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BAD ROBOT! BAD! PARALLELING DARK SIDE OF AI AND CONSUMERS' MISUSE INTENTION: A FINANCIAL SCENARIO-BASED STUDY

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Abstract

Artificial intelligence (AI) chatbots are increasingly deployed in financial services, yet their potential misuse by consumers remains underexplored. This study investigates how dark-side perceptions of AI-based banking chatbots influence consumers' intention to misuse these systems. Drawing on cognitive, technological, and service-related perspectives, the study examines ten dark-side factors using a scenario-based survey of 393 postgraduate students. Data were analysed using covariance-based structural equation modelling (CB-SEM) and fuzzy-set qualitative comparative analysis (fsQCA). CB-SEM shows that sense of insecurity, distrust, perceived inauthenticity, service inequality, and service discrimination significantly increase misuse intention, whereas perceived risk, lack of familiarity, lack of personalization, confusion, and technophobia are not significant. The fsQCA results reveal multiple configurational pathways to misuse, demonstrating equifinality and highlighting the importance of interacting conditions. The findings extend AI dark-side research by conceptualizing misuse as a reactive behavioural response and emphasize trustworthy, transparent, secure, and fair chatbot design

Keywords: Dark side of AI, Intention to misuse, AI chatbots, Finance

1 Introduction

Artificial intelligence (AI)-based systems, particularly popular large language model backed systems like chatbots, enable organizations to automate interactions and enhance efficiency (Lei *et al*., 2025; Sun *et al*., 2022). However, the projected global energy consumption of such systems is 134 TWh by 2027, equivalent to the annual consumption of Argentina. Current annual freshwater consumption of Google and Meta AI data centres alone, is 2.2 billion cubic litres annually, which is twice Denmark's yearly consumption. (Raza, 2024). In response, organizations like OpenAI encourage effective engagement with AI systems to reduce operational strain. However, a huge contributor to such operational strain is the "dark side" of AI systems, often leading to unethical behaviours, such as AI misuse - an underexplored context in information systems (IS) literature (Kim *et al*., 2023). Matching previous descriptions of IS misuse (Chu *et al*., 2015), AI misuse may be defined as "situations

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where users engage with systems in ways that deviate from authorized or intended use, including manipulating inputs, withholding information, or exploiting system limitations". Such misuse may arise from the said dark side constructs such as privacy concerns, or perceived system inadequacies (Zheng *et al*., 2025). For instance, users may avoid sharing personal data due to privacy risks or deliberately provide misleading inputs, that produce unusable outputs adding to the operational strain. Despite its relevance, the dark side drivers of such behaviour remain insufficiently understood (Kim *et al*., 2025) and is an emerging area of research (Deng *et al*., 2026). From a theoretical standpoint, prior research has begun to explore unethical or opportunistic behaviour in AI interactions. For instance, Lei *et al*. (2025) examine how framing AI as servant versus partner, shapes unethical behaviour. Weirup *et al*. (2025) analyse unethical behaviours when dealing with cooperative versus competitive AI agents. Others employ psycho-constructs like privacy invasion and loss of control, as behavioural antecedents (Sun *et al*., 2022; Ribeiro *et al*., 2025). Deng *et al*. (2016) investigate how perceived monitoring impacts unethical behaviour. However, as Cheng *et al*. (2022) argue, the literature remains fragmented, yielding a hampered view of the dark side, particularly in explaining behavioural outcomes beyond disengagement or resistance. From a practitioner perspective, misuse may have important operational implications. A Morgan Stanley (2026) report states global investment on AI-driven operational systems (like customer services) stand at $1.4 trillion and incur substantial maintenance costs (projected $2.9 trillion by 2028). Particularly in sectors such as banking, a forerunner in AI technology adoption (Parthiban and Adil, 2024), we argue that misuse can be more pronounced, as they involve sensitive financial information that amplifies concerns related to privacy and security (Sun *et al*., 2022). Building on this premise, the present study draws on the dark side framework proposed by Bhardwaj *et al*. (2025), incorporating Cognitive, Technological and Service-related constructs. While Bhardwaj *et al*. (2025) have examined these factors in relation to system evaluation (system design and perceived lack of empathy), this study reconceptualizes them as antecedents of behavioural responses, specifically users' intention to misuse AI-based Banking chatbots (AIBCs). In doing so, the focus gets shifted from systems evaluations to behavioural outcomes concerning system dark side, thereby addressing an important gap in the literature. Accordingly, the following research question (RQ) is presented: RQ1: How and why do dark-side perceptions of AI systems influence user intent to misuse AIBCs?

To address this question, the study employs a scenario-based survey design and analyses data using a combined predictor–causal approach, integrating covariance-based structural equation modelling (CB-SEM) and fuzzy-set qualitative comparative analysis (fsQCA). By doing so, it captures both net effects and configurational pathways underlying misuse behaviour. The conclusions of this research support theory through providing an alternative conceptualization of misuse as a reactive behavioral response due to perceived ethical, relationship and fairness issues related to AI system design, versus as limited in terms of cognition.

In addition, from a practical perspective, it identifies the necessity for developing AI systems which are not only functional but also provide users with a level of trustworthiness; transparency and fairness.

Finally, it includes suggestions for future research studies based upon some of the identified limitations.

2 Literature Review and Framework Conceptualization

2.1 The Dark Side of AI and Intention to Misuse AIBCs

Research on AI and digital assistants has been overwhelmingly guided by an adoption–continuance paradigm, where negative perceptions (e.g., risk and distrust) are expected to reduce usage intentions, satisfaction, or loyalty (Shahzad *et al*., 2026; Zheng *et al*., 2025; Silva *et al*., 2023). This perspective assumes that adverse experiences primarily lead to withdrawal behaviours such as avoidance or discontinuance (Zheng *et al*., 2025). However, emerging work on the dark side of AI challenges this assumption by showing that negative evaluations can also generate active, deviant, or retaliatory responses (Kim *et al*., 2023; Zhu *et al*., 2025). Extant literature on the dark side of AI introduces fragmented causes of immoral AI-related consumer behavioural outcomes such as general unethical consumer behaviour in stores (Zhu *et al*., 2025) and unethical behaviours during financial negotiations (Weirup *et al*., 2025). These are preceded by antecedents such as, privacy concerns, uniqueness neglect (Barari *et al*., 2024) and information overload

(Sun *et al*., 2022). Such factors may be imperative in high-stakes contexts such as finance, as users are not merely passive recipients of service—they can manipulate, or exploit systems (Siering *et al*., 2017). This study advances the literature by shifting the outcome from prevalent passive resistance constructs (Husain and Shalini, 2025; Zheng *et al*., 2025) to intentional misuse of AIBCs. Hence, we offer critical theoretical distinction by stating that negative perceptions do not only reduce engagement but also motivate counterproductive engagement. The resultant multi-theoretical conceptual framework (see Fig. 1) pits dark side antecedents coined by Bhardwaj *et al*., (2025), against the misuse construct to analyse configurational perspective of causality. The model will help the research find out how misuse is developed through a combination of psychological, technological and service related variables and not by single variables. The model also provides the basis for developing theory on equifinality; i.e., multiple routes to misuse. Dark side antecedent categories are categorized into three large categories. Cognitive antecedents reflect users' internal thinking and feelings (e.g. confusing, fearful of technology, at risk). Technological antecedents arise due to technological systems design and functionality constraints (e.g. no customization options). Service related antecedents capture the relational and equity based assessment of users regarding their interaction with an artificial intelligence mediated interaction (e.g. as though being interacted with through a robot, unfair treatment by an AI). Below are detailed definitions and explanations of each construct and a discussion of their relationships to misuse intent.

2.1.1 Cognitive Factors: Ethical issues are an important part of the "dark side" of the digital economy with respect to user feelings of insecurity and perceived risks (Bhardwaj et al., 2025). The need for consumers to provide large amounts of data and allow algorithms to make decisions regarding those data can be problematic from a privacy and security perspective (Silva et al., 2023; Ebbers et al., 2021). Studies have found that perceived risk negatively impacts both trust in systems and willingness to use them (Ebbers et al., 2021; Bouhia et al., 2022), however recent work (Lissillour and Shahut, 2026) suggests that when organizations demonstrate an ethic responsible approach, users will generally be more positive toward the organization. In contrast, few studies (Zheng et al., 2025) have researched how ethical concerns result in intentional misuse versus passive avoidance. Therefore, we contribute to the body of knowledge on this subject by establishing insecurity and perceived risk as predictors of intended misuse behavior. Users who believe their personal data is at risk or that the system could potentially harm them will likely rationalize that using the system in a manipulative manner or to intentionally violate compliance regulations is acceptable (Adhikari and Panda, 2018). Accordingly, we hypothesize that

H1a: Sense of insecurity positively influences intention to misuse AIBCs.

H1b: Perceived risk positively influences intention to misuse AIBCs.

Second, in addition to ethical concerns, cognitive adoption barriers such as lack of familiarity and distrust play a critical role in shaping user behavior (Bhardwaj *et al*., 2025). These constructs are grounded in innovation resistance theory and trust theory, which emphasize the importance of user knowledge and confidence in technology adoption (Woodside, 1996; Pavlou 2003). Lack of familiarity limits users' understanding of systems (Schulenberg *et al*., 2008), leading to uncertainty and other challenges (Attard *et al*., 2016), while distrust reflects a lack of confidence in the system's intentions and reliability (Shahzad *et al*., 2026). Despite these proven relationships in extant literature, the relationship between these constructs and misuse behavior remains underexplored. This study extends AI literature by examining how lack of familiarity and distrust influence intention to misuse AI systems. It is argued that users who lack understanding of AI may feel less accountable for their actions (Titah, 2024), while those who distrust the system may perceive a risk of harm and engage in misuse as a form of defensive or adversarial behaviours (Knowles *et al*., 2022). Therefore, it is hypothesized that

H2a: Lack of familiarity positively influences intention to misuse AIBCs.

H2b: Distrust positively influences intention to misuse AIBCs.

2.1.2 Technological Factors: Prior work indicates that lack of personalization is significant in terms of satisfaction and engagement (Teepapal, 2025), although Rita et al. (2026) indicate that users may tolerate a lack of personalized interaction so long as the functional performance of the system is satisfactory. The discrepancy illustrated by Rita et al. (2026) demonstrates the need for an exploration of other potential outcomes than just satisfaction. The impersonality of digital interactions can lead to a form of opportunistic behavior through the mechanism of "on-line disinhibition," where Suler (2004) implies that humans will engage in unethical behavior when they have the perception that they are anonymous/invisible on-line and there are no direct social cues present. Thus, it is hypothesized that lack of personalization will positively impact the intention to misuse AI-based chatbots.

H3: Lack of personalization positively influences intention to misuse AI-based chatbots.

Another group of factors relate to difficulties associated with deploying the AI-based chatbot, specifically confusion and technophobia (Bhardwaj et al., 2025) based on Cognitive Load Theory and Technology Readiness. When poorly developed AI systems provide too much information, unclear communications or technological limitations, they may cause user-cognitive burden (Sun et al., 2022; Wang et al., 2026; Chirayath et al., 2025). Users experience confusion when they cannot process/interpret information. Technophobia represents a general fear/anxiety towards technology (Bhardwaj et al., 2025; Dang, 2020; Khasawneh, 2018). Previous research generally portrayed these constructs as barriers to adopting new technologies (Dang, 2020; Khasawneh, 2018). The purpose of this study however is to examine their role in post-technology adoptions. Although Evans et al. (2024) indicated that overloading the cognitive capacity of users leads to disengagement, Khalid et al. (2022) suggested that subsequent frustration can result in counter-productive/deviant behavior. Henceforth, it is proposed that both confusion and technophobia will positively impact intention to misuse AI-based chatbots.

H4a: Confusion positively influences intention to misuse AIBCs.

H4b: Technophobia positively influences intention to misuse AIBCs.

2.1.3 Service-related Factors: Fifth, a central concern in AI-enabled interactions is perceived inauthenticity, a construct grounded in service-dominant logic. Authenticity reflects the extent to which consumers perceive service interactions as genuine, transparent, and trustworthy. In AI-mediated contexts, the substitution of human agents with chatbots can disrupt emotional engagement and relational bonds, particularly when users perceive the interaction as deceptive or insincere (Kirk and Givi, 2025; Greve, 2025; McGuire *et al*., 2023). Prior studies (such as Kummer and Bick, 2025) have presented conflicting perspectives: while anthropomorphic design elements are often found to enhance user engagement (Kumar *et al*., 2025), uncanny valley effects including excessive mimicry without transparency can backfire, leading to perceptions of manipulation, reduced trust, and consumer-technology connection severance (Bhardwaj *et al*., 2025; Song and Shin, 2024; Yam *et al*., 2021). Existing research has largely examined authenticity in relation to satisfaction and engagement (Bhardwaj *et al*., 2025; Phan and Bui, 2025); however, the present study advances this stream by proposing that perceived inauthenticity may also trigger negative behavioral responses, such as misuse of AI systems.

H5: Perceived inauthenticity positively influences intention to misuse AI-based chatbots.

Sixth, service discrimination and inequality represent critical ethical and fairness-related concerns in AI-driven services (Bhardwaj *et al*., 2025; Zheng *et al*., 2025). These constructs capture users' perceptions of unjust or unequal treatment. AI systems, particularly those driven by algorithms, have been criticized for reinforcing biases and creating differential service experiences across users (Bhardwaj *et al*., 2025; Zheng *et al*., 2025). Prior research has linked perceived unfairness to dissatisfaction (Sainz *et al*., 2023), rejection (Kordzadeh *et al*., 2022) and negative

emotions (Howard *et al*., 2010). However, its impact on misuse behavior within the AI systems context has received limited attention. This study extends literature by proposing that perceived inequality and discrimination can provoke counterproductive behaviors. When humans perceive that they are treated unfairly compared to others, they may experience moral disengagement and justify engaging in deviant actions (Hystad *et al*., 2014). Thus, it is hypothesized that

H6a: Service inequality positively influences intention to misuse AI-based chatbots.

H6b: Service discrimination positively influences intention to misuse AI-based chatbots.

3 Research Methodology

This study adopts a scenario-based survey design, a commonly used approach in examining unethical behavioral intentions in technology-mediated contexts (Sun *et al*., 2023; Seegebarth *et al*., 2019). The design allows respondents to evaluate a controlled and standardized service interaction and subsequently report their perceptions and intended behaviors (D'Arcy and Devaraj, 2012). Participants were exposed to a set of simulated chatbot interaction scenarios, presented as mobile chat screenshots (See supplementary file appendix A). These scenarios depicted interactions between a customer and a banking chatbot in the context of financial service inquiries (e.g., loan-related assistance). The scenarios were designed to reflect varying degrees of service quality, system responsiveness, and AI-related characteristics identified in prior literature on the dark side of AI (Bhardwaj *et al*., 2025). In certain cases (e.g., Service Discrimination), participants were shown comparative scenarios, where their interaction was presented alongside that of other users undergoing similar interactions. This approach enabled respondents to form perceptions related to fairness, discrimination, and service inequality in a more realistic and contextually grounded manner. Following exposure to the scenarios, participants were asked to evaluate their perceptions of the chatbot and indicate their intention to misuse the system (refer supplementary file Appendix A). A total of 450 postgraduate students were recruited to participate in this study. The participants were drawn from a large university in India that attracts both national and international students across a wide range of academic programs. The university hosts over 16,000 on-campus students and approximately 40,000 online learners, providing a diverse and heterogeneous student population. Postgraduate students were considered for this study after asking them the following filter questions: 1) Are you familiar with AI-based banking chatbots, 2) Have you been exposed to AI-enabled banking systems, and 3) Have you interacted with such systems in the past month. Data were collected using a self-administered online questionnaire, distrustributed through student networks. Participation was voluntary, and respondents were assured of anonymity and data confidentiality. The chatbot interaction scenarios were presented in the form of chat-based screenshots resembling a mobile messaging interface, enhancing ecological validity and realism (Aguinis and Bradely, 2014). The screenshots intentionally shared no similarities to prevent design-induced response bias. The conversational structure included user queries and chatbot responses, designed to simulate typical banking chatbot interactions. The scenarios were carefully constructed to avoid explicit mention of the constructs, embed subtle cues reflecting system limitations and biases, and allow participants to form their own perceptions of the interaction (Fisher, 1993). All constructs of the study were measured using previously validated scales, adapted to the current context (refer Supplementary File Appendix A). After removing manually invalid data (such as extreme responses and incomplete responses), 393 valid responses were used for data analysis.

4 Data Analysis and Results

4.1 Measurement Model

Data analysis was performed using Covariance-Based Structural Equation Modelling (CB-SEM), and the model showed good fit. The robust CFI (0.942) and TLI (0.935) exceeded the 0.90 threshold, while RMSEA (0.045) and SRMR (0.062) were within acceptable ranges (Dash and Paul, 2021). Standardized factor loadings ranged from 0.611 to 0.950 across constructs, all above the 0.60 cutoff (Dash and Paul, 2016). HTMT ratios were below 0.8, confirming discriminant validity (Cheung *et al*., 2023). Reliability and convergent validity were supported, with Cronbach's alpha (0.785–0.924), composite reliability/omega (0.785–0.926), and AVE (0.550–0.773) all exceeding recommended thresholds,

indicating strong internal consistency and substantial variance explained (Cheung *et al*., 2023).

4.2 CB-SEM results

The CB-SEM results showed a mixed pattern of support across the hypotheses (see Fig 1). H1a (sense of insecurity) was strongly supported (β = 0.39, p < 0.001), while H1b (perceived risk) was not (β = 0.07, p = 0.221). H2a (lack of familiarity) was rejected (β = 0.09, p = 0.143), but H2b (distrust) was supported (β = 0.18, p = 0.032). H3 (lack of personalization) was insignificant (β = 0.12, p = 0.097). H4a (confusion) and H4b (technophobia) were rejected (β = -0.08, p = 0.312; β = -0.11, p = 0.184). H5 (perceived inauthenticity) was supported (β = 0.31, p = 0.001). Finally, H6a (service inequality) and H6b (service discrimination) were supported (β = 0.27, p = 0.018; β = 0.16, p = 0.041).

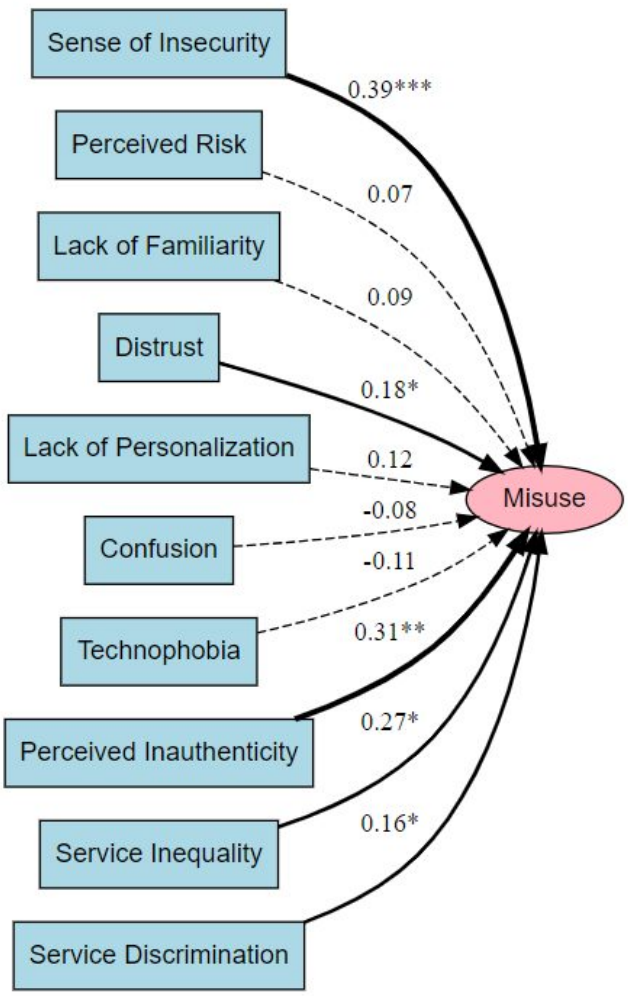


Fig. 1 Structural Model (Source: Authors' own)

4.3 fsQCA results

Although the framework resembles a regression model with multiple predictors and a single outcome—I sought a method to uncover the causal configurations among variables, considering the complex interdependencies highlighted by Bhardwaj *et al*. (2025). Unlike Bhardwaj *et al*. (2025), who relied on a limited qualitative dataset, we aimed to identify complex, potentially non-linear relationships using quantitative data from a larger, more representative population through the fsQCA technique. The fsQCA results reveal strong evidence of equifinality, with multiple configurational pathways leading to the outcome variable. The intermediate solution has an overall solution coverage of 0.695 and consistency of 0.918, indicating that the configurations explain a large proportion of the outcome (Pappas and Woodside, 2021). Four higher-order solution families emerge. The dominant high risk–constraint pathway centers on

Sense of Insecurity, Perceived Risk, and Lack of Personalization, supported by peripheral conditions such as Perceived Inequality, Distrust, and Service Discrimination, with high relevance (coverage 0.508–0.601; consistency 0.977–0.991). A technology-driven pathway highlights Technophobia, Perceived Risk, Lack of Personalization, and Lack of Familiarity as core conditions, showing high consistency (>0.974) but lower coverage (0.189–0.226). The absence-based pathway, marked by the core absence of most causal conditions, shows that misuse intention can arise even in low-constraint environments, though coverage (0.156–0.160) and consistency (0.905–0.950) are lower, implying unobserved structural factors. Finally, a hybrid pathway combines Sense of Insecurity, Technophobia, Lack of Personalization, and Lack of Familiarity, with high consistency (0.986) but modest coverage (0.181). Across all families, Lack of Personalization, Perceived Risk, and Technophobia consistently drive misuse intentions, while other conditions mainly serve as contextual modifiers. Complete results and screenshots are presented in supplementary file Appendix B and C.

Table 1 fsQCA table (source: Authors' own)

Conditions	F1: High Risk–Constraint	F2: Technology Path	F3: Absence Path	F4: Hybrid Path
Sense of Insecurity	●		⊗	●
Perceived Inequality	⊙		○	⊙
Distrust	⊙		○	○
Technophobia		●	⊗	●
Perceived Risk	●	●	⊗	○
Service Inequality	⊙	⊙	○	○
Lack of Personalization	●	●	⊗	●
Service Discrimination	⊙	⊙	○	⊙
Lack of Familiarity		●	⊗	●
Confusion	⊙	⊙	○	○
Raw Coverage	0.508 – 0.601	0.189 – 0.226	0.156 – 0.160	0.181
Unique Coverage	0.014 – 0.026	0.005 – 0.009	0.002 – 0.005	0.004
Consistency	0.977 – 0.991	0.974 – 0.976	0.905 – 0.950	0.986
Configurations	C1, C2, C3, C11	C9, C10	C4, C5, C6, C7	C8 (minor path)

Legend: ● = core presence (from parsimonious + intermediate); ⊗ = core absence; ⊙ = peripheral presence (intermediate only); ○ = peripheral absence; blank = irrelevant (“don’t care”)

5 Discussion

This study challenged the conventional adoption-continuance model for research of AI and IS by investigating if negative beliefs about AI systems result in both deactivation and intentional misbehavior. Perceived artificiality, distrust, inequitable services, bias/discrimination, and insecurity all were significant positive predictors of misuse intentions and insecurity was identified as the most significant predictor; this suggests that percieved vulnerability and lack of user control are key drivers of maladaptive behavior. These results support the assertion made by Adhikari & Panda (2018), that when users believe AI systems are dangerous, deceitful or unfair, users will not just opt-out; they will actively respond via maniuplative/exploitive interaction. These results extend previous work (Zheng et al., 2025; Ebbers et al., 2021; Bouhia et al., 2022) which have primarily focused on passive responses (disengagement/ discontinuance) as opposed to providing evidence that negative experience with AI can elicit adverse engagement. Conversely, several commonly cited factors related to technology acceptance (confusion, fear of technology, unfamiliarity, lack of personalization, perceived risk) did not meet statistical significance for predicting misuse. This is a significant deviation from the large body of prior research (Dang, 2020; Khasawneh, 2018; Sun et al., 2022; Wang et al.,

2026; Chirayath et al., 2025; Teepapal, 2025; Rita et al., 2026; Titah, 2024; Adhikari and Panda, 2018) who consistently have framed these variables as critical impediments to successful implementation/adoption of technologies. We base this argument on prior work in IS security and AI ethics which reiterate that system misuse is better understood as a behavioral and ethical response to socio-technical conditions, not merely a usability defect. (Chatterjee *et al*., 2015; Pérez-Portabella *et al*., 2026). In addition to studies including those from Phan and Bui (2025), the significant impact of perceived inauthenticity in the financial AI context, provides evidence to support the necessity of both transparency and clear identity definitions in all AI interactions. In the event that users feel an AIBC is being insincere or misleading in its responses, the basis of a relationship in the conversation will be impacted negatively along with the normative constraint placed upon the users' behavior (Song and Shin, 2024; Yam et al., 2021). Moreover, the importance of distrust in this study, illustrates once again that relational governance mechanisms are crucial components of any type of AI-based system. Without trust, users may act in a manner that could be considered adversarial towards the AI (Knowles et al., 2022). Finally, results from this study provide significant information regarding the potential of fairness to function as a component of AIBCs. Significant influences were discovered on service inequality and discrimination, providing substantial insight into how sensitive users are toward their perception of differential treatment through algorithmic-based systems (Sainz et al., 2023; Zheng et al., 2025; Bhardwaj et al., 2025). It has been established in the current study that there are consequences to deviance due to unfairness and/or bias within algorithmic systems beyond mere dissatisfaction and trust (Kordzadeh et al., 2022; Draws et al., 2021); specifically, deviance resulting from unfairness/bias can result in active exploitation of the system.

The results of the fsQCA analysis reveal numerous different paths to misuse and therefore supports the concepts of equifinality and causal asymmetry. Perceived risk and technophobia, which did not demonstrate any statistical significance when analyzing the net-effect models, appear to be relevant conditions within various misuse inducing configurations. These results lend credibility to previous research concerning misuses of technology based upon interacting conditions, i.e., the arguments presented by Adhikari and Panda (2018), and Khasawneh (2018). Therefore, the data support the notion that misuse is not solely influenced by one factor but rather by a combination of factors that interact with each other.

6 Theoretical Implications

This research contributes to the literature on artificial intelligence, financial digital assistants, and information systems by challenging dominant assumptions, and developing new frameworks that expand our knowledge. Firstly, the research contributes to the body of knowledge concerning the adoption and continuation of AIBCs through a shift in the scope of what we measure as outcomes. Most studies have been based on a "adoption--continuation" paradigm (Silva et al., 2023; Shahzad et al., 2026; Zheng et al., 2025). Studies using this paradigm expect negative perceptions about risk, distrust, or complexity will reduce usage, encourage avoidance, and/or lead to discontinued use. However, the results from this study demonstrate these same types of negative perceptions can be associated with active misuse behaviors within financial contexts. Therefore, this study develops the theoretical boundaries of AI research beyond mere passive resistance (Zheng et al., 2025; Husain & Shalini, 2025). Additionally, this study develops the concept of misuse as an additional type of behavioral outcome for financial technology adoption research. Thus, it emphasizes that users of AI technologies are not simply passive consumers of AI products/services. Rather, they may behave as strategic actors who can act against adverse system experiences.

Secondly, the research develops the IS misuse literature through the re-conceptualization of misuse in relation to services enabled by AI. Historically, most of the IS misuse literature has concentrated on unauthorized use related to opportunity or the individual's intent (Weirup et al., 2025; Zhu et al., 2025; Sun et al., 2022; Barari et al., 2024). Conversely, this research conceptualizes misuse as a form of deviant reaction caused by socio-technical conditions related to perceived inequitable treatment, security concerns, and perceived inauthenticity. The conceptualization of misuse as a reaction to these issues provides a connection between broader behavioral/ethical reactions (Khalid et al., 2022; Adhikari & Panda, 2018; Hystad et al., 2014) and the traditional IS misuse literature. Through this

conceptualization, this research connects the IS misuse literature with evolving discussions concerning AI ethics and algorithmic governance (Fuchs et al., 2009) to provide a contextualized understanding of user behavior in AI mediated financial environments.

Thirdly, the research contributes to both trust and authenticity literature in digital finance contexts by establishing that trust and perceived authenticity prevent both negative behaviors and influence positive relational outcomes. Previous studies have demonstrated that trust and perceived authenticity positively relate to user satisfaction and engagement (Yam et al., 2021; Song & Shin, 2024; Shahzad et al., 2026), while this study demonstrates that their absence relates to users acting outside norms and engaging in adversarial behaviors. As a result of this finding, relational governance theories are extended to include that trust and authenticity serve as informal control mechanisms that limit opportunistic user actions in AI interactive relationships.

Fourth, the research enhances service fairness literature in AI domains through empirical demonstration of the relationship between perceived service inequality/discrimination and misuse intention. The results from this research show that users' perception of being treated unfairly can result in counterproductive behaviors directed towards the system itself. This extends the previously researched relationship between unfairness/deviance (Draws et al., 2021; Sainz et al., 2023; Kordzadeh et al., 2022; Howard et al., 2010) into AI enabled financial service contexts and illustrates the behavioral consequences of algorithmic bias in AI systems.

Fifth, the study clarifies theoretically between cognitive barriers and ethical triggers of behavior. The lack of significance for confusion, technophobia, and unfamiliarity indicates that cognitive barriers alone do not directly result in AIBC misuse. Misuse is therefore primarily influenced by affective and ethical evaluations related to security, distrust, and perceived unfairness. These findings contradict previous emphases on usability/cognitive load (Evans et al., 2024; Bhardwaj et al., 2025; Chirayath et al., 2025) in technology research and advocate for greater consideration of ethical design and relational assessments in AI systems.

Sixth, by combining CB-SEM and fsQCA methods, this study contributes to theory development through demonstrating causal complexity in AI-related behaviors. The existence of multiple configurational pathways supports the principles of equifinality and causal asymmetry. Furthermore, it shows that different combinations of factors can cause misuse. Therefore, the findings support the necessity to move away from linear/net effect models and toward configurational/ interaction based theorizing (Di Paola et al., 2025) especially in complex socio-technical systems similar to those found with AI.

7 Practitioner Insights

The research results demonstrate that the misuse of AIBCs is not an error of technology, however it is a result of design driven by the way users perceive and experience trust, fairness and security. As such this changes the scope of the design process from merely being functionally designed to being ethically engineered through a system engineering approach. Accordingly, this study offers the following insights to financial AI systems designers, implementors and managers.

First, the significant influence of a sense of lack of security and distrust demonstrates that security needs to be both technically reliable and communicatively visible. Privacy-by-design (PbD) engineering principles should be adopted and include data minimization, encryption, and user control dashboards. In addition to PbD, engineers should also develop interface level indicators that provide reassurance to users regarding how their personal information will be protected and therefore reduce the likelihood of an adverse response.

Second, the fact that users' perception of the inauthenticity of a chatbot significantly influences their willingness to engage with it creates a need for developing fair and transparent interaction designs. Chatbots should avoid over-anthropomorphism and clearly indicate that they are AI systems, using clear and consistent language. Using Explainable AI (XAI), which provides explanations for chatbot responses, increases user's confidence in what the chatbot says and reduces user's skepticism regarding the reliability of the chatbot's responses.

Third, the finding that service equality and discrimination have a statistically significant relationship with chatbot use, supports the need for

fairness awareness when designing systems. Engineers should include functionality into their systems that detects bias and allows for fairness to be implemented as constraints during design. Furthermore, engineers should continuously monitor systems to ensure that all users receive equitable services. System performance metrics related to fairness should become primary concerns rather than secondary considerations.

Fourth, because the study found no statistically significant relationships between cognitive factors (confusion and technophobia) and misuse of AIBCs, usability improvements alone cannot eliminate misuse. Even well-designed systems can be misused if users believe that they are unfair or unsafe. Therefore, there exists a necessity to move away from usability centric design towards perception centric design. Perception centric design is concerned with designing systems to proactively address both the ethical and emotional responses of users.

Lastly, the configurational nature of misuse demonstrates that single point solutions will not prevent misuse. Institutions should consider adopting a holistic design methodology to address multiple aspects of misuse simultaneously. Holistic methodologies would allow organizations to assess potential misuse of chatbots prior to deployment. Additional methods companies could utilize to prevent misuse would be to implement misuse aware technologies (e.g., detecting manipulative input from users).

8 Conclusion

Misuse of AIBCs is to be seen in this paper as a reactive deviant behaviour that is influenced by an individual's ethical, relational and fairness concerns instead of their cognitive limits. The study has demonstrated the net effect and configural pathway(s) to explain how individuals misuse these services via the combination of CB-SEM and fsQCA. As with all studies, there are some limitations. For example, the sample was comprised of students; it used a cross sectional design; and the study focused on one type of service setting. All three factors could potentially limit the generalisability of the findings. Therefore future research should include multiple types of users; assess the impact over time; and explore multiple industry settings. It would also be beneficial to investigate the mediation and moderation mechanisms involved in explaining misuse such as moral disengagement or AI literacy. In addition to improving our understanding of misuse dynamics through investigating real behavioural data beyond just self reports will improve our understanding of misuse.

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