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ARTIFICIAL INTELLIGENCE IN FINANCIAL SERVICES: BALANCING INNOVATION AND EMERGING RISKS

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Abstract

Artificial Intelligence (AI) is rapidly reshaping the financial services landscape, particularly through the emergence of AI-powered financial advisors (AFAs) that offer automated, personalized, and data-driven investment solutions. Despite the promise of enhanced efficiency, reduced human bias, and increased accessibility, consumer adoption of AFAs remains cautious and uneven, especially in high-stakes financial contexts. This study explores the underlying factors contributing to the gap between the technological potential of AFAs and their actual uptake among consumers. Drawing on insights from behavioral finance and technology adoption theories, the paper examines how psychological, perceptual, and trust-related concerns influence user attitudes toward AI-driven financial decision-making.

The analysis highlights that while AFAs are designed to optimize investment outcomes through advanced algorithms and machine learning, issues such as perceived loss of control, lack of transparency, and limited understanding of AI processes hinder widespread acceptance. Evidence from early adopters, including reactions to platforms such as Wealthfront and Betterment, reveals that algorithmic opacity and the autonomous nature of AI systems can generate skepticism and resistance among users. These concerns are further amplified in financial decision-making environments where risk and uncertainty are inherently high.

The study argues that successful adoption of AFAs depends not only on technological sophistication but also on building consumer trust, enhancing transparency, and improving user engagement. It emphasizes the need for financial service providers to address behavioral barriers by incorporating explainable AI features, fostering user education, and maintaining a balance between automation and human oversight. By bridging the gap between innovation and user acceptance, AFAs can achieve their full potential in transforming investment practices.

Ultimately, this paper contributes to the growing discourse on AI adoption in financial services by highlighting the dual dynamics of innovation and intimidation, offering insights for practitioners, policymakers, and researchers seeking to promote responsible and inclusive financial technology adoption.

Keywords: Artificial Intelligence, Financial Services, Robo-Advisors, Consumer Trust, Technology Adoption

Introduction

Artificial Intelligence (AI) has emerged as a disruptive force across industries, redefining how consumers interact with products and services. In the financial sector, AI-driven innovations are transforming traditional investment paradigms, most notably through AI-powered financial advisors (AFAs). These technologies offer the promise of automated, personalized, and data-driven investment advice that minimizes human biases and improves financial decision-making. Yet, despite their potential, the consumer uptake of AFAs remains cautious and uneven, especially in contexts involving high financial stakes. This gap between technological potential and actual adoption reflects a complex interplay of psychological, behavioral, and perceptual factors.

AFAs, first popularized by companies like Wealthfront and Betterment in the early 2010s, operate by leveraging machine learning algorithms to assess investor profiles and recommend personalized investment strategies. Proponents of AFAs tout several benefits, including cost reduction, objectivity, and accessibility. Nevertheless, consumer trust in these systems has not kept pace with their technical capabilities. A notable case involved backlash against Wealthfront's AFA, where users expressed concern over the opacity of the AI algorithms and a perceived loss of control over financial decisions. These reactions highlight a broader issue: while consumers may acknowledge the efficiency of AI, they often struggle with its intangible and autonomous nature.

The disconnect between technical sophistication and consumer adoption can be partially explained through the lens of Technology Affordances and Constraints Theory (TACT), proposed by Markus and Silver (2008). TACT posits that a technology's adoption is shaped not merely by its inherent functionalities but also by what users perceive it allows or restricts them to do. In this context, affordances are the actionable possibilities offered by a technology, as perceived by users. Constraints, on the other hand, are the limitations users associate with that same technology. This theory is especially pertinent in understanding consumer responses to AFAs. While AI may afford benefits such as personalization and efficiency, perceived constraints—like data privacy risks, loss of autonomy, and lack of transparency—can overshadow these affordances.

Importantly, consumer perceptions of affordances and constraints are not uniform; they are influenced by individual psychological states and traits. A central concept in this regard is Consumer Technology Vulnerability (CTV), which refers to the psychological state in which consumers feel powerless or insecure when interacting with advanced technologies. As defined by Baker et al. (2005) and extended in the current study, CTV is not merely about access or digital literacy—it involves deeper anxieties regarding control, understanding, and decision-making. In financial contexts, where outcomes are tied to personal wellbeing and long-term security, such vulnerabilities are magnified.

Moreover, consumers vary in their responses to AFAs based on personal traits such as innovativeness and self-efficacy. Consumer innovativeness reflects an individual's openness to and interest in experimenting with new technologies. Highly innovative consumers are more likely to explore and integrate emerging tools like AFAs into their financial routines. Self-efficacy, in this context, refers to a consumer's belief in their ability to understand and use AI technologies effectively. Consumers with high AI-related self-efficacy are more confident in navigating digital platforms and less likely to perceive AI as threatening.

Prior research on technology adoption has extensively examined constructs such as perceived usefulness, ease of use, and convenience (e.g., Hess et al., 2014). However, most of this research has focused on traditional digital tools rather than AI-driven systems that interact autonomously with users. As such, there is a gap in the literature regarding how the unique characteristics of AI—particularly its perceived opaqueness and decision-making autonomy—affect consumer vulnerability and adoption behavior. Furthermore, while many studies have treated

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technology users as a homogenous group, the role of individual psychological traits in shaping adoption decisions remains underexplored.
In high-stakes environments like finance, where decisions have long-term consequences, the stakes of misjudging technology adoption are particularly high. Consumers are not only concerned with functionality but also with trustworthiness, accountability, and perceived fairness. The rise of AFAs challenges the traditional model of advisor-client relationships, shifting from human judgment to algorithmic logic. While this shift can improve efficiency, it can also create feelings of alienation and lack of control. These feelings, rooted in psychological vulnerability, are crucial to understanding consumer resistance.
To address this gap, our study investigates two primary research questions: (1) How do consumers respond to the main affordances of AI technology in AFA products, and how does consumer technology vulnerability (CTV) affect the AI affordances–adoption relationship? (2) How do individual traits (e.g., consumer innovativeness and self-efficacy) influence consumers' perceptions of AI affordances and their own vulnerability?
By integrating CTV and consumer traits into the TACT framework, we aim to provide a more nuanced understanding of the dynamics at play in AI technology adoption. This extension is significant both theoretically and practically. Theoretically, it highlights that technology affordances are not universally perceived but are mediated by individual psychological and behavioral factors. Practically, it offers actionable insights for financial firms looking to enhance AFA adoption. Strategies that reduce consumer vulnerability—such as increasing algorithmic transparency, improving AI education, and offering tailored onboarding experiences—can help bridge the gap between technological capability and consumer trust.
In conclusion, the future of AI in finance depends not only on technological advancement but also on the industry's ability to address the psychological and perceptual barriers that consumers face. By understanding the factors that mediate the perception of AI affordances, and by acknowledging the role of vulnerability and personal traits, financial service providers can design more effective strategies for deploying AI tools like AFAs. This research contributes to the growing field of AI-human interaction by placing the consumer's psychological experience at the center of technology adoption discourse, particularly in high-impact domains like personal finance.

Literature Review and Hypothesis Development

AI Product Adoption

AI technology adoption research has yielded several theories. Classical theories (e.g., technology acceptance model [TAM], unified theory of acceptance and use of technology [UTAUT]) have been widely used to understand technology adoption—defined as a consumer's likelihood or readiness to begin using a new product or technology (e.g., Kim et al. 2021). Psychological drivers such as PU, trust in AI, social influence, and cognitive and hedonic instrumental processes (Laukkanen 2017; Longoni and Cian 2022; Pillai et al. 2020) have been considered to influence AI adoption, underscoring the interplay of psychological and social elements. Despite extensive literature on factors contributing to technology and AI adoption (Freisinger et al. 2024), studies have mostly examined benefits that incentivize people to adopt. However, adoption decisions may not always be rational or unitary. Benefits of AI technologies may come with restrictions on consumers' control over and access to resources, inhibiting their rational adoption decisions and engagement with AI technology. Despite this, limited attention has been paid to consumers' propensity to adopt AI products irrationally. Cintamür (2024) reveals that technology anxiety and risk aversion can moderate acceptance in banking services, suggesting that affective responses influence adoption. Barone et al. (2024) highlight that adoption is driven by both rational benefits and cognitive overload and emotional factors. Karageyim and Durmusoglu (2025) identify relationship marketing challenges that compound trust issues and hinder technology adoption.

2.1 | CTV

Understanding CV in digital environments is challenging (Ng and Wakenshaw 2017). Consumers are more exposed to technology than ever, especially with the rise in AI- empowered tools and the ubiquity of technology. This intensifies CTV concerns. CV in technology usage has mainly been discussed in marketing and technology innovation literature, primarily regarding areas of daily life for organizations and individuals (e.g., Hermann et al. 2024). Per prior studies, CTV is defined as a state in which consumers are temporarily or permanently subject to harm due to limited resources and restricted control that significantly inhibit their abilities to function before and after AI usage (Supporting Information: Appendix A details how our concept theoretically compensates for deficiencies in existing literature on vulnerability). Further, we propose that CTV fluctuates based on conditions affecting people's ability to function optimally during technology encounters. CTV is triggered by interactions between human actors and technology features, making it fluid. Moreover, it extends beyond typical vulnerable demographics (e.g., the elderly), suggesting that anyone can experience CTV regardless of socioeconomic status. For instance, when using AI- facilitated applications (e.g., AFAs), CTV may arise due to AI limitations, reluctance to adopt new technology, reduced decision- making autonomy, or restricted interaction with human agents, ultimately shaping consumer behavior and inhibiting their rational evaluation and adoption of AFAs as decision tools.

Based on the above, and taking AFAs as an example, we believe that CTV manifests through both the limited product and cognitive resources, and restricted emotional or personal control over AFA offerings and marketing persuasion. These causes of restriction can be described as: (1) limited knowledge of how AFA works (e.g., lack of consideration over potential harms, limited understanding of AFA risks, absence of evaluation criteria, limited knowledge of alternatives, absence of comparison between AFA services and human agents); (2) predominant product persuasion combined with marketing and emotional influences that inhibit consumers' capacity to rationally evaluate AFAs—this dual effect diminishes their self- control over marketing messages and emotional responses during financial decision- making, potentially leading to an overreliance on AFA recommendations

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and increased vulnerability to anticipated risks; (3) limited distinguished cognition (e.g., lack of cognitive resources to identify fraudulent information provided by AFAs or marketing manipulations); and (4) restricted purchase behavior (e.g., limited alternatives; having to settle for substitutes based on AFA's recommendations).

Overall, these dimensions indicate CV with respect to unanticipated risks of AFA biases and errors. Uncertainty regarding potential harm could make consumers more susceptible to negative outcomes and increase their risk of making poor decisions. However, a lack of alternatives to AFAs, and a lack of autonomy, could lead to an overreliance on AFAs' recommendations, resulting in a greater risk of being deceived by unethical practices facilitated by AI advisors.

2.2 | TACT

We examine CTV in the context of AFAs, where the complexity of AI systems can lead to feelings of uncertainty and powerlessness. TACT helps to explain this dynamic by highlighting the balance between what technology enables (its affordances) and the limitations it imposes (its constraints). For AFAs, constraints include reduced user control, lack of transparency, and concerns over data privacy; affordances comprise personalized financial advice and decision- making efficiency. Consumers' overall CTV level is determined by the combined influence of both sides. The relational nature of affordances and constraints is particularly significant in the context of AI technologies, as technology is both a product and a mediator of human action (Leonardi 2011). AFAs' affordances are contingent on how well the technology aligns with users' goals, financial needs, and understanding of the system. For example, an AFA may afford users the ability to make more informed investment decisions, but if its operations are too opaque, the constraints (e.g., perceived risks, complexity) may outweigh the benefits. This tension in AI- driven financial tools calls for cross- disciplinary research combining insights from consumer psychology and sociology. Understanding how different user groups perceive and utilize AFAs is essential for maximizing the technology's potential. Users' subjective perceptions (e.g., sense of autonomy and trust in the AI system) directly influence the extent to which they actualize the technology's affordances.

Affordances do not exist in isolation—they depend on the user's engagement with technology and their psychological readiness to adopt it. In the AI context, the rapid pace of updates and constant evolution of AI capabilities make it difficult for users to fully grasp the technology's affordances. Perceived constraints (e.g., inability to understand how AI financial advice is generated) may limit the actualization of AI's affordances, reducing adoption. Therefore, for AFAs, affordances and constraints must be understood through a user perception lens to realize the full potential of AI. Per TACT (see Supporting Information: Appendix B), the success of AFAs hinges on both the capabilities of the technology and how effectively users perceive and engage with its affordances while managing its constraints. Recent studies (see, e.g., Hess et al. 2024) emphasize that continuous user engagement and adaptive learning are crucial for mitigating constraints and enhancing the realization of technology affordances.

Affordances of AFAs

Affordances mostly refer to the capabilities provided by technologies (Treem and Leonardi 2013). Studies have begun to associate affordances with both these inherent features and potential actions that technologies enable (Leidner et al. 2020). While acknowledging the importance of potential actions, we focus on the inherent technological capabilities. Specifically, we define AFA affordances as the characteristics and capabilities enabled by the AFA technology. Synthesizing prior literature, we identify five core AFAs affordances: information optimization, automation, prediction ability, customizability, and human- likeness (see Supporting Information: Appendix C). Information optimization is the technological capability to improve data relevance and alignment; automation is the capability to automate tasks and reduce consumers' workload; prediction ability is the capability to furnish statistical forecasts of probable decisions and results; customization denotes the capability of the technology to suit the unique preferences of each consumer; and human-likeness describes the techno logical capacity to be human-like.

The Effect of Information Optimization on Adoption Intention

Information optimization refers to the enhancement of perceived relevance and alignment of information through AI algorithm augmentation (Jain et al. 2018). We expect that information optimization is derived from four aspects: information accuracy, completeness, currency, and format (Nelson et al. 2005). Specifically, accuracy is the correctness of information, completeness is the degree to which all relevant information is covered, currency is the extent to which information is up to date, and format is the understandability and interpretability of information (Nelson et al. 2005). Optimized information—information that is accurate, complete, up to date, and interpretable—improves the perceived capability and accuracy of AI's decision-making. Further, it increases consumer satisfaction with AI and ultimately drives consumers to adopt the technology (Kar et al. 2021). Moreover, information optimization enables consumers to access this correct, complete, updated, and understandable information. It is an indication of high information quality, and opens opportunities for consumers to make well- informed decisions, enhancing AI adoption (Hajiheydari et al. 2021). Information accuracy and completeness have been found to drive PU of AI and adoption intention (Iranmanesh et al. 2024). Moreover, consumers are more inclined to make adoption decisions when technology offers up-to- date information, and format positively influences consumers' evaluations and adoption intention of AI (Kim et al. 2021). For AFAs, we anticipate that optimized information will lead consumers to perceive AFAs as useful and high quality. Information optimization may also create the feeling that AFAs can provide sound financial advice. Thus, information optimization is expected to contribute to consumers' AFA adoption intention.

H1a. Information optimization is positively associated with adoption intention.

2.2.1 The Effect of Automation on Adoption Intention

Automation denotes the technological capability to free consumers from time- consuming and energy- intensive tasks by allowing technologies to perform without human help (Leung et al. 2018; Longoni and Cian 2022). Automation enhances productivity and is viewed as a driver of AI adoption. It increases productivity by enabling rapid task completion and decision-making without human involvement. Further, auto mation may replace manual tasks traditionally performed by humans, simplifying consumers' interaction with technology and enhancing AI's ease of use (Leung et al. 2018). We expect this increased productivity and ease of use afforded by automation to positively influence consumers' adoption intention of AI. Regarding AFAs, automated financial analysis and recommendations aid consumers' decision-making. This makes AFA use more convenient and increases consumers' perceived productivity enabled by AFA, thus enhancing their adoption intention. Therefore:

H1b. Automation is positively associated with adoption intention.

2.2.2 The Effect of Prediction Ability on Adoption Intention

Prediction ability refers to the technological capability to provide statistical projections of a user's potential behavior, decisions, or outcomes (Lewis and Marsh 2022). This affordance enables AI to aid consumers' decision-making by predicting outcomes and probable future decisions. Prediction ability is considered a core function associated with AI's reliability and efficiency. High prediction ability indicates that the AI can assist consumers' decision- making effectively, enhancing AI's PU and convenience, which are crucial for AI adoption (Chatterjee et al. 2021). With the prediction ability affordance, AI- informed decisions may consider consumers' historical behaviors and preferences, ensuring that suggested options align with their historical likes and behavioral patterns and thereby increasing their likelihood of acceptance. Prediction ability thus enhances consumers' PU of AI and comfort with decisions and recommendations it generates, enhancing their AI adoption intention (Baabdullah 2024). Prediction ability allows AFAs to analyze historical data on financial product performance and consumers' preferences and behavioral patterns, generating informed predictions utilizing such information and thereby enhancing perceived effectiveness of the AFAs, incentivizing their adoption. Thus:

H1c. Prediction ability is positively associated with adoption intention.

The Effect of Customizability on Adoption Intention

Customizability is the technological capability to adapt effectively to individual consumers' preferences and information needs, and to proactively tailor products and experiences (Hiezl and Gyurácz- Németh 2021). Customizable features can improve convenience and usability, which are important in driving technology adoption (Wang et al. 2023). Customizability affordance provides consumers with an intuitive and satisfying experience, as if the user owns the AI and the AI understands the user. Moreover, Russo (2024) suggests that customizability is a crucial factor for consumers' perceived ease of use (PEOU) of AI—a recognized antecedent of adoption intention. For AFAs, high customizability implies adaptation to consumers' financial preferences and habits, and a modified interactive interface (Huang and Rust 2018). For instance, the AFA may alert consumers about investment opportunities based on their own risk tolerance, evaluation criteria, and investment goals. Such adaptation to individual preferences creates a sense of convenience, ease of use, and ownership, leading to AFA adoption. Hence:**H1d.** Customizability is positively associated with adoption intention.

The Effect of Human-Likeness on Adoption Intention

Human-ikeness refers to the technological capability of being anthropomorphic (Kim et al. 2022). This is often associated with how consumers perceive the human- like entity's features. Consumers often enjoy interacting with human-like AI technol ogies and are inclined to use and reuse them (Kim et al. 2022). Human- likeness can create a sense of familiarity and enhance AI's perceived approachability. It also leads to natural and intuitive interactions with AI, facilitating consumers' interactions with it and creating a sense of human warmth and social presence (Qiu and Benbasat 2010). Moreover, consumers are likely to build attachments with and trust toward human- like AI. These benefits drive consumers to adopt AI. AFAs that communicate in a human- like manner, understand natural language, and exhibit empathy may be perceived as more human- like by consumers. Such characteristics lead to enjoyable and intuitive interactions that enhance trust and attachment, encouraging consumers' AFA adoption. Thus:

H1e. Human-likeness is positively associated with adoption intention.

2.3 The Mediating Role of CTV

2.3.1 CTV'S Mediating Effect on the Information Optimization–Adoption Intention Relationship

We expect that CTV acts as an important psychological mechanism through which information optimization is positively related to adoption intention. When information is complete, accurate, up to date, and comprehensible, AI technology can provide, for instance, financial advice based on large amounts of detailed information without specifying what is taken into account and how, while creating a sense of urgency for consumers to make quick decisions in order to keep up to date (Kooper et al. 2011). This may significantly increase the difficulty level in human processing, restricting their control over relevant resources and diminishing their rational cognitive evaluation. For example, the optimized information provided by AFAs may create cognitive burdens for consumers, making it hard for them to cognitively process financial information. The up- to- date financial information may also create a sense of urgency, causing emotional stress in consumers' financial decision-making, restricting consumers' rational assessment of risks, and inhibiting their rational evaluation of the AFA and the financial goods it recommends. Thus, consumers have limited cognitive resources to discern the most beneficial alternatives. The technological capability of optimizing information may therefore open consumers to harm, making them feel powerless and leading them to experience a state of CTV (Shi et al. 2017). CTV further reduces consumers' self- confidence, increases their reliance on AI, makes them more likely to be persuaded by AI-generated solutions, and, consequently, drives them to adopt AI (Kandul et al. 2023). Although consumers may avoid using AI if they fear that the information it provides is overly complex, or if they attribute the disadvantage in decision-making to AI, we posit that AI may be perceived as an easy and powerful solution to the very challenges it posts. Consequently, consumers may be inclined to associate the difficulty with their own lack of capability rather than with the use of AI, and turn to a tool that they perceive as more capable—AI. When consumers' abilities to function and make decisions are inhibited, they may be inclined to comply and are likely to enjoy their experience with AI since it requires low cognitive effort (Westbrook and Braver 2015). This increases their likelihood of AI adoption.

H2a. CTV mediates the positive effect of information optimization on adoption intention.

2.3.2 | CTV's Mediating Effect on the Automation–Adoption Intention Relationship

Automation reduces human involvement in, and control over, decision- making (Yarlagadda 2017). Due to AI's automation affordance, consumers may lack information about how things work, which restricts them from evaluating all available information and making informed decisions. They may be exposed to limited alternatives and lack control regarding such decisions. Leung et al. (2018) also note that automation may diminish people's perceived level of control. For example, AFA's automation enables consumers to have automated assessment and visualization of financial information, and automated financial advice and investment suggestions. It simplifies consumers' financial decisions, but often also restricts their access to complete financial information and limits control over their financial decision- making. By taking away consumers' chance to evaluate all possibilities, automation inhibits their decision- making ability. This increases their likelihood of being subject to harm, leading to CTV. In turn, CTV restricts consumers' own capability and confidence in decision- making because they have restricted access to, and control over, resources to select the best option, and thus rely more on AI to handle information processing and decision- making (Martin et al. 2017). Although vulnerable consumers may choose not to use AI as a means of avoiding potential harm, when CTV is caused by AI's automation affordance, we anticipate that consumers will compromise by accepting the limited resources and restricted control rather than trying to combat it, and thus tend to adopt AI.

H2b. CTV mediates the positive effect of automation on adoption intention.

2.3.3 | CTV'S Mediating Effect on the Prediction Ability–Adoption Intention Relationship

AI's prediction ability affordance is associated with predictive algorithms and predicted outcomes (Kandul et al. 2023). AI may present only what the algorithm deems optimal, restricting consumers' access to data inputs and possible alternative outputs, and limiting their resource access. Thus, consumers will miss opportunities deemed unsuitable by AI technologies but that they would have otherwise considered. For example, an AFA algorithm may predict that a consumer is unlikely to achieve positive returns on an investment based on historical data, such that limited investment options are presented, indirectly restricting the consumer's access to certain data and financial options. Moreover, without knowing how predictive algorithms work, consumers have limited cognitive resources to evaluate predicted outcomes, restricting their decision- making control. The AI's prediction ability may therefore lead to CTV, driving consumers to turn to AI solutions to lower cognitive demands (Lerch and Harter 2001). Further, the lack of knowledge will likely make consumers optimistic about these algorithms and believe them to be competent and reliable, further encouraging AI adoption (Kandul et al. 2023).

H2c. CTV mediates the positive effect of prediction ability on adoption intention.

2.3.4 | CTV'S Mediating Effect on the Customizability– Adoption Intention Relationship

While customizability enhances convenience and personalization, it may compromise the diversity, coverage, and comprehensiveness of available information (Wang et al. 2023). While offering tailored advice, customization algorithms inevitably exclude information outside the consumer's preferences (Wang et al. 2013), potentially impeding their financial decision- making ability (Levin et al. 2002). Taking AFA algorithms as an example, they may not recommend high-risk investments to typically risk- averse clients, even though the investments may have the highest expected returns, thereby limiting the client's access to potentially profitable opportunities. Further, alignment with consumer preferences may undermine their privacy and ability to make rational evaluations and decisions, restricting their control over resources (Wang et al. 2013). In addition, tailored interfaces may enhance consumer experiences and lead consumers to embrace AFAs without thoroughly considering their downsides. Therefore, customizability likely restricts consumers' resource access, causing CTV. CTV may further reduces consumers' confidence in their own decision- making and increase the likelihood of selection bias favoring AI technologies such as AFAs, and thus lead consumers to overly trust AI, driving AI adoption.

H2d. CTV mediates the positive effect of customizability on adoption intention.

CTV'S Mediating Effect on the Human-Likeness and Adoption Intention Relationship

Consumers often enjoy interacting with human-like AI technolo gies; however, this may divert their attention from core information to the interaction experience itself, limiting their knowledge. Human- like AI technologies may also create unrealistic expectations, costing consumers time and effort in trying to meet them. Excessive human- likeness could cause consumers to pay more attention to the AI's human-like interactive patterns and lead to unrealistic expectations of consistent human-like responses or ca pabilities, causing consumers to be easily persuaded by the technology (Huang and Wang 2023). For example, human- like AFAs may have speech patterns like real human and this could divert consumers' attention from core financial information to such human- like interaction experiences, thereby diminishing their ability to make rational and well-informed financial decisions, such as deciding which financial products to invest in (Epley et al. 2007). Moreover, perceptions of human characteristics or human- like behaviors can create a sense of familiarity and psychological proximity, leading users to feel comfortable during interactions with AI technologies and further enhancing their appeal (Ahn et al. 2021). Consumers are also likely to build attachment and trust in more human-like AI technologies. This may reduce their motivation to make cognitively demanding evaluations, rational evaluations of perceived risks, and cognitive effort invested in making decisions. This could result in consumers investing their time and effort in interactions or requests, limiting their access to useful technological and financial information, restricting their resources and control, and creating CTV. CTV reduces consumers' confidence in their decision- making capability, leading them to seek alternative tools to augment this. Given the pleasing experience that human-likeness creates, consumers are likely to rely on AI to augment their decision- making, driving AI adoption intention.

H2e. CTV mediates the positive effect of human- likeness on adoption intention.

The Moderating Role of Consumer Innovativeness

In addition to technology- related variables, consumers' dispositional capabilities may play a key role. Consumer innovativeness refers to "the tendency of customers to buy new products more often and more quickly than other people" (Li et al. 2015, 215). Consumers who are high in innovativeness like to consume new products; they are often creative and embrace new technologies such as AI, and tend to perceive fewer risks versus those who are less innovative. Thus, when innovative consumers encounter AI technologies, they are more likely to embrace the affordances and recommendations and exhibit less concern about potential risks (Casidy et al. 2022). Highly innovative consumers are open to relying on the information provided by AI. They are more likely to feel a sense of urgency to adopt new technologies and less likely to note the cognitive burden associated with AI's information optimization (Shi et al. 2017). That is, their interest in new technologies weakens their capability and awareness of the risk of information optimization, enhancing their potential exposure to harm caused by this optimization and strengthening its potential positive effects on CTV (Casidy et al. 2022). Conversely, less innovative consumers may be more habit- driven and less excited by AI, reducing their reliance on information optimization. Thus, optimization is less likely to impede these consumers' decision- making ability and create much harm. Therefore, we expect consumer innovativeness to moderate the relationship between information optimization and CTV, such that the positive impact of information optimization on CTV is stronger when there is a high level of consumer innovativeness.

H3a. The positive impact of information optimization on CTV is strengthened by consumer innovativeness.

Highly innovative consumers tend to be inquisitive and open to new information sources, and thus more receptive to AI automation. This can lead them to favor automated systems and exhibit less caution, weakening their psychological defenses. That is, when consumers are high in innovativeness, they are more likely to trust AI-enabled automation and more open to relying on it for decision- making, making them less likely to notice the loss (Rogers 2003). This enhances their risk of exercising insufficient caution regarding AFA automation and strengthens the potential positive effects of automation on CTV (Casidy et al. 2022). Conversely, less innovative consumers may prefer to rely on familiar information sources and their own judgment, and be hesitant to base decisions solely on predictions. This makes them more resilient to potential harm generated by automation. Thus, we propose that consumer innovativeness moderates the relationship between automation and CTV, such that the positive impact of automation on CTV is stronger when consumer innovativeness is high.

H3b. The positive impact of automation on CTV is strengthened by consumer innovativeness.

Customers high in innovativeness likely place greater trust in AI's prediction ability. They tend to trust predictive algorithms and believe the algorithms will offer the most suitable options (Rogers 2003). This trust may cause highly innovative consumers to feel more comfortable with AFAs' prediction ability and overlook their limited access to underlying data and alternative outputs (Baabdullah 2024). This enhances their exposure to harm and increases their potential vulnerability. Conversely, less innovative consumers may be more skeptical of AFAs' prediction ability and likely explore alternatives more consciously, reducing their vulnerability. Therefore, we expect consumer innovativeness to moderate the effect of prediction ability on CTV, such that the positive impact of prediction ability on CTV is stronger when consumer innovativeness is high.

H3c. The positive impact of prediction ability on CTV is strengthened by consumer innovativeness.

Consumers high in innovativeness tend to value advanced AI algorithms in adapting to their preferences and needs. Thus, highly innovative consumers may welcome AI's customizability and defer to it for decision- making. Highly innovative consumers tend to be more willing to accept the trade- off between personalized information and potentially reduced information breadth, and more flexible with their customized information exposure and reduced decision- making autonomy (Hiezl and Gyurácz- Németh 2021). This enhances the effect of customizability on CTV. Conversely, consumers low in innovativeness are more reluctant to accept new ideas, and are thus potentially more resistant to AI's customization affordance (Rogers 2003). These individuals are more likely to search and think beyond AFAs' customized information and solutions, so customization may not cause significant harm. Thus, we expect consumer innovativeness to moderate the relationship between customizability and CTV, such that the positive impact of customizability on CTV is stronger when there is a high level of consumer innovativeness.

H3d. The positive impact of customizability on CTV is strengthened by consumer innovativeness.

Consumers high in innovativeness are more open to interacting with human- like AI technologies, and thus more likely to be excited about human- likeness. They are more likely to enjoy AI designs that demonstrate familiarity and warmth and more likely to develop trust in such AI (Qiu and Benbasat 2010). Such excitement and enjoyment may strengthen how customizability drives these consumers to overlook potential drawbacks, such as having unrealistic expectations. Consumers low level in innovativeness may find human-likeness less interesting. These individuals may be more capable of rationally evaluating information for well- informed decision- making, and human- likeness may not cause significant harm. Therefore, we propose that consumer innovativeness moderates the relationship between human-likeness and CTV, such that the positive impact of human- likeness on CTV is stronger when consumer innovativeness is high.

H3e. The positive impact of human- likeness on CTV is strengthened by consumer innovativeness.

The Moderating Role of Self- Efficacy

Self- efficacy is defined as a consumer's belief regarding their ability to deliver specific desired outcomes in certain domains (van Esch et al. 2021). Literature has examined individuals' confidence in their ability to organize and perform tasks related to internet usage in order to attain expected results—a pivotal form of self-efficacy in the adoption of electronic services. Research shows that internet self- efficacy is directly associated with willingness to use new technologies (Baabdullah 2024). Hence, individuals naturally have a need and desire to feel competent in various aspects of their lives, including interactions with AI technologies such as AFAs. Consumers' self- perceived ability can shape their reactions to their technological capabilities; thus, we expect consumers' self- efficacy to moderate the effects of AI affordances on CTV. Customers high in self- efficacy generally exhibit more confidence in their opinions and decisions. When AI technologies are perceived to provide accurate, complete, up- to- date and interpretable information, such consumers are likely to be confident in trust in and reliance on AI for decision- making (Hajiheydari et al. 2021), and to believe in their ability to make accurate decisions with AI's information optimization affordance. Meanwhile, because self- efficacy can lead to overconfidence, consumers high in self- efficacy may not acknowledge that they may experience limited cognitive processing resources and could be harmed when relying on AI information optimization (Moores and Chang 2009). Conversely, those with low self- efficacy may question their ability to use AI effectively to make decisions, and thus might be more careful when dealing with the information optimization afforded by AI technologies. This may allow them to be more resistant to potential risks and harms caused by information optimization. Therefore, the effect of information optimization on CTV is stronger when consumers have high self- efficacy. We thus propose that consumer's self- efficacy moderates the relationship between information optimization and CTV, such that the positive impact of information optimization on CTV is stronger when consumer innovativeness is high.

H4a. The positive impact of information optimization on CTV is strengthened by consumer self-efficacy .

Customers high in self-efficacy often perceive themselves as knowledgeable about AI technologies. They may thus be overly positive about delegating decisions to such systems, and fail to recognize restrictions and limitations—perhaps not realizing that they are not making fully informed decisions based on the most comprehensive information available (Leung et al. 2018). Their high self- efficacy may cause them to underestimate risks associated with AI's automation affordance, as they feel they have a good understanding of AI. In contrast, consumers low in self- efficacy tend to be more cautious about the automated process and outcome, and more sensitive to potential risks and harms stemming from information optimization. Therefore,

we expect the effect of automation on CTV to be stronger when consumers have high self-efficacy. We thus propose that consumer self-efficacy moderates the relationship between automation and CTV, such that the positive impact of automation on CTV is stronger when consumer innovativeness is high.
H4b. The positive impact of automation on CTV is strengthened by consumer self-efficacy .
Consumers high in self- efficacy may believe they are knowledgeable about AI technologies and also tend to be confident in their understanding and capacity to manage AI's prediction ability. They may believe they fully comprehend how predictive algorithms operate and be overly assured of their cognitive resources when evaluating predicted outcomes. Additionally, such consumers might be reluctant to admit they rely on AI solutions simply because these solutions demand less cognitive effort. Instead, they are likely to attribute decision- making that utilizes AI's prediction ability to their own skills, and take credit for it. This can reduce their awareness of the risks they are exposed to (Lerch and Harter 2001). Conversely, consumers low in self- efficacy approach AI's prediction ability with more balance. Their caution enables them to be more sensitive to the risks linked to AI's prediction capabilities. Therefore, we posit that the effect of prediction ability on CTV is stronger when consumers have high self- efficacy. That is, consumer's self- efficacy moderates the relationship between prediction ability and CTV, such that the positive impact of prediction ability on CTV is stronger when consumer innovativeness is high.
H4c. The positive impact of prediction ability on CTV is strengthened by consumer self- efficacy.
Consumers high in self- efficacy may see themselves as highly knowledgeable about AI and its customizability and be confident in their ability to manage customized information. However, they may be overly confident in their capacity to compensate for loss of information diversity, coverage, and depth in the pursuit of personalization (Haim et al. 2018). This can significantly limit their knowledge while obscuring these information oversights. Thus, when customizability is present, these consumers are likely to experience greater CTV. Conversely, consumers low in self- efficacy may treat AI's customizability affordance with caution and question the implications of customized information and resulting outcomes. This makes them more aware of potential harms associated with customization. Thus, we hypothesize that consumer's self- efficacy moderates the relationship between customizability and CTV, such that the positive impact of customizability on CTV is stronger when consumer innovativeness is high.
H4d. The positive impact of customizability on CTV is strengthened by consumer self- efficacy.
Consumers high in self- efficacy may be overly confident in their ability to handle AI, and thus unable to recognize potential risks associated with human- like AI technologies. They are likely unaware that their decisions might not be entirely rational and could be influenced by a disproportionate focus on AI's human- like affordances rather than on the informative features needed for sound decision- making. Additionally, they may be reluctant to admit that their decisions are influenced by AI's human- likeness because of their perceived familiarity, psychological

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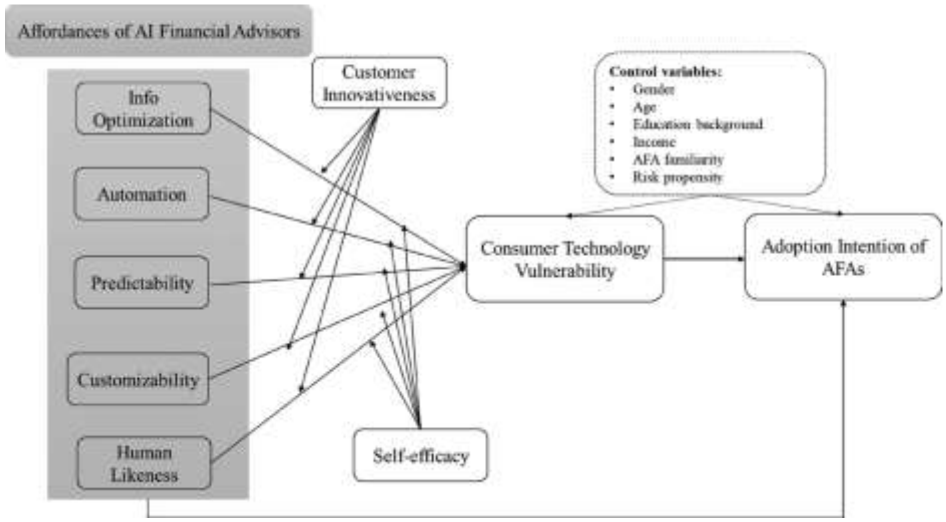

proximity, and attachment (Huang and Wang 2023). This overconfidence significantly impairs these consumers' capacity to make rational evaluations, making them more vulnerable. Consequently, for consumers high in self-efficacy, human- likeness is more likely to have a strong positive influence on CTV. Conversely, consumers low in self- efficacy may be more cautious and hesitate to make decisions based on their judgment of AI; instead, they may seek additional information and consider a wider range of possible solutions. The impact of perceived AI affordances on CTV is weaker when there is self- efficacy. Thus, we propose that consumers' self- efficacy moderates the relationship between human-likeness and CTV, such that the positive impact of human- likeness on CTV is stronger when consumer innovativeness is high.

FIGURE 1 | Research framework.

H4e. The positive impact of human- likeness on CTV is strengthened by consumer self- efficacy.

3 | Empirical Study

3.1 | Method

3.1.1 | Survey Sample

To empirically test the relationships between AI characteristics, CTV, and AFA adoption intention (see Figure 1), we surveyed individual consumers who had knowledge of or experience with AFAs. Access to respondents was provided via a professional market research company specializing in consumer surveys in the US. Before answering key questions on the research variables, respondents were asked: (1) Have you ever received investment advice from an AI algorithm? (2) Have you ever been helped by an AI agent to manage your financial situation? Respondents who answered “yes” to either filter question were invited to continue with the main part of the survey. In total, 712 individuals were contacted. Respondents were asked for information on how they made financial investments based on advice from an AI agent. After receiving several reminder emails, 616 respondents completed our questionnaires. In our sample (N = 616), 49.2% of respondents were female (N = 303) and 50.8% were male (N = 313); most (N = 393) were aged 26–40. In terms of educational attainment, 54.1% had an undergraduate degree, 20.1% had completed a master's degree, and 3.4% had not completed high school. Non-response bias was assessed using the time- trend extrapolation test. Early responses were compared to late responses using chi- square tests. A low chance of non-response bias was observed in the results, which did not differ between groups.

3.1.2 | Measurement Items

Following Shi et al. (2017), we measured CTV as a reflective second-order construct, with product knowledge, product pro motion, marketing and emotional pressure, distinguishing ability, and purchase ability as first-order constructs. Information optimization was measured as a reflective second- order construct from Nelson et al. (2005), which was reflectively measured by completeness, accuracy, format, and currency. AFA adoption intention was assessed using the scale from Li et al. (2015). Three items for human- likeness were adapted from Kim et al. (2022). Items for customizability were adopted from Hiezl and Gyurácz- Németh (2021). Two items were included under the automation construct. We incorporated four items of prediction ability adapted from Thatcher et al. (2010). To measure self- efficacy, we chose van Esch et al.'s (2021) three-item scale (e.g., “I am con fident in my ability to collaborate with an AI financial advisor for my financial investments”). Consumer innovativeness was assessed using three items from Li et al. (2015). All constructs were measured on a 7-point Likert scale (1 = “strongly disagree”; 7 = “strongly agree”). Supporting Information: Appendix D lists the measurement items.

Three categories of control variables were incorporated into the model to address alternative explanations: (1) Respondent demographics, such as gender, age, education background, and annual income. Gender was denoted with a binary variable. Age was given as a categorical number of years by the respondent. Education levels include elementary school, middle school, high school, undergraduate degree, or postgraduate degree. (2) Respondent familiarity with AI-related financial investments. (3) Risk propensity, which is a crucial variable identified by Davvetas and Diamantopoulos (2016) for its impact on technology- related outcomes.

Analysis and Results

Measure Validity and Reliability

Since all data were self-reported and gathered via the same questionnaire design, we sought to mitigate common method bias (CMV) via multiple procedural remedies and statistical adjustments. First, we adopted Harman's single-factor test (Podsakoff et al. 2012). Specifically, we conducted factor analysis on all scale items, and the unrotated factor-loading matrix was then assessed. The size of the homology deviation was determined based on the first principal component of the matrix. Results showed that the first principal component was 23.61% (threshold value < 50%). Second, where conflicting answers were provided, phone calls were made to several respondents (picked at random) to clarify and confirm their rationale for their answers, particularly regarding AFA adoption intention. Third, we utilized the correlation-based marker variable technique (Lindell and Whitney 2001) as the statistical approach. The autonomy scale was selected as the marker variable since it is theoretically unrelated to the main variables (Podsakoff et al. 2012). A partial correlation was conducted by controlling the marker variable, and all significant correlations between key construct scales remained significant. Thus, CMV is unlikely to be a concern.

Structural equation modeling was used to evaluate the measurement and structural models. First, the measures were subjected to confirmatory factor analysis (CFA) using AMOS 24. All factors and outcome variables were included in one CFA model. The measurement model fit the data reasonably well (X^2/df = 2.494, $p < 0.001$, CFI = 0.961, GFI = 0.935, NFI = 0.938, RMSEA = 0.049; see Supporting Information: Appendix F). Composite reliability and Cronbach's alpha were used to assess reliability. Composite reliability for all scale items was between 0.71 and 0.95, greater than the threshold of 0.70. Moreover, alpha coefficients were greater than 0.70, indicating appropriate internal reliability. These values indicate acceptable reliability. Moreover, the low to moderate correlations indicate discriminant validity. All reliability estimates, including coefficient alphas, average variance extracted (AVE) values for each construct, and AMOS- based composite reliabilities, were close to or beyond the thresholds. Further, the square root of the AVE for each construct was greater than the latent factor correlations between construct pairs, suggesting discriminant validity. This indicates the unidimensionality and adequate reliability and discriminant validity of the measures.[2]

Hypothesis Testing

Direct effects (H1) were tested using regression analysis. The results show that, without CTV, information optimization (H1a: b = 0.349, $p < 0.001$), customizability (H1d: b = 0.408, $p < 0.01$), and human- likeness (H1a: b = 0.259, $p < 0.01$) had significant positive effects on adoption intention, while the effects of automation (H1b: b = 0.042, $p > 0.05$) and prediction ability (H1c: b = 0.039, $p > 0.05$) on AFA adoption intention were not significant. Thus, H1a, H1d, and H1e are supported, while H1b and H1c are rejected. Moreover, information optimization (b = 0.242, $p < 0.001$), customizability (b = 0.211, $p < 0.001$), and human- likeness (b = 0.104, $p < 0.001$) had positive and statistically significant effects on CTV, but the effects of automation and prediction ability on CTV were not significant. CTV had a significant and positive influence on adoption intention (b = 0.534, $p < 0.001$).

The mediating effect of CTV on the relationship between affordances and adoption intention was tested using PROCESS macro model 4 (simple mediation model). Bootstrapped bias- corrected confidence intervals with 5000 resamples were implemented with a 5% significance level. Results (see Supporting Information: Appendix G) demonstrate that CTV significantly mediates the positive effects of information optimization (b = 0.208, $p < 0.05$, LLCI = 0.130 and ULCI = 0.289), customizability (b = 0.134, $p < 0.05$, LLCI = 0.072 and ULCI = 0.207), and human- likeness ($b = 0.085$, $p < 0.05$, LLCI = 0.040 and ULCI = 0.137) on adoption intention, supporting H2a, H2d, and H2e. However, the indirect effect of CTV on the effect of automation and prediction ability on adoption intention is not significant. Thus, H3b and H3c are not supported.

The conditional indirect effects at different values of consumer innovativeness and self- efficacy moderators were also examined. We adopted PROCESS model 9 to examine these effects (Hayes 2013). The high and low levels of consumer innovativeness and self- efficacy, respectively, were obtained by adding one standard deviation and subtracting one standard deviation from the mean value (see Supporting Information: Appendix G). The index of moderated mediation showed that conditional indirect effects of information optimization ($b = 0.021$, $p < 0.01$, LLCI = 0.003 and ULCI = 0.057), automation ($b = 0.031$, $p < 0.001$, LLCI = 0.010 and ULCI = 0.065), and prediction ability ($b = 0.061$, $p < 0.001$, LLCI = 0.006 and ULCI = 0.059) on AFA adoption intention via CTV were significantly strengthened by consumer innovativeness, while consumer innovativeness significantly weakened the conditional effect of human-likeness ($b = −0.019$, $p < 0.05$, LLCI = −0.052 and ULCI = −0.002) on AFA adoption intention via CTV. Thus, H3a–H3c are supported. Moreover, conditional indirect effects of information optimization ($b = 0.025$, $p < 0.001$, LLCI = 0.007 and ULCI = 0.028), automation ($b = 0.490$, $p < 0.001$, LLCI = 0.016 and ULCI = 0.082), and prediction ability ($b = 0.044$, $p < 0.001$, LLCI = 0.012 and ULCI = 0.078) on AFA adoption intention via CTV were significantly strengthened by self-efficacy, while the conditional effect of human-likeness ($b = −0.048$, $p < 0.001$, LLCI = −0.085 and ULCI = −0.011) on AFA adoption intention via CTV was significantly weakened by self-efficacy. Hence, H4a–H4c are supported. However, the conditional indirect effect of customizability ($b = 0.008$, LCI = −0.004 and ULCI = 0.029) on AFA adoption intention through CTV did not significantly vary at high versus low consumer innovativeness. The conditional indirect effect of customizability ($b = −0.007$, LLCI = −0.022 and ULCI = 0.009) on AFA adoption intention through CTV also did not significantly vary at high versus low self- efficacy. Hence, H3d and H4d are rejected.

In sum, per our hypotheses, we show positive and significant mediating effects of CTV on the positive links between information optimization, customization, and human-likeness on AFA adoption intention. However, we find non-significant mediating effects of CTV on the relationships between automation and prediction ability on AFA adoption intention. Considering the moderating effects of consumer innovativeness and self- efficacy, most of the findings support CTV research that has provided theoretical explanations for how firms overcome CTV by targeting different consumer groups. Surprisingly, our findings indicate both innovativeness and self- efficacy negatively moderate the relationship between human- likeness and CTV.

General Discussion

This study reveals how several factors influence AFA adoption through CTV as a psychological mechanism. Our study situates CTV as a modern construct that integrates anticipatory skepticism toward AI benefits with relational triggers of consumer–AI interactions. CTV helps explain how consumers react to and adopt AI features. Unlike technostress, which entails negative outcomes consumers face when interacting with technologies (Kumar et al. 2022), CTV describes a state of powerlessness and vulnerability caused by AI features, which does not necessarily involve stress or negative emotions (Shi et al. 2017; Hill and Sharma 2020). Further, CTV stems from anticipation of unknown AI features that create feelings of uncertainty and error- proneness. While prior literature (e.g., Amine and Gatfaoui 2019) argues that technology vulnerability manifests primarily following actual harm (e.g., data breaches or system failures), we extend this perspective by demonstrating that CTV arises from perceived susceptibility to harm, even in the absence of actual incidents. Specifically, we incorporate psychological risks (e.g., marketing manipulation, transparency biases, and algorithmic exploitation) into the CTV conceptualization. These risks have been discussed as barriers to AI adoption, particularly in contexts involving sensitive consumer data (Hermann et al. 2024). By framing these risks within the relational nature of CTV, we highlight how perceived manipulative practices and lack of transparency exacerbate CV, shaping adoption outcomes. This complements prior work on vulnerability arising from skepticism toward promised benefits of technology (Mani and Chouk 2018) and resistance to algorithmic decision- making (Koponen et al. 2025).

Our findings show positive indirect effects of information optimization, customizability, and human- likeness on AFA adoption via CTV, reinforcing the hypothesized relationships and introducing CTV as a mediator in AI adoption (e.g., Zhang et al. 2024). CTV is not a static condition but fluctuates based on consumer–technology interactions and AI's contextual affordances. For instance, customizability and human- likeness may reduce CV, but their effectiveness depends on user-specific traits such as innovativeness and self-efficacy. This perspective aligns with the relational view of affordances (Treem and Leonardi 2013), wherein effects of technology are co-constructed through user–technology interactions. Contrary to existing studies, we found that automation and prediction ability do not directly or indirectly promote AFA adoption. However, research showing that automation and prediction ability improve adoption by simplifying complex tasks and automating routine activities (Lee et al. 2009) involved professionals, whose motivations differ from those of general consumers. Dohale et al. (2024) also found that AI prediction ability facilitates system responsiveness without involving end users' psychological engagement, which may explain this inconsistency.

We show that consumer innovativeness and self-efficacy moderate the AI features–adoption relationship. These traits weaken the effect of human-likeness on CTV, suggesting that innovative and self-confident consumers may not feel vulnera ble when encountering human-like AI features. This contrasts Wilberz et al.'s (2020) findings that human-likeness enhances adoption intention. Miller et al. (2021) suggested that individual differences play a significant role, as demonstrated in our study. We also found self- efficacy and innovativeness to strengthen the impact of information optimization, automation, and prediction ability on CTV, supporting theoretical perspectives on the consumer traits–technology features interaction.

Lastly, our findings advance TACT by integrating the psychological construct of CTV, specifically regarding AI innovations in financial services (e.g., Pöyry et al. 2024). By addressing gaps between anticipatory and post-incident vulnerability, we demon strate that CTV operates across multiple AFA adoption stages, aligning with the relational view of technology affordances and constraints (Treem and Leonardi 2013). We thus enrich TACT by illustrating how consumer perceptions of AFA affordances (e.g., automation, customizability, predictability) mediate AFA adoption intention through emotional and cognitive mechanisms like CTV. Furthermore, the findings emphasize the dual role of CTV as both facilitator and barrier to AFA adoption, thereby broadening the framework's applicability to consumer- centric AI innovation processes. By incorporating the variability of AFA affordances and constraints, alongside the ethical complexities they introduce, we enhance understanding of how AI affordances shape consumer behavior in AFA context (Markus and Silver 2008; Freisinger et al. 2024). This perspective extends traditional adoption models to explore broader innovation dynamics, stakeholder engagement, and ethical governance regarding AFAs (Freisinger et al. 2024).

Contributions to TACT in the Product Innovation Process

TACT emphasizes the functional and material dimensions of technology, focusing on how technological affordances and constraints shape user behavior (Markus and Silver 2008). We extend this framework to encompass the psychological dimension of CTV regarding AI technologies, thus shifting the focus from purely technical affordances to a more relational and human- centered approach.

Our study suggests that the adoption of AI- enabled technologies cannot be fully understood without considering the emotional and cognitive responses elicited by these technologies. Specifically, CTV mediates the AI affordances–adoption intention relationship, highlighting the importance of how consumers perceive and react to AI features. Unlike traditional TACT applications, which focus on the functional advantages or disadvantages of technologies, we show that consumers' psychological engagement—specifically, their feelings of vulnerability, uncertainty, and dependency—is critical in determining their AI adoption. This aligns with Treem and Leonardi's (2013) perspective on TACT as a relational construct, where technology affordances are not simply inherent in the technology itself but are co- constructed through user–technology interactions. By integrating CTV, we enhance understanding of how consumer perceptions influence the actualization of AI affordances.

Furthermore, our study addresses a research gap by demonstrating how AI affordances (e.g., customizability, human- likeness, and information optimization) interact with consumers' CTV. Research in information systems and marketing has often examined these features in isolation, focusing on their technical capabilities rather than their psychological impacts (Huang and Rust 2024). By contrast, we show that the effectiveness of these affordances is highly dependent on how they are perceived by consumers, particularly regarding how they influence feelings of vulnerability. This is especially relevant in the context of financial products, where consumer trust and emotional comfort are crucial for adoption (Pöyry et al. 2024).

Our research also contributes to innovation theory by deepening understanding of consumer engagement with new technologies. Traditional innovation theory often emphasizes the alignment of product features with consumer needs and market demands (Reynolds et al. 2025; Verganti et al. 2020); we show that psychological safety—the sense that a technology will not cause harm or discomfort—is equally important for adoption. This enriches affordance theory by demonstrating that the perceived psychological effects of technology affordances can be just as pivotal as their functional benefits (Pöyry et al. 2024; Koponen et al. 2025).

Lastly, our study has ethical implications for AI design and implementation, particularly in sensitive sectors such as finance. AI- driven products often raise privacy, autonomy, and security concerns, which can exacerbate CV (Huang and Rust 2024; Freisinger et al. 2024). By showing that CTV mediates the adoption of AI products, we suggest that addressing these ethical concerns requires both technical solutions (e.g., stronger data security) and a deeper understanding of how consumers emotionally engage with AI technologies. This contributes to the broader discussion on sustainable innovation (Afeltra et al. 2023; Browder et al. 2023), where technology designers must account for both functional and psychological factors to ensure AI products are effective and ethically sound.

CTV as an Important Mediator of AFA Adoption Intention

Regarding CTV as a mediator in AFA adoption, we advance CV literature beyond traditional technology adoption models that rely on functional attributes (e.g., Browder et al. 2023; Kautish et al. 2023). We propose that the psychological experiences consumers encounter when interacting with AI technologies, particularly feelings of vulnerability, uncertainty, or powerlessness—are central to understanding the adoption process (Gama and Magistretti 2023).

Specifically, our findings show that CTV plays a dual role in AI adoption. First, it reflects consumers' anticipation of risks and uncertainties associated with AI technologies, which can cause feelings of unease or hesitancy. While Hermann et al. (2024) demonstrate how AI technologies can enhance consumer welfare by improving service accessibility and interactivity, we reveal that these same affordances (e.g., automation and predictability) may also evoke concerns about reduced control and increased reliance on AI. Importantly, CTV entails skepticism tied not necessarily to actual harm but to anticipated risks and reduced control. This aligns with Mani and Chouk's (2018) findings on resistance to new technologies, which stems from skepticism about promised benefits and reluctance to embrace changes prior to evaluating the innovation. Second, CTV can drive adoption, as consumers become more aware of the affordances and benefits offered by AI. This challenges the assumption that negative psychological states always hinder technology adoption (e.g., Kautish et al. 2023)—we argue that CV, when understood and addressed by product designers, can promote greater engagement with AI technologies by making consumers attuned to potential advantages of the technology. This understanding of CTV is crucial for explaining why certain AI affordances (e.g., information optimization, customizability, and human- likeness) positively influence AFA adoption through their impact on CV. These affordances, when well- designed, can mitigate feelings of powerlessness by giving consumers more control over their AI interactions, which is an emerging critical issue (Martin et al. 2017; Hermann et al. 2024). For instance, customizability allows consumers to tailor AI- driven financial tools, reducing anxiety and fostering empowerment. Similarly, information optimization helps consumers navigate complex financial information, thereby reducing cognitive overload and enhancing trust in AI systems.

Interestingly, our study also highlights the differential effects of AI affordances on CTV. While some features, like automation and prediction ability, are typically seen as advantageous, our findings suggest that they do not always directly influence CTV or technology adoption intention. Conversely, prior research suggested that automation and prediction ability simplify decision- making, improving adoption outcomes (Huang and Rust 2024). Our study implies that the impact of these features depends on the context and the consumer's psychological state. This extends prior research (Hermann et al. 2024) that has conceptualized technology affordance as interactive by nature, depending on the socio- psychological circumstances of innovation scenarios. For instance, automation may be viewed positively in professional settings, as it enhances efficiency. However, for consumers in financial contexts, automation may evoke concerns about loss of control, leading to heightened CV rather than increased adoption intention.

Additionally, we enrich the literature by emphasizing consumers' role as active agents in realizing AI affordances. Extant research has often focused on the role of developers and organizations in shaping how technology affordances are actualized (Jónasdóttir and Müller 2020); we show that consumers' psychological responses—particularly feelings of vulnerability—are just as key in determining how AI affordances are perceived and utilized. This insight shifts the focus from organizational control to consumer agency, suggesting that successful AI product adoption hinges on both technical features and emotional alignment between technology and consumer.

Thus, we also offer a novel perspective on the human–technology relationship, augmenting debates in socio-materiality and the ontological fusion of humans and technology (Gama and Magistretti 2023). While the socio-materiality framework posits humans and technologies as inseparable in determining outcomes, we reveal that CTV introduces psychological distance between consumers and AI technologies. This deepens understanding of how consumers navigate trust–vulnerability tensions when interacting with AI- driven products.

Lastly, our study has implications for AI- enabled financial services, which are often met with resistance due to security, trust, and data privacy concerns (Koponen et al. 2025). Positioning CTV as a mediator of AFA adoption provides a framework for understanding how these concerns can be addressed through thoughtful product design. Further, responsible AI innovation in the finance sector requires a balance between technical capabilities and client emotional engagement to ensure that AI financial goods and services are both functional and psychologically reassuring. Thus, emotional transparency (Koponen et al. 2025) and trust- building strategies (Mariani et al. 2023) should be prioritized in product offerings to foster sustainable adoption and long- term trust.

Implications for Product Innovation Practice

Our study initially explored the relationship between AFA affordances, CTV, and AFA adoption intention, offering insights to help financial product developers leverage benefits and costs of AI technologies. For instance, AFAs are received more favorably when perceived characteristics of the source and actual preferences align, and communication from AFAs is more effective when it highlights the "how"—instead of the "why"—in its service delivery (Lee et al. 2009). Accordingly, Kim et al. (2022) suggest that information provided by AI agents is more persuasive when consumers understand how the agent functions, and that their welfare and security are ensured. For example, as a major movement of its digital transformation, Bank of America launched an AI personal assistant Erica that could deliver natural responses to 676 million times of real inquiries for millions of customers in 2024 (Cocheo 2025). Furthermore, AFA or AI companies in general should seek to extend the principles of design thinking by shifting from "people-centered design" to "cen tering around the individual," meaning they should create more personalized solutions catering to individual user preferences and circumstances. Further, they should promote creativity across segments, stakeholders, and industries to allow for innovative that goes beyond the original product scope.

Moreover, endowing vulnerable consumers with AFA solutions and alleviating CV carries significant societal implications, and can directly contribute to improving societal well-being and re ducing unequal market participation. AI-enabled service com panies that strive to mitigate, resolve, or—ideally—prevent CTV play a key role in reducing social inequalities, thereby actively contributing to social justice—a central antecedent of consumer well-being (Johns and Davey 2019)—especially regarding AI. Conversely, justice is pivotal in AI development and deployment. For instance, NatWest introduced the Cora+ AI and data platform to serve as the initial interaction point when customers face difficulties. The system can efficiently summarize the conversation, enabling human agents to grasp the customer's needs and the context of their interaction (NatWest Group 2024). Financial firms should advocate fairness, avoid unwanted impacts of technology, and promoting the equitable sharing of benefits and cultivation of solidarity—which will ultimately strengthen social cohesion (Thiebes et al. 2021). In fact, there are several industry- specific regulations that promote the fair treatment of vulnerable consumers, such as International Organization for Standardization 22458 (ISO 2022) and the United Kingdom's Financial Conduct Authority guidelines. These guidelines require companies to (a) understand the needs of vulnerable consumers; (b) train their staff to recognize and respond to these needs; (c) address these needs in product design, service provision, and communication; and (d) monitor and evaluate whether these needs are being met. Notably, AI advancements offer companies opportunities to support and enhance these efforts. Of note, companies' socially responsible efforts to mitigate CV can elicit positive responses from consumers, irrespective of their vulnerability state, while also capitalizing on win–win outcomes facilitated by AI's integration within services, including profit generation, enhanced reputation and corporate image, and doing good for society (Chandy et al. 2021).

Our results also show that innovativeness and self- efficacy determine the CTV level under exposure to different AFA features. Since AFAs are now a primary element of modern automated consumer choice processes, financial service providers should focus more on eliminating user concerns about their offerings, specifically by highlighting how their products and offerings could enhance users' capability and autonomy in making their own financial decisions. For example, the effective deployment of AI solutions requires a change in perspective, beginning with the user experience of early adopters. This involves reimagining processes and developing AI agents that are user- centric and capable of adapting through reinforced user learning experiences and human feedback. Furthermore, financial institutions improve accountability and credibility by increasing AFAs' intelligence to ensure consumer welfare (Tucker 2014). Institutions could also educate consumers about AFA functions and regulations, so they are better informed about their rights and potential harms, and confident adopting AI products in their daily lives (Martin et al. 2017).

Limitations and Future Research Directions

This study reveals how AI affordances influence AI- driven new product adoption through CTV. Some limitations, however, suggest future research directions. First, we utilize surveys to investigate cognitive constructs of CTV. It may be useful to replicate the proposed causal effect via field experiments to capture real-marketplace reactions. Second, as industries utilizing AI technology vary, the effect of AI characteristics within AFAs may differ from those used, for example, in "intelligent" driving; thus, our findings may not apply across industries. Indeed, each industry is unique regarding AI engagement and consumer response (Huang and Rust 2021). Third, our study considered USA respondents. Previous studies have indicated that country level should be considered as a moderator when studying AI impacts (Kopalle et al. 2022); therefore, research could compare the impact of CV on new product adoption in other settings or countries. The study's restricted sampling may also disproportionately reflect experienced users, inadvertently marginalizing barriers faced during early adoption phases. Thus, researchers could include experience in the model to enhance understanding of consumer perspectives based on experience level (e.g., novices vs. experts). Fourth, we adapted existing CV scales to the AI context. Although these scales use established constructs, they were developed in non-AI settings and may lack sensitivity to the rapid, iterative changes of AI technologies (e.g., real-time ana lytics, opaque decision processes). Thus, nuances of AI- driven CV may remain underexplored. Research could develop and validate a pure measurement scale for AI- driven CTV, ideally with longitudinal and multi-context designs, to capture how CV shifts as users gain familiarity with, or skepticism about, evolving AI systems. Lastly, system intelligence matters in AI product adoption. Henkens et al. (2021) found a negative AI features–consumer engagement

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association in a smart service system setting (i.e., smart products and service providers that deliver smart services). System intelligence manifested as connectivity, awareness, and actuation, which is not comparable with the AI-enabled algorithm we study, resulting in a dispar ity in technology trade- offs.
Further, AI engines are complex, such that the consequences of AI affordances have yet to be defined, and investigation can only focus on what is observable based on the functional façade. AI affordances are also dynamic, and conditions that enable transitions from AI affordances to constraints should be researched. This study considered consumer- mediated affordance actualization that facilitates AFA adoption, wherein restricted control over AI technology and limited knowledge of how AI tools function raise CV regarding to major decision-making. Being pressured by AI agents to replace human alternatives, vulnerable consumers might fully delegate decisions to AI systems during information collection, consideration, and decision- making. However, this can backfire and compromise consumer well- being when they overly depend on AI systems (Banker and Khetani 2019). Some individuals may face a technological dilemma or impaired resource efficiency (e.g., cost of information search, cognitive resources), which could impact their efficacy in performing other tasks. Hence, a framework that empowers consumers by reinstating their control over resources (at individual, structural, and interpersonal levels) must be formulated based on empirical research, with a focus on the explicit role of each stakeholder. Given the challenge of developing and deploying consumer- centric AI ethically and accountably, collaboration among companies, ethicists, consumers, and policymakers is imperative for creating a globally integrated, equitable technological system that optimally facilitates AI affordance actualization. The first step therein is to explicitly define the many variables that hinder or facilitate such a process. Most importantly, our findings should be incorporated as a general framework for AI frontline engineers to refer to in their product-development process, as innovation can and should be leveraged as a catalyst for positive change.
Additionally, we exclude perceived usefulness (PU) and PEOU from the TAM (Venkatesh et al. 2023) to focus on TACT- based explanations and CTV. While valuable in explaining technology acceptance (Zin et al. 2023; Tamilmani et al. 2021), PU and PEOU could moderate or mediate certain relationships in our framework. Future research might reintroduce these constructs to examine how their interactions with CTV influence AI- based product adoption, especially in contexts where sophisticated algorithms and rapid innovation cycles demand both technological effectiveness and user comfort. Thus, scholars could uncover a more holistic view of consumer acceptance and deepen understanding of how functional benefits and psychological vulnerability jointly shape AI adoption.

Concluding Thoughts

Business Transformation is inevitable, and firms need to embrace it sooner than later (Kumar 2018). By empirically investigating the AI affordances–product adoption relationship through CTV, this research explains how consumers respond to the introduction of AI- enabled technological products within a setting that encompasses financial security and socio-psychological risks. To promote adoption intention, AI engineers, product designers, and other stakeholders must understand and account for consumers' powerless state of mind when exposing them to novel AI features and consider the unknown consequences of their product offerings and service delivery.

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