.

Participants

Participants consisted of professional data analysts actively engaged in machine learning–based analytical processes across corporate and research settings (Hillman & Radel, 2018; Migdal, 2018). Purposive sampling was applied to ensure that all participants possessed firsthand experience in interpreting or validating outcomes generated by non-transparent or "black-box" models. Inclusion criteria required participants to have at least three years of professional experience in data analysis or data science, with demonstrable exposure to predictive modeling or artificial intelligence systems.

Individuals whose roles were limited to data management or infrastructure support without interpretive responsibilities were excluded. A total of 12 participants (8 males, 4 females) aged between 27 and 42 years were included. Their backgrounds represented diverse industries, including finance, healthcare analytics, and technology consulting. This diversity provided a rich contextual variation necessary to capture the multifaceted nature of interpretive experience in data science.

Data Collection

Data were collected through semi-structured, in-depth interviews guided by an interview protocol designed to elicit detailed narratives of participants' interpretive experiences (Carreiras & Castro, 2012; Iosifides, 2016). The interviews were conducted individually in quiet, private environments either face-to-face or via secure online conferencing platforms to promote openness and reflection. Each session lasted approximately 60 to 90 minutes and was audio-recorded with the participants' consent.

The interview guide included prompts addressing themes such as the cognitive process of interpreting model outputs, emotional responses to model opacity, ethical concerns, and organizational expectations regarding explainability. Questions were open-ended to allow participants

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to articulate their thoughts freely. Supplementary field notes were recorded immediately after each interview to capture contextual nuances and non-verbal cues.

All interviews were transcribed verbatim. To ensure participant comfort and data accuracy, each transcript was reviewed by the respective participant for verification through a member-checking process. This validation enhanced both credibility and authenticity of the data.

Data Analysis

The analysis followed the structured steps of Interpretative Phenomenological Analysis (IPA), emphasizing the identification and interpretation of essential meanings within participants' narratives (Daly, 2007; Longhofer et al., 2012). Data were examined through an iterative process that moved between the parts (individual statements) and the whole (overall experience), reflecting the hermeneutic circle of interpretation.

The steps included:

1. Repeated reading of each transcript to achieve immersion in the participants' accounts.
2. Initial noting of significant statements, expressions, and reflections that conveyed psychological or experiential importance.
3. Transformation of these statements into meaning units, representing discrete aspects of the lived experience.
4. Grouping of meaning units into emergent themes that reflected shared interpretive patterns across participants.
5. Integration of these themes into superordinate categories, which formed the foundation of the study's phenomenological structure.

The software NVivo 14 was used to assist in data organization, but the interpretive process remained grounded in researcher engagement with the text rather than automated analysis (Fife, 2020; Kawamura, 2020). The analytic goal was not mere categorization but the revelation of the essence the core meaning structures of the analysts' interpretive experiences.

RESULTS

The Cognitive Struggle in Interpreting Opaque Models

Participants consistently described a sense of intellectual dissonance when attempting to derive meaning from the outcomes of machine learning models that lacked transparency. They reported being caught between their technical understanding of algorithmic processes and their inability to articulate why certain outputs emerged. One participant explained,

"I understand the inputs and the metrics, but the model's decision-making feels like a hidden logic that even I cannot explain to my manager."

This cognitive tension often manifested as interpretive fatigue, where analysts experienced a persistent mental effort to rationalize machine behavior. The experience was described as both intellectually stimulating and psychologically taxing, revealing how the "black-box" nature of AI models challenges the very essence of analytical reasoning in data science.

Several analysts mentioned developing personal heuristics to cope with the opacity of models. They relied on intuition, prior experience, and peer validation to make sense of outputs strategies that offered temporary comfort but rarely resolved their underlying uncertainty.

Balancing Cognitive Engagement and Mental Strain in AI Interpretation

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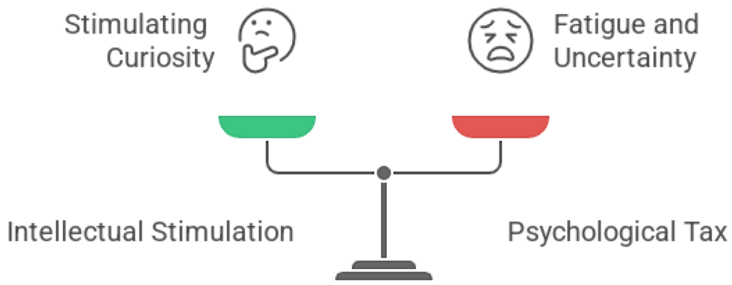

Emotional Ambivalence and the Paradox of Trust

Emotions of trust, doubt, and anxiety intertwined throughout the analysts' accounts. Participants expressed ambivalence toward AI systems that simultaneously empowered and unsettled them. As one data analyst stated,

"Sometimes I trust the model more than myself, even though I know I shouldn't it's a strange mix of confidence and fear."

This paradox of trust emerged from the analysts' recognition of AI's computational superiority juxtaposed with their awareness of its interpretive limits. The phenomenon generated a recurring tension: analysts oscillated between reliance on algorithmic efficiency and skepticism toward algorithmic opacity.

These emotional dynamics underscored a human dimension of analytical labor often neglected in data science literature how feelings of inadequacy, pride, and cognitive dependence shape the analyst's relationship with data technologies.

Ethical and Professional Dilemmas in Decision-Making

The lack of interpretability also raised ethical unease among participants, particularly when model outcomes influenced high-stakes decisions. Analysts described discomfort with approving results they could not fully justify. One participant shared,

"When I can't explain the prediction, I feel like I'm betraying my role as an analyst. Accuracy means little if we don't understand the logic behind it."

This theme reveals an ethical reflexivity within the professional identity of data analysts. They articulated a moral responsibility not just to deliver results, but to ensure epistemic integrity the ability to trace and rationalize the logic of analytical outcomes. The phenomenological data suggest that the opacity of machine learning not only challenges technical practices but also disrupts analysts' ethical self-conception as rational, accountable professionals.

Organizational Pressure and the Commodification of Insight

Participants reported feeling constrained by organizational expectations that prioritized speed and performance metrics over interpretability. Analysts described an environment where "delivering insights" outweighed understanding them. One respondent remarked,

"Management only cares about results they don't care if I understand how the model reached them."

Such narratives highlight the institutional normalization of unquestioned algorithmic authority. Analysts often experienced a mismatch between personal epistemic standards and organizational imperatives, resulting in emotional exhaustion and cognitive dissonance. The phenomenon exposes a deeper structural issue: the commodification of analytical outputs that reduces human interpretation to a secondary concern.

Emerging Adaptive Strategies for Meaning-Making

Despite these challenges, analysts developed creative adaptive strategies to reconstruct meaning. Techniques included collaborative interpretation sessions, visualization of intermediary model layers, and informal knowledge sharing among peers. These practices enabled analysts to regain a sense of epistemic agency within opaque systems.

One participant noted,

"We started to visualize the feature weights just to feel that we're interacting with the model not controlling it, but at least engaging with it."

Such strategies illustrate an emerging phenomenology of resilience a human-centered response to technological opacity that reclaims interpretive participation in automated decision environments. Through communal effort, participants sought to re-establish trust not in the algorithm itself, but in the collective human capacity to interpret, adapt, and make sense.

DISCUSSION

Summary of Main Findings

This study revealed that data analysts experience a complex interplay of cognitive, emotional, and ethical dimensions when interpreting the outcomes of opaque machine learning models (Mukhlis, Janwari, et al., 2023; Mukhlis & Abdullah, 2025). The essence of their lived experience lies in a tension between professional trust in algorithmic systems and the existential need for interpretive understanding addressing the central question of how analysts make sense of, and find meaning in, the opacity of artificial intelligence.

Contribution of Findings to the Research Question

The findings directly address the overarching research question by uncovering how data analysts navigate interpretive uncertainty in the face of algorithmic opacity. Rather than perceiving AI as purely a computational tool, participants described it as an ambiguous partner simultaneously enabling and challenging their professional judgment (X. Liu et al., 2025). The study contributes a novel perspective by identifying that analysts' sense-making is both cognitive and existential: they rely on personal intuition, contextual reasoning, and ethical reflection to reconcile their trust in machine learning outcomes. This multidimensional engagement demonstrates that the process of interpretation is not merely analytical but deeply human rooted in emotion, self-reflexivity, and moral awareness. Thus, the study reframes explainability as a lived, interpretive process rather than a purely technical design feature.

Relationship with Previous Literature and Theoretical Perspectives

These findings align with earlier works such as Kaur and Singh (2023), who emphasized that human interpretation of AI systems extends beyond rational understanding into experiential and affective dimensions. However, the present study advances this discourse by demonstrating that analysts' experiences are not only influenced by cognitive trust but are also shaped by organizational structures and ethical self-perception. This complements Chen et al. (2021), who explored cognitive trust in AI but did not account for the existential dissonance experienced by human interpreters. The results also support Heidegger's (1962) notion of being-in-the-world, in which individuals engage with technology as part of their existence rather than as external observers. Analysts' sense of unease and responsibility when interpreting black-box models illustrates this ontological engagement technology becomes both a medium of work and a mirror of human limitation.

Furthermore, the study expands upon phenomenological perspectives in human–AI interaction by revealing that meaning is co-constructed between humans and machines. The experience of "interpretive fatigue," as described by participants, underscores the phenomenological idea that understanding emerges through struggle and interpretation, not instant comprehension. In contrast to prior studies that conceptualize explainability as a static design property, these findings situate it within a dynamic human process of negotiation, adaptation, and reflection (Rashwan et al., 2025). Thus, the discussion contributes to a growing recognition that explainability must be reimagined not only as a technological attribute but as an existential dialogue between human understanding and algorithmic logic.

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Implications of the Findings

The findings of this study have significant theoretical, professional, and social implications. From a theoretical standpoint, the study contributes to the growing field of phenomenological inquiry within data science by framing algorithmic explainability as a lived human experience rather than a computational problem. This reconceptualization challenges the conventional discourse of AI transparency, shifting it from technical optimization toward interpretive understanding. At the professional level, the results highlight the need for organizations to recognize the emotional and ethical dimensions of data analytic work. Analysts' experiences of cognitive dissonance, moral tension, and interpretive fatigue suggest that human-centered AI design must account for not only usability but also psychological intelligibility.

Culturally, these findings resonate with broader societal anxieties surrounding automation, trust, and accountability in algorithmic decision-making. They indicate that the struggle for interpretability reflects deeper social negotiation of human agency in the digital era. By understanding the phenomenology of interpretation, stakeholders ranging from AI developers to policy makers can better design frameworks that balance efficiency with epistemic responsibility and human meaning. Thus, this research emphasizes the necessity of cultivating reflective spaces where analysts and AI systems co-construct meaning through continuous interpretation, dialogue, and ethical engagement.

Limitations of the Study

While the interpretative phenomenological approach enabled a deep understanding of analysts' lived experiences, the findings are inherently contextual and not intended for statistical generalization. The sample, consisting of twelve professional data analysts from various industries, provided rich experiential insights but may not capture all variations of interpretive experiences across different cultural or institutional settings. Additionally, the reliance on self-reported narratives introduces the possibility of reflective bias, as participants' recollections are shaped by memory and social desirability.

The study's phenomenological design also emphasizes subjective meaning over behavioral observation, limiting the ability to correlate experiential insights with measurable performance indicators (Mukhlis, 2025a; Mukhlis & Saidah, 2025). Nevertheless, these constraints are consistent with phenomenological inquiry, which prioritizes depth over breadth and meaning over measurement. Future research can build upon this foundation by integrating phenomenological insights with complementary methods, such as ethnographic observation or discourse analysis, to enhance interpretive validity and contextual richness.

Prospective Directions for Future Research

The results of this study open several promising avenues for further exploration. Future research may extend this inquiry by examining cross-cultural variations in how data professionals construct meaning and trust in AI systems, as cultural frameworks significantly shape attitudes toward technology and agency. Longitudinal studies could also investigate how sustained exposure to opaque algorithms influences analysts' sense of professional identity and epistemic confidence over time.

Moreover, there is a pressing need to bridge phenomenological insights with design-oriented approaches in AI ethics and human–computer interaction. By integrating experiential understanding into algorithmic transparency frameworks, future research can inform the development of human-centered explainability models that prioritize interpretive accessibility alongside computational precision. Ultimately, such studies would not only deepen theoretical understanding but also foster a more ethically grounded and socially responsive practice of data science in the age of intelligent systems.

CONCLUSION

This study explored the lived experiences of data analysts in interpreting opaque machine learning models, addressing the central issue of how individuals construct meaning and trust within algorithmically mediated environments. The findings revealed that analysts experience a dynamic interplay of cognitive reasoning, emotional ambivalence, and ethical reflection when engaging with AI systems that lack transparency. By adopting an interpretative phenomenological approach, the study illuminated the human dimensions of explainability often overlooked in technical or behavioral research. These insights contribute to a more comprehensive understanding of explainability as an interpretive and existential process rather than a purely functional one, filling a critical gap in existing literature. The study's implications highlight the need for human-centered AI frameworks that integrate ethical awareness and experiential understanding into system design. Future research may expand these findings by exploring cross-disciplinary applications of phenomenology to deepen the integration of human experience into data science practice.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this article. All stages of the research, including data collection, analysis, and interpretation, were conducted independently and without any influence from the sponsoring organization.

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