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Algorithmic Transparency and Consumer Trade-Offs in AI-Based Financial E-Commerce Services

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Abstract

Algorithmic transparency is widely considered essential for fostering trust in AI-based financial e-commerce services. However, empirical evidence remains limited on whether transparency benefits all consumers uniformly and how it is evaluated relative to other service attributes in realistic decision contexts. This study examines how consumers trade off transparency, personalization, and user control in robo-advisor (RA) services across different consumer segments. Through a discrete choice experiment and latent class logit modeling, two distinct segments are identified: selective high-expertise investors, who prioritize personalization and user control over transparency, and receptive general consumers, who respond strongly to enhanced explainability. These findings indicate that algorithmic transparency does not serve as a universal design solution but operates conditionally based on consumer expertise and attribute interactions. Simulation results further show that while a regulation-compliant, uniform service design may facilitate market entry, it constraints long-term expansion in heterogeneous markets. In contrast, a segment-based service portfolio calibrated to the distinct preferences of each group significantly increases overall adoption under the same regulatory constraints. These results suggest that sustainable AI diffusion in financial e-commerce requires a nuanced approach that balances disclosure with functional autonomy to address the diverse needs of both sophisticated and novice users.

Keywords: algorithmic transparency; robo-advisors; AI-based financial services; discrete choice experiment; latent class model

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1. Introduction

The diffusion of artificial intelligence (AI) has fundamentally transformed consumer decision-making processes in electronic commerce environments. On online platforms, algorithm-based recommendation systems serve as essential mechanisms for reducing information overload and facilitating consumer choice by curating and personalizing available options [1,2]. In addition to their technical functions, these systems shape how users interpret and evaluate algorithmic outputs, thereby playing a critical role in establishing the trust required for technology adoption [3,4]. In this context, algorithmic transparency,

defined as the extent to which the underlying logic and criteria of algorithmic outcomes are explained, has emerged as a primary determinant of service acceptance [4,5].

However, existing evidence indicates that the impact of transparency is neither uniform nor exclusively positive. While transparency can enhance trust, excessively detailed explanations may impose significant cognitive burdens, resulting in information overload [6]. This phenomenon is particularly pronounced in knowledge-intensive sectors such as financial services, where consumers must navigate complex trade-offs among interacting attributes. For example, the benefits of personalization, which enhance perceived usefulness and satisfaction [7], often conflict with privacy concerns, and transparency may either mitigate or exacerbate these concerns [8,9]. Furthermore, the efficiency provided by automation may conflict with the desire for user control, creating a performance-control dilemma [10] that transparency alone may not resolve. These dynamics indicate that consumers evaluate algorithmic transparency as part of a bundled configuration, weighing perceived utility against cognitive and psychological risks.

This multi-attribute evaluation is particularly significant for robo-advisors (RAs), a prominent category of AI-based financial e-commerce services. RAs deliver algorithmic investment recommendations and portfolio management via digital platforms, operating in financial environments characterized by high uncertainty and risk [11,12]. Despite the expansion of RAs, existing research has primarily examined general adoption intentions or the isolated effects of individual service attributes [12–14]. Additionally, although global regulatory bodies such as those in the European Union, United States, and Korea emphasize transparency as a core requirement for AI systems [15–17], it remains unclear how these mandates influence actual consumer choices. Notably, empirical evidence is limited regarding how these trade-offs are moderated by consumer heterogeneity, including differences in domain expertise and cognitive capacity [18].

In response, this study investigates how consumers make trade-offs among key service attributes—algorithmic transparency, personalization, and user control—in AI-based financial e-commerce services, and how these trade-off structures differ across consumer segments. By integrating the Extended Technology Acceptance Model (TAM) with Cognitive Load Theory, the study proposes a framework to elucidate the dual pathway mechanisms of AI adoption under uncertainty. Methodologically, a discrete choice experiment (DCE) combined with a latent class logit model is used to simulate realistic multi-attribute choice environments. The study addresses the following research questions:

RQ1. How do consumers make trade-offs among algorithmic transparency, personalization, and user control in AI-based financial e-commerce services?
RQ2. Do these trade-off structures systematically differ across consumer segments?
RQ3. How do alternative service design configurations influence RA adoption under realistic market and regulatory conditions?

This study offers three primary contributions. First, it introduces a conceptually driven framework that clarifies how transparency serves as a trust-building signal to enhance perceived usefulness (PU), while also acting as an information burden that can reduce perceived ease of use (PEOU). This provides a theoretical basis for understanding the mechanisms by which consumers navigate trade-offs. Second, from a methodological perspective, the study advances beyond simple attitudinal scales by employing a DCE. This approach simulates integrated choice environments in which consumers make realistic trade-offs among bundled attributes, enabling the quantification of preference heterogeneity that average-user models do not capture. Third, by linking regulatory mandates with empirical consumer responses, the study provides actionable evidence for differentiated service design. Simulation results demonstrate that segment-specific portfolios, rather than

a uniform transparency approach, are more effective in balancing regulatory compliance with market acceptance.

2. Theoretical Background

2.1. Financial Decision Uncertainty and the Signaling Role of Trust

Consumer decision making in AI-based financial services, such as RAs, is characterized by significant uncertainty. Financial decisions often involve delayed outcomes and the possibility of losses, which contribute to psychological tension and information asymmetry [19,20]. Simon's theory of bounded rationality explains that individuals seek satisfactory rather than optimal solutions due to cognitive limitations [21]. Prospect Theory further indicates that losses are weighted more heavily than gains [22]. In algorithm-driven financial services, this loss aversion leads consumers to perceive not only potential investment losses but also risks associated with algorithmic errors or opacity, often fostering advice aversion [23].

Under conditions of heightened uncertainty, consumers often rely on heuristics rather than comprehensive information processing [24]. Trust functions as a key evaluative mechanism, lowering decision costs and reducing cognitive effort. According to the trust theory, trust is defined as the willingness to accept vulnerability based on positive expectations of another party's competence (ability), intentions (benevolence), and fairness (integrity) [25]. Therefore, the adoption of RA services, which delegate asset management to algorithmic systems, requires confidence in the system's ability and reliability [7].

In this context, RA service attributes, such as algorithmic transparency, personalization, and user control, function as salient signals that reinforce perceptions of trustworthiness. Algorithmic transparency, defined as the degree to which users can access and understand aspects of a system that are otherwise hidden, such as its operational logic and output interpretation [3,26], is a crucial signal of both ability and integrity. Increased transparency enhances system intelligibility, allowing users to more effectively evaluate algorithmic outcomes [18,27]. This process supports the formation of critical trust based on system understanding rather than blind reliance [28].

Similarly, personalization signals benevolence by demonstrating that the algorithm prioritizes the user's unique interests [29], while user control acts as a mechanism to mitigate perceived risk and algorithm aversion by allowing human intervention [30]. By providing users with cognitively accessible cues regarding system competence and fairness [4], these attributes reduce psychological barriers under uncertainty and promote technology acceptance [1].

2.2. Choice Mechanisms and Heterogeneous Acceptance Across Consumer Characteristics

The signaling effects of algorithmic transparency described in Section 2.1 are processed within a complex trade-off mechanism, which can be explained by integrating the TAM and the Cognitive Load Theory. While the trust theory identifies the perceived benefits of service attributes, the Cognitive Load Theory addresses the associated costs. Together, these perspectives determine the key drivers of technology adoption defined in the TAM: PU and PEOU [31].

This study proposes a conceptual framework in which trust-building attributes also serve as cognitive burdens. Within the TAM, trust functions as a critical antecedent that enhances both PU and PEOU by reducing perceived risk and uncertainty [32,33]. However, according to the Cognitive Load Theory, the information necessary to establish trust, such as detailed algorithmic explanations, imposes an information-processing cost [34]. Consequently, a systematic trade-off emerges: increased transparency may enhance PU through

greater trust, but PEOU may decrease if the information load exceeds the consumer's cognitive capacity [6,10,35].

This integrated mechanism is particularly evident in the tension between algorithmic transparency and user control. Transparency is theorized to reduce uncertainty and increase PU; however, when combined with high user control, it requires consumers to interpret system logic and make decisions actively. This dual demand increases mental effort and decision complexity [36], resulting in a performance-control dilemma where gains in trust are offset by reductions in PEOU [10]. Consumers must therefore seek an equilibrium, potentially sacrificing transparency for ease of use, or vice versa.

Similarly, the interaction between transparency and personalization is determined by the balance between trust-driven utility and cognitive or psychological costs. Personalization increases PU by providing relevant recommendations, yet the transparency required to explain data usage can create a privacy paradox, heightening both privacy concerns and mental effort [37,38]. This increased cognitive burden may reduce PEOU, compelling consumers to weigh the advantages of tailored services against the mental costs of managing privacy risks [29].

These theoretical pathways connecting trust signals, cognitive load, and TAM constructs are moderated by consumers' expertise, such as domain knowledge and prior experience. This moderation operates through two cognitive mechanisms: information processing efficiency and evaluative criteria. Expertise influences the efficiency with which technical information is processed. Individuals with high expertise may sustain greater PEOU even when presented with complex transparency cues, as their established mental models reduce the cognitive effort required to interpret system logic [39,40]. In contrast, individuals with limited expertise experience a higher cognitive burden, leading them to depend on simpler external heuristics, such as transparency or explanations, to reduce uncertainty and conserve cognitive resources [41].

Furthermore, consumers with greater expertise typically rely on internal evaluative standards rather than external informational signals. For these individuals, PU is not derived from system transparency, but from the system's functional capabilities, such as high personalization and user control that correspond with their internal decision logic [42]. As a result, experts may demonstrate algorithm aversion when they are unable to override or adjust algorithmic outputs [43]. In contrast, individuals with less expertise are more likely to exhibit algorithm appreciation as a strategic response to increased cognitive demands [44].

Despite these theoretical insights, previous research has not adequately examined how consumers trade off multiple RA design attributes when presented together in integrated choice environments. Empirical studies on bundled attribute effects and preference heterogeneity are especially scarce in AI-driven financial services. This study addresses this gap by using a DCE to quantify attribute trade-offs and preference heterogeneity.

2.3. Literature Synthesis and Research Gap

Although the previous sections have provided theoretical insights, existing research has not sufficiently examined how consumers evaluate multiple RA design attributes when these are presented simultaneously in integrated choice environments. Table 1 offers a systematic overview of the current empirical landscape by summarizing key prior studies, their theoretical frameworks, principal findings, and the specific gaps identified in the literature.

Table 1. Prior studies on transparency and service attributes in algorithmic advisory contexts.

Author	Research Context	Theoretical Framework	Key Findings	Research Gap
Cramer et al. [1]	Recommendation agent	Technology acceptance model (TAM)	Transparency enhances perceived competence	Single-attribute effect; limited generalizability
Komiak and Benbasat [29]	Recommendation agent	Theory of Reasoned Action (TRA)	Personalization increases trust; emotional trust mediates in delegation intention	No multi-attribute trade-off design
Aguirre et al. [8]	Online advertising	Psychological Ownership Theory	Privacy concerns weaken personalization benefits	Non-financial context; no multi-attribute evaluation
Shin and Park [4]	Recommendation systems, chatbots	Algorithmic affordance	Fairness, accountability, and transparency (FAT) enhance user experience through trust	Attributes examined independently; context-dependency
Grimmelikhuijsen [45]	Algorithmic decision making	Procedural Fairness Theory	Algorithmic transparency is conceptualized as accessibility and explainability	Non-financial context; restricted to non-biased algorithmic scenarios
Dietvorst et al. [43]	Forecasting tasks	-	Asymmetric tolerance for errors; asymmetric confidence updating mechanism	No examination of interventions to reduce algorithm aversion
Dietvorst et al. [30]	Forecasting tasks	-	Minimal modification options reduce algorithm aversion significantly	No examination of the mechanism underlying the sense of control
Logg et al. [44]	Judgment tasks	Advice-taking paradigm	Algorithm appreciation among lay people; wanes with self-involvement/expertise	No examination of appreciation persistence after observing errors
Belanche et al. [7]	RA adoption	TAM; TRA	Attitude and subjective norms drive RA adoption intention; familiarity moderates the role of social influence	No attribute-level trade-off analysis; solely reliant on attitudinal scales
Rühr [10]	RA configuration	Signaling Theory; Illusion of Control	Transparency partially mitigates the performance-control dilemma at medium levels	Limited to system-design attributes only; small student sample
Kofman [23]	RA market regulation	Signaling Theory	Gateways-and-ratings framework builds trust in RA	No empirical examination; no consideration of consumer responses

As indicated in Table 1, individual attributes such as transparency, personalization, and control have typically been studied in isolation. However, there is limited empirical evidence concerning their simultaneous interactions and the resulting trade-offs. Most prior studies employ single-attribute analyses or attitudinal scales, which do not adequately capture the complex decision-making processes in which consumers must prioritize one benefit over another.

This study addresses this research gap by employing a DCE. By simulating bundled RA service configurations, this study examines attribute trade-offs and identifies heterogeneous preference structures within the consumer market. This methodological approach enables a more detailed understanding of how various consumer segments prioritize RA design features.

3. Methodology

3.1. Experimental Design

The effectiveness of a DCE depends on the cognitive feasibility of the choice tasks presented to respondents. Increasing task complexity by including too many attributes often prompts respondents to use simplification heuristics, such as attribute non-attendance [46]. This behavior increases random error variance and may undermine the reliability of estimated preferences [47,48]. Existing literature recommends using approximately four to five attributes to maintain cognitive manageability and support compensatory decision-making [49,50]. Accordingly, five core attributes were selected for this study.

The attribute selection emphasized intrinsic technological characteristics to isolate the independent influence of AI service design. External environmental factors, including brand credibility and financial performance expectations, were not incorporated in the experimental design. Brand credibility functions as a subjective institutional cue that can trigger pre-existing biases, leading respondents to adopt heuristic-driven decisions or non-trading behavior [51,52]. Financial performance represents a stochastic and market-dependent outcome rather than a stable system feature, and its inclusion as a fixed experimental level could mislead respondents, as actual returns are not guaranteed at the adoption stage [53]. Cost structures were held constant because RA services typically employ uniform low pricing with minimal variation, which could otherwise create dominance effects and hinder the independent identification of technological trade-offs [52,54,55].

Consequently, the five identified attributes were categorized according to three theoretical perspectives. First, from the perspective of signals of system and integrity, algorithmic transparency and information sources were included as key attributes [3,4]. An information source serves as an external credibility cue, enabling users to assess the expertise and reliability of algorithmic recommendations. In contrast, transparency reduces uncertainty related to the system's internal operations, often referred to as the black-box problem [27]. From the perspective of signals of benevolence and functional value, personalization was incorporated as an attribute [7]. Personalization increases the relevance and anticipated performance of recommendations, thereby strengthening PU, which is a central determinant of technology acceptance [2,31]. Lastly, from the perspective of mechanisms for agency and interaction efficiency, user control and communication style were included as attributes. User control allows consumers to intervene in automated decisions, which may reduce algorithm aversion [30]. Communication style reflects how the framing of interactions influences cognitive effort, perceived social presence, and trust development [56,57].

Table 2 summarizes the attributes and levels included in the DCE design.

The first attribute, algorithmic transparency, denotes the extent to which an RA service offers explanations regarding the processes and logic underlying its investment recommendations. Previous research on recommendation systems and algorithmic services demonstrates that providing explanations improves users' understanding and trust, which in turn increases service acceptance [1]. Shin and Park [4] identify transparency, alongside fairness and accountability, as a core determinant of user satisfaction in algorithmic service contexts and empirically demonstrate a positive effect of transparency on service satisfaction.

In this study, algorithmic transparency is operationalized as the level of explanation, highlighting its role as a mechanism rather than an abstract concept. Rader et al. [3] contend that transparency in algorithmic systems is most effectively conceptualized as a mechanism that communicates internal logic to users, with explanations serving as the primary means for this process. Shin [58] further suggests that explainability functions as a critical antecedent, enabling users to perceive broader systemic values such as fairness, accountability, and transparency. While fairness and accountability are essential for fostering long-term

trust, the depth of technical explanation (global versus local) directly influences users' immediate cognitive effort and PEOU in decision-making environments [26]. Fairness and accountability are often evaluated based on users' perceptions shaped by explanations, making these constructs theoretically intertwined rather than entirely distinct. To maintain the rigor of the DCE and to isolate the trade-off between information transparency and decision-making efficiency, other dimensions were held constant or addressed within the broader framework of algorithmic accountability. By focusing on explanation levels—ranging from no explanation to personalized feature-attribution logic—this study aims to identify the primary cue influencing consumer perceptions of systemic integrity, without the confounding effects of measuring fairness or accountability as separate variables.

Table 2. Attributes and levels used in the discrete choice experiment.

Attribute	Description	Levels
Algorithmic Transparency	The extent to which users are provided with explanations about how the algorithm operates and generates recommendations	(1) No explanation (2) Global model explanation (3) Global model explanation with personalized explanation
Personalization Level	The degree to which the service tailors information and recommendations to individual user characteristics	(1) Low (simple group-level personalization) (2) Medium (segmented group-level personalization) (3) High (individual-level personalization)
Information Source	The source from which the robo-advisor collects and utilizes user data	(1) User-provided information only (2) User-provided information plus external data
Communication Style	The extent to which the robo-advisor communicates information in a friendly and easily understandable manner	(1) High warmth (2) Low warmth
Portfolio Adjustability	Whether users can directly modify or adjust the recommended investment portfolio	(1) Adjustable (2) Not adjustable

Consistent with this approach, algorithmic transparency was defined at three levels. The lowest level (no explanation) provides only the investment recommendation outcome, without any explanation of the algorithm's operation. The second level (global model explanation) offers an overview of the algorithm's general operating principles, including its criteria and structure. This level corresponds to what the literature on recommendation systems refers to as global explanations [26,27]. Respondents were presented with the following example, representative of realistic RA usage: "This service recommends a diversified portfolio based on your investment profile and risk tolerance. The overall model is built on modern portfolio theory and optimizes asset allocation by analyzing correlations across asset classes." The highest level (global model explanation with personalized explanation) combines a global explanation with individualized, user-specific explanations that clarify how personal characteristics contributed to the recommendation. This level aligns with feature-attribution-based explanations that explicitly link user attributes to recommendation outcomes [59]. Respondents were shown the following example: "You have been classified as an 'active investor' with investable funds of KRW 500,000 per month and an investment horizon of over three years. Based on this profile, we set the portfolio risk level at medium-high (volatility 12%) and designed a diversified strategy emphasizing asset classes with strong medium- to long-term returns while managing short-term volatility."

The second attribute, personalization level, reflects the extent to which the RA service customizes its recommendations based on individual user characteristics. A key distinction of RAs compared to traditional financial advisory services is their capacity to generate customized portfolios using investor-specific information [14]. Prior research indicates that personalization aligned with individual risk preferences can improve portfolio efficiency, including Sharpe ratios and return distributions [12]. Drawing on previous studies and industry practices, personalization was operationalized at three levels: low (simple group-based personalization), medium (segmented group-based personalization), and high (individual-level personalization). The low level involves minimal information, such as age group or broad risk category, to provide identical strategies to predefined user groups (e.g., "Portfolio for aggressive investors in their 30s"). The medium level considers multiple shared characteristics—such as age, investment horizon, and income level—to deliver more refined group-specific strategies, a format commonly observed in mainstream RA services. Respondents were presented with examples such as "A bond-focused ETF strategy suitable for stable investors in their 40s with middle-income levels." The high level entails fully individualized personalization, integrating multidimensional personal information—including financial goals, constraints, and preferences—to generate a unique portfolio for each user. An illustrative example was "A personalized stock–bond mixed strategy designed for User A, reflecting a 30% risk tolerance and a preference for U.S. markets."

The third attribute, information source, concerns the scope of user information utilized by the RA service. This attribute is closely associated with privacy concerns and plays a critical role in service acceptance. Kim et al. [60] demonstrate that consumers generally find information explicitly provided within a service more acceptable, whereas externally collected or inferred data often elicit resistance. The personalization paradox further suggests that increased privacy concerns during personalization may reduce satisfaction, particularly when data collection is perceived as covert or intrusive [8]. In line with these findings, the information source was defined at two levels. User-provided information only involves constructing portfolios solely from information directly entered by users. User-provided plus external information incorporates additional external data sources, such as financial institution records or consumption data, to potentially generate more refined portfolio recommendations.

The fourth attribute, communication style, describes how the RA conveys information to users and the degree of warmth and approachability in its interactions. This attribute is closely related to social presence, defined as the extent to which users perceive the service as socially engaging and human-like. Prior research indicates that social presence in RA services enhances perceived usefulness and promotes acceptance [61], while socially oriented communication styles improve satisfaction in AI and chatbot contexts [56]. Accordingly, communication style was operationalized at two levels: high warmth and low warmth. The high-warmth level employs empathetic, conversational language similar to that of human advisors. Respondents were shown examples such as "We've slightly adjusted your portfolio to better match your investment preferences. Please feel free to reach out if you have any questions." The low-warmth level utilizes concise, impersonal, and mechanical language, exemplified by "Your portfolio has been updated. Please review the changes."

The fifth attribute, portfolio adjustability, indicates whether users are permitted to directly modify the recommended portfolio, reflecting the degree of user control. Rühr [10] reports that users prefer RA systems that offer some degree of control rather than fully automated, non-interactive structures. Accordingly, this attribute was specified at two levels: adjustable (users can modify the recommended portfolio) and not adjustable (users cannot make changes to the recommended portfolio).

The combination of all attributes and levels results in $3 \times 3 \times 2 \times 2 \times 2 = 72$ possible service profiles. Implementing a full factorial design would impose excessive cognitive burden and fatigue on respondents, potentially reducing response quality. Therefore, a Bayesian D-efficient design was employed to construct the choice tasks. D-efficient designs maximize statistical efficiency by minimizing the variance–covariance matrix of parameter estimates [62]. Bayesian D-efficient designs further incorporate prior information, enabling more precise estimation with limited sample sizes [63].

The Bayesian D-efficient design was generated using the software JMP 18. Priors were derived from a pilot survey (n = 100), from which prior means and variances for attribute levels were estimated and incorporated into the design. Initial priors were informed by prior literature and theoretically grounded assumptions regarding relative preferences [63,64]. Both the pilot and main surveys consisted of four choice tasks per respondent, each featuring three hypothetical RA alternatives (alternatives A, B, and C) and one *no-choice* option. The inclusion of a *no-choice* alternative allowed respondents to opt out when none of the presented services were preferred, thereby mitigating forced-choice bias and enhancing consistency with real-world market behavior [65,66].

3.2. Survey Design

The survey comprised three sequential components: assessment of respondents' basic characteristics and prior experience, administration of the DCE, and the collection of additional socio-economic information.

Before the choice experiment, respondents answered questions designed to elicit their demographic characteristics and their experience with AI and financial services. These questions included standard demographic variables such as gender, age, and region of residence, as well as items measuring prior use of AI-based services. AI-based services were defined broadly to include AI-enabled search, video, shopping, financial services, and generative AI across online platforms and applications. Respondents were also asked about their experience with the direct management of financial assets and investment activities. These measures captured respondents' general level of technology adoption and financial decision-making experience, enabling them to contextualize the subsequent RA choice tasks more realistically.

Respondents then participated in the core component of this study, the DCE. Prior to completing the choice tasks, the survey included a brief introduction to the concept of RA services, followed by clear explanations of each attribute and its corresponding levels. This approach ensured that respondents understood the decision context and the meaning of the alternatives presented. All respondents completed an identical set of choice tasks, selecting their most preferred alternative among the presented options or choosing a no-choice option if none were acceptable.

After completing the choice experiment, respondents answered additional questions to capture their socio-economic background. These items included education level, occupation, and income, enabling a more comprehensive characterization of respondents' socio-economic profiles.

3.3. Latent Class Logit Model

This study quantitatively examines consumer preferences for RA service attributes using choice data from a DCE. DCE data are typically analyzed within the framework of random utility theory and the assumption of utility maximization. Among discrete choice models, the multinomial logit (MNL) model—assuming independently and identically distributed Gumbel errors—has been most commonly applied [67]. However, as the MNL

model imposes homogeneous preference parameters across all individuals, it is inherently limited in capturing preference heterogeneity within the consumer population [67].

To overcome this limitation, this study adopts a latent class logit (LCL) model. The LCL model assumes that the population consists of a finite number of unobserved segments (i.e., latent classes), each characterized by a distinct utility function [67,68]. Compared with mixed logit models, which model heterogeneity continuously, the latent class approach offers greater interpretability and facilitates the identification of clearly defined consumer segments, making it particularly suitable for policy analysis and service design.

Formally, conditional on individual n belonging to latent class q, the utility derived from alternative j in choice task t is specified as follows:

$$U_{njt|q} = V_{njt|q} + \varepsilon_{njt|q} \tag{1}$$

where $V_{njt|q}$ denotes the deterministic component of utility, and $\varepsilon_{njt|q}$ represents a stochastic error term. The deterministic utility is modeled as a linear function of dummy variables capturing the attributes and levels of the RA service:

$$\begin{aligned} V_{njt|q} = {} & \beta_{q,Trans1} Trans1_{njt} + \beta_{q,Trans2} Trans2_{njt} + \beta_{q,Pers1} Pers1_{njt} \\ & + \beta_{q,Pers2} Pers2_{njt} + \beta_{q,Info} Info_{njt} + \beta_{q,Comm} Comm_{njt} \\ & + \beta_{q,Cont} Cont_{njt} + \beta_{q,NoChoice} NoChoice_{njt} \end{aligned} \tag{2}$$

Here, $Trans1_{njt}$ and $Trans2_{njt}$ denote dummy variables indicating the algorithmic transparency levels of "no explanation" and "global model explanation," respectively. $Pers1_{njt}$ and $Pers2_{njt}$ denote "low" and "medium" levels of personalization. $Info_{njt}$ indicates whether only user-provided information is used, while $Comm_{njt}$ captures a high-warmth communication style. $Cont_{njt}$ denotes whether portfolio adjustment is allowed. Finally, $NoChoice_{njt}$ represents an alternative-specific constant (ASC) that equals one when alternative j corresponds to the no-choice option. The coefficients β_q represent class-specific preference parameters.

Conditional on class membership, the probability that individual n chooses alternative j in task t follows the standard multinomial logit form:

$$P_{njt|q} = \frac{\exp(V_{njt|q})}{\sum_k \exp(V_{nkt|q})} \tag{3}$$

In the latent class framework, class membership probabilities are modeled as a function of user expertise, consistent with the theoretical framework developed in Section 2.2. In the context of AI-based financial services, this expertise is operationalized through two primary dimensions: technological familiarity and financial domain knowledge [69,70]. Accordingly, this study considered several candidate covariates reflecting these dimensions, such as demographic traits, general digital service proficiency, and various levels of investment involvement. After systematically comparing alternative specifications, the model including the prior use of AI services and experience with the direct management of financial assets provided the most coherent class separation and yielded statistically significant and interpretable parameter estimates. The class membership probability is therefore specified as follows:

$$\pi_{nq} = \frac{\exp\left(\theta_{q0} + \theta_{q1} AIuse_n + \theta_{q2} Inv_n\right)}{\sum_{r=1}^{Q} \exp(\theta_{r0} + \theta_{r1} AIuse_n + \theta_{r2} Inv_n)} \tag{4}$$

where $AIuse_n$ indicates whether respondent n has prior experience using AI-based services, and Inv_n indicates experience with directly managing financial assets. The parameters θ_q capture class-specific effects in the membership function.

The unconditional probability that individual n selects alternative j in task t is obtained by weighting class-specific choice probabilities by the corresponding membership probabilities:

$$P_{njt} = \sum_{q=1}^{Q} \pi_{nq} P_{njt|q} \quad (5)$$

Model parameters were estimated via maximum likelihood estimation (MLE). Estimation was implemented using the lclogit2 command in Stata/MP 19, which employs an expectation–maximization (EM) algorithm [71]. The number of latent classes was determined by jointly considering information criteria (i.e., Akaike and Bayesian Information Criteria) and the interpretability of the resulting class structure [67,68].

4. Results

4.1. Data

The survey for this study was conducted online over a four-day period in August 2025 through Embrain, a professional survey research firm in Korea. Participants were recruited from Embrain's online panel, and purposive quota sampling was employed to reflect the national distribution of gender, age, and region in Korea.

The final sample consisted of 500 respondents and exhibited a relatively balanced distribution across key demographic characteristics, without excessive concentration. A substantial proportion of respondents reported prior experience with AI-based services and direct management of financial assets, indicating that the sample is appropriate for evaluating choice situations involving AI-based financial services such as RAs.

Detailed descriptive statistics for respondents' demographic characteristics and experience-related variables are presented in Table 3.

4.2. Latent Class Logit Model Results

To address unobserved preference heterogeneity, the LCL models with two to four classes were estimated. Consistent with the established literature, the optimal number of classes was determined by balancing statistical fit, classification reliability, and substantive interpretability [72,73]. Model comparisons incorporated log-likelihood, Bayesian Information Criterion (BIC), and Consistent Akaike Information Criterion (CAIC).

As shown in Table 4, the log-likelihood improved as the number of classes increased. However, the complexity-adjusted criteria yielded divergent results: the BIC favored the four-class model, whereas the CAIC indicated optimal fit for the three-class specification. Importantly, the three- and four-class solutions produced segments with relatively small sample shares (e.g., 16.8% and 11.7%) and limited differentiation in preference structures. This pattern may indicate over-specification, where additional classes capture statistical noise rather than substantive heterogeneity [72,73].

By contrast, the two-class specification produced a high entropy value of 0.96. Entropy serves as a diagnostic measure of classification precision, reflecting how distinctly the model assigns individuals to classes based on posterior probabilities; values near 1 indicate clear separation between segments [74,75]. Although the class distribution was uneven (22% versus 78%), such disproportionate shares are typical when identifying distinct behavioral groups and do not compromise segmentation validity if entropy and behavioral distinctiveness remain high [76,77].

Table 3. Sample characteristics.

Category	Item	Value
Gender	Male	238 (47.6%)
	Female	262 (52.4%)
Age group	20~29	53 (10.6%)
	30~39	146 (29.2%)
	40~49	145 (29.0%)
	50~59	110 (22.0%)
	60~69	46 (9.2%)
Region [a]	Seoul metropolitan area	301 (60.2%)
	Non-metropolitan area	199 (39.8%)
Education	High school or lower	69 (13.8%)
	Bachelor's degree	365 (73.0%)
	Graduate degree or higher	66 (13.2%)
Education	High school or lower Bachelor's degree Graduate degree or higher	69 (13.8%) 365 (73.0%) 66 (13.2%)
Monthly income [b]	≤KRW 1.99 million KRW 2.00~3.99 million KRW 4.00~6.99 million ≥KRW 7.00 million	67 (13.4%) 204 (40.8%) 155 (31.0%) 74 (14.8%)
Experience with AI services	Yes No	443 (88.6%) 57 (11.4%)
Direct management of financial assets	Yes No	428 (85.6%) 72 (14.4%)

[a] The Seoul metropolitan area includes Seoul, Incheon, and Gyeonggi Province. [b] KRW denotes Korean won. USD 1 was approximately equivalent to KRW 1350 at the time of the survey (August 2025).

Table 4. Model selection criteria for latent class logit models.

Number of Classes	Log-Likelihood	Bayesian Information Criterion	Consistent Akaike Information Criterion	Class Shares (%)
2	−2254.65	4627.39	4646.39	22.0/78.0
3	−2208.62	4603.67	4633.67	16.8/22.5/60.7
4	−2170.68	4596.17	4637.17	11.7/17.8/21.9/48.6

Therefore, the two-class specification was selected as the final model because it ensures parsimony and offers a stable, theoretically interpretable framework for consumer orientations.

Table 5 presents the estimation results for the class membership probability function, with Class 2 as the reference category. The findings demonstrate that respondents with prior experience using AI-based services and those who have directly managed financial assets are significantly more likely to be classified as members of Class 1. Consistent with the theoretical framework, this supports the interpretation of Class 1 as selective high-expertise investors, characterized by domain expertise and established mental models that facilitate efficient information processing [39,40]. Conversely, Class 2 comprises receptive general consumers with limited prior experience, who may rely more on external cues to manage decision complexity [41].

Table 5. Estimation results for the class membership probability function.

Class	Variable	Coefficient	Std. Error
Class 1	Experience with AI services	0.6689947 **	0.3161476
	Direct management of financial assets	0.7504593 ***	0.2866347
	Constant	−2.903451 ***	0.4762097

Note: *** $p < 0.01$ and ** $p < 0.05$. Class 2 is the reference category.

Table 6 reports the class-specific estimates of consumer preferences for RA service attributes. For selective high-expertise investors (Class 1), the level of personalization and the capability for portfolio adjustment emerge as the statistically significant and most relatively important determinants of choice. This finding is consistent with the proposed theoretical framework, which posits that experts rely on internal evaluative standards and prioritize functional PU over external informational signals [42]. The strong preference for high personalization and the statistically significant positive coefficient for portfolio adjustment capability indicate that retaining final decision authority is essential for this group. In contrast, algorithmic transparency, information source, and communication style are not statistically significant for Class 1, suggesting that these signals may be regarded as redundant cognitive noise that does not contribute to their internal decision-making logic [78]. Additionally, the positive and significant coefficient for the no-choice alternative demonstrates a clear algorithm aversion among these investors, wo tend to opt out when the service does not satisfy their stringent functional requirements [43].

For receptive general consumers (Class 2), algorithmic transparency emerges as the most important attribute. This finding reinforces the role of transparency as a trust-building heuristic that reduces uncertainty for individuals with limited expertise [41]. Regarding personalization, Class 2 avoids low, group-based customization and demonstrates no significant preference between medium and high levels. This pattern indicates a cognitive equilibrium, where the marginal PU of high personalization is balanced by the increased mental effort required to process greater complexity [37]. With respect to information sources, Class 2 prefers the integration of external data with user-provided data, which demonstrates the system's capability and enhances PU [8]. Communication style exerts a weak but positive influence at the 90% significance level, with a preference for a high-warmth style. This suggests that a friendly and approachable interface may provide psychological comfort, modestly improving PEOU [56]. Portfolio adjustment capability also has a significant positive effect, although its magnitude is smaller than that observed for Class 1 as it enhances cognitive load. The large, negative, and statistically significant coefficient for the no-choice alternative further indicates a strong tendency toward algorithm appreciation [44]. By perceiving the RA as an expert that alleviates the cognitive burden of financial management, these consumers experience enhanced PEOU and greater overall receptivity to the service.

4.3. Simulation Analyses

Simulation analyses were conducted using the estimated LCL model to examine how consumer choice and adoption rates change when the key design attributes of RA services are combined in alternative configurations. The objective is to quantitatively demonstrate how heterogeneous preference structures translate into market outcomes under specific service design scenarios.

Simulations combine class-specific utility functions with estimated class membership probabilities. For each scenario, hypothetical RA alternatives are constructed, and class-specific adoption probabilities are computed by modeling choice tasks in which respondents

select between a given RA alternative and a no-choice option. Overall adoption rates are obtained as weighted averages using the class membership model, incorporating AI service usage experience and direct financial investment experience as covariates.

Table 6. Estimation results of consumer preferences.

Class	Attribute	Level	Coefficient	Std. Error	Relative Importance
Class 1	Algorithmic transparency	No explanation	−0.75809	0.582372	15.6%
		Global model explanation	0.053305	0.760857	
	Personalization level	Low	−2.37503 ***	0.812352	45.6%
		Medium	−1.28366 **	0.586441	
	Information source	User-provided only	0.05199	0.369957	1.0%
	Communication style	High warmth	0.10178	0.880653	2.0%
	Portfolio adjustment	Adjustable	1.870926 ***	0.385653	35.9%
	No choice		2.546575 ***	0.417737	-
Class 2	Algorithmic transparency	No explanation	−1.22042 ***	0.113241	29.1%
		Global model explanation	−0.74313 ***	0.167583	
	Personalization level	Low	−0.87347 ***	0.114413	23.9%
		Medium	0.13003	0.127754	
	Information source	User-provided only	−0.74252 ***	0.105432	17.7%
	Communication style	High warmth	0.33431 *	0.188090	8.0%
	Portfolio adjustment	Adjustable	0.892432 ***	0.100037	21.3%
	No choice		−2.957203 ***	0.195128	-

Note: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

To isolate the effects of focal attributes, all non-focal attributes are fixed at representative and empirically plausible levels commonly observed in existing RA services.

4.3.1. Scenario 1: Effects of Personalization–Control Bundles

The first scenario examines the impact of simultaneously providing personalization and user control on the adoption of RA. Six distinct service configurations are constructed by combining three levels of personalization (i.e., low, medium, high) with two levels of portfolio adjustment capability (i.e., not adjustable and adjustable).

All other attributes, aside from personalization and user control, remain constant. Algorithmic transparency is maintained at the global model explanation level, which is a commonly observed explanation format in existing RA platforms. This level represents an intermediate approach that enhances user trust compared to no explanation, while imposing a lower cognitive burden than fully personalized explanations [3,4,6]. Information sources consist of both user-provided and external data, reflecting current RA practices that balance improved recommendation precision with privacy considerations [8,9]. Communication style is standardized at a neutral, low-affinity level to minimize confounding effects of social presence and to ensure that observed differences in adoption are attributable to the personalization and control bundle [56].

Table 7 indicates that overall adoption rates are lowest when both personalization and user control are minimal, with adoption among selective high-expertise investors (Class 1) being nearly nonexistent. Intermediate configurations elicit limited engagement from this group, suggesting that both personalization and control are necessary to meet

their internal evaluative standards. Conversely, receptive general consumers (Class 2) demonstrate consistently high adoption rates, as they prioritize the cognitive offloading offered by the algorithm regardless of minor changes in control.

Table 7. Predicted adoption probabilities under the personalization–control bundle.

Personalization	User Control	Overall Adoption (%)	Class 1 Adoption (%)	Class 2 Adoption (%)
Low	No	66.4	0.8	79.3
Low	Yes	76.3	4.8	90.3
Medium	No	76.6	2.2	91.2
Medium	Yes	82.5	12.9	96.2
High	No	76.6	7.6	90.2
High	Yes	85.7	34.9	95.7

4.3.2. Scenario 2: Effects of Algorithmic Transparency

The second scenario examines the effects of incremental increases in algorithmic transparency on RA adoption. Three alternatives are assessed within an otherwise identical service configuration, differing only in transparency level: no explanation, global model explanation, and global model explanation with personalized explanation.

Personalization is maintained at the medium level, representing a practical configuration that avoids the operational and regulatory challenges of full individual-level personalization while surpassing basic group-based customization [12,79]. Portfolio adjustment capability is set to adjustable, reflecting a common design strategy to reduce perceived risk associated with automation by permitting user intervention [10]. Information source and communication style remain constant at the levels used in Scenario 1.

As indicated in Table 8, overall adoption increases with greater transparency; however, this effect is primarily attributable to receptive general consumer (Class 2). For this group, transparency serves as a significant heuristic. In contrast, adoption among Class 1 remains largely unchanged, indicating that enhanced explanation is not a universal mechanism for engaging selective high-expertise investors, whose utility is determined by functional capability rather than informational cues.

Table 8. Predicted adoption probabilities under alternative transparency levels.

Transparency Level	Overall Adoption (%)	Class 1 Adoption (%)	Class 2 Adoption (%)
No explanation	72.6	1.0	86.6
Global model explanation	76.6	2.2	91.2
Global model explanation With personalized explanation	80.3	2.1	95.6

4.3.3. Scenario 3: Regulation-Compliant Uniform Design Versus Segmented Service Portfolio

Recent regulatory developments in AI-based financial services emphasize investor protection and accountability. The European Union's AI Act designates AI applications in financial services as high-risk and requires explainability, risk management, and meaningful human oversight [15]. Comparable initiatives are being considered in the United States, where the Securities and Exchange Commission has proposed frameworks to strengthen transparency and accountability in predictive analytics and algorithmic decision making, including automated investment advisory services [16]. Korea adopts a similar regulatory approach. The Financial Services Commission has issued AI operational guidelines

for the financial sector, establishing explainability, user control, and responsible data use as the minimum requirements for AI-based financial services [17]. These regulatory environments are likely to encourage financial institutions to prioritize standardized, conservative service designs that emphasize compliance and risk minimization rather than aggressive differentiation.

Accordingly, the third scenario contrasts a regulation-compliant uniform service design with a segmented service portfolio that explicitly addresses consumer preference heterogeneity. The uniform design serves as a baseline RA configuration likely to be adopted under current regulatory constraints: global model explanation, medium-level personalization to limit regulatory and operational burden, and portfolio adjustment capability to ensure user protection. This configuration represents a pragmatic balance between regulatory compliance and operational efficiency [11,12]. In contrast, the segmented portfolio scenario assumes that two differentiated RA services are offered simultaneously under the same regulatory constraints. One service prioritizes high personalization and strong user control, targeting the preferences of Class 1, while the other focuses on personalized algorithmic explanations and a relatively approachable communication style, catering to Class 2.

As summarized in Table 9, the regulation-compliant uniform design effectively promotes adoption among receptive general consumers (Class 2) but does not engage selective high-expertise investors (Class 1). In contrast, a segmented portfolio maintains the high adoption rate among Class 2 and simultaneously engages selective investors by explicitly accommodating their preference for functional autonomy.

Table 9. Predicted adoption probabilities under uniform and segmented service design.

Scenario	Service Design	Overall Adoption (%)	Class 1 Adoption (%)	Class 2 Adoption (%)
Regulation-Compliant	Uniform	76.6	2.2	91.2
Segmented Portfolio	Product A	40.3	34.4	41.4
	Product B	47.7	1.5	56.7
	Total Portfolio	87.9	35.9	98.1
ΔAdoption (Portfolio–Uniform)		11.3	33.7	6.9

5. Discussion

This study demonstrates that consumer choice in AI-based financial services is shaped by complex combinations of attributes and structural heterogeneity, rather than by the isolated effects of individual features. Using a discrete choice analysis, the findings show that consumers evaluate service attributes as an integrated bundle (addressing RQ1). The results identify a compensatory trade-off mechanism; for example, the negative utility associated with low personalization can be offset by high user control or transparency, although the extend of this compensation varies. This approach extends prior research on RAs, which has primarily focused on general acceptance intentions or the effects of individual design elements [1,4,7].

The relative importance analysis presented in Table 6 further elucidates these trade-offs, demonstrating that the contributions of transparency, personalization, and user control to utility formation differ substantially across latent classes (addressing RQ2). For Class 1, representing selective high-expertise investors, personalization (45.6%) and user control (35.9%) account for most of the variation in utility, while transparency (15.6%) has a comparatively limited effect. This finding is consistent with Alba and Hutchinson's suggestion [42], which posits that knowledgeable users rely more on internal evaluative criteria and outcome-oriented cues than on external informational signals. For these ex-

perts, whose established mental models facilitate efficient information processing (high PEOU), the primary barrier to adoption is not a lack of understanding but rather insufficient functional utility (PU) that aligns with their internal decision logic.

The coexistence of a positive no-choice ASC and the observed insensitivity to transparency in Class 1 aligns with algorithm aversion in high-stakes domains. As prior research [43,78] indicate, sophisticated investors often exhibit heightened sensitivity to algorithmic errors and may perceive automated explanations as redundant cognitive noise that fails to surpass their internal decision logic. For these users, detailed transparency without corresponding functional capability, defined as the combination of high personalization and direct user control, may inadvertently emphasize the perceived limitations of the algorithm rather than fostering trust. Consequently, Class 1 consumers prioritize the RA functionality to maintain autonomy and self-efficacy, choosing to opt out when they cannot override or adjust outputs [43].

In contrast, transparency (29.1%) emerges as the most influential attribute for Class 2, representing receptive general consumers, functioning as a trust-building heuristic that facilitates uncertainty reduction. This interpretation is consistent with Mayer et al.'s trust model [25] and demonstrates that individuals with limited expertise rely on external signals to reduce the cognitive burden of decision-making [41]. Their preferences for external information sources and a high-warmth communication style further indicate their perception of the RA as a competent and approachable expert. By delegating complex financial tasks to the system, these consumers exhibit algorithm appreciation as a strategic means to conserve cognitive resources [44]. However, their indifference to high personalization suggests a cognitive saturation threshold, where the marginal benefits in PU are offset by the mental effort required to manage increased system complexity [37].

The simulation analyses further underscore the practical significance of attribute bundling (addressing RQ3). The results show that, for Class 1 consumers, adoption probabilities increased substantially only when personalization and user control were enhanced simultaneously (Scenario 1), whereas enhancing transparency alone (Scenario 2) resulted in negligible changes in choice behavior. This empirical finding suggests that, for selective high-expertise investors, transparency alone may be insufficient to compensate for the absence of functional flexibility or decision agency. Although transparency is typically intended to address concerns by clarifying data use, the simulation results demonstrate that its effectiveness is context-dependent and may be secondary to the perceived utility derived from personalization and control. Rather than serving as a universal driver of adoption, transparency appears to function as a supporting attribute that must be integrated with other core service features to be effective.

Although these findings are situated within the RA context, the research framework developed in this study provides a transferable perspective for understanding AI adoption in broader electronic commerce environments. By integrating the TAM with Cognitive Load Theory, the framework clarifies a dual pathway through which algorithmic design influences user responses: transparency may enhance PU by reducing uncertainty, yet it may also reduce PEOU when informational demands exceed users' cognitive capacity. The preference patterns observed across latent classes further suggest that transparency does not serve as a universally dominant adoption driver, but rather as one element within a compensatory configuration of system attributes. Comparable trade-off dynamics are likely to arise in other AI-enabled domains, such as generative AI tools, recommendation systems, or automated decision-support platforms, where users must balance explainability, functional performance, and decision autonomy. Therefore, the diffusion of AI-based services may depend less on maximizing transparency in isolation and more on achieving

an appropriate alignment between disclosure, usability, and user agency across varying levels of expertise.

5.1. Managerial Implications

The simulation results yield significant managerial implications for financial institutions and fintech firms involved in the design and operation of RA services.

First, the findings suggest that recent stagnation in RA adoption may be mitigated by shifting from uniform service designs to calibrated, segment-oriented service portfolios. Although industry practices have converged on standardized, regulation-compliant architectures to reduce operational and compliance risks [11,80], the simulation results from Scenario 3 indicate that such designs primarily serve receptive general consumers (Class 2). For these users, standardized transparency lowers cognitive barriers; however, it does not address the high adoption threshold of selective high-expertise investors (Class 1), who may perceive uniform explanations as redundant. This observation aligns with prior research highlighting scalability limitations due to insufficient service differentiation [81]. To address this, firms are advised to implement a dual-track strategy: transparency-led models for novice-oriented segments to foster trust through warm communication and external credibility cues, and control-centric models for expert-oriented segments that emphasize high-granularity personalization and portfolio intervention. This strategy ensures that the service complexity aligns with the information-processing capacity of each segment.

Second, the findings emphasize that personalization and user control should be developed as integrated functionalities rather than as separate features. Scenario 1 results show that, for Class 1 consumers, the combined enhancement of these attributes produces a non-linear increase in adoption probability. From a managerial standpoint, this suggests that algorithmic optimization (personalization) and interface design (control) should be managed cohesively. Firms should therefore prioritize hybrid RA service designs in which the system's capacity to tailor advice is directly linked to the user's ability to intervene. Such integration is necessary to meet both the performance expectations and autonomy needs of sophisticated, high-stakes investors.

5.2. Policy Implications

From a regulatory perspective, these findings provide a critical assessment of the current global and domestic emphasis on standardized algorithmic transparency, as exemplified by the European Union's AI Act and Korea's AI Security Guideline.

First, the results support a shift tiered disclosure frameworks and the adoption of segment-aware regulatory sandboxes. While mandated transparency is essential for protecting and guiding less-experienced consumers (Class 2), rigid or extensive disclosure requirements may increase cognitive overload for experts without providing meaningful protection [82,83]. Policymakers are therefore encouraged to move beyond uniform disclosure mandates and establish environments, such as regulatory sandboxes, where firms can test differentiated service models. This approach facilitates empirical identification of the optimal balance between transparency and functional autonomy, protecting vulnerable users while fostering the innovation required to address the needs of expert segments [84]. By monitoring the real-time impact of these attribute combinations, regulators can refine governance structures that promote market growth without impeding service differentiation.

Second, the concept of algorithmic accountability should be expanded to include the right to control as a functional requirement for consumer empowerment, particularly within Korea's evolving regulatory landscape. Although the Korean authorities require explainability and user control as minimum standards in the operational AI guideline [17],

enforcement under the Financial Consumer Protection Act (FCPA) has primarily emphasized accountability through the right to an explanation, focusing on disclosure of internal logic to prevent consumer harm [85]. However, this study demonstrates that, for a certain market segment, the ability to intervene has a greater impact on choice probabilities than the provision of algorithmic logic alone. Regulators in Korea should therefore standardize control interfaces in addition to traditional transparency reports, ensuring that consumers have effective means to override or adjust algorithmic recommendations. This change would redefined user control as a proactive mechanism for autonomy, such as a human-in-the-loop (HITL) framework, rather than as a procedural safeguard [30,57,86].

5.3. Limitations and Future Research

Although this study provides systematic insights into RA acceptance, several limitations remain.

First, the analysis is based on hypothetical choice data from a DCE, which restricts direct inference regarding actual usage behavior. The discrepancy between hypothetical scenarios and real investment decisions constitutes a fundamental limitation of DCE methodology. As Hensher [53] observes, respondents in hypothetical settings may not fully account for the risk of real monetary losses, resulting in hypothetical bias and potentially overstated preferences for certain technological attributes. Consequently, adoption probabilities may be overestimated in real-world contexts. Future research should validate these findings using revealed preference data or longitudinal adoption records to assess the relationship between stated choices and actual behavior.

Second, the empirical analysis focuses exclusively on Korean consumers, which necessitates caution when generalizing the results. The distinct regulatory and cultural environment of Korea may have shaped consumer responses. Korea simultaneously provides a theoretically informative context of examining AI-based financial services. As a digitally advanced economy with high levels of technology adoption and digital literacy [87], Korea offers a relevant setting for observing how consumers respond to variations in algorithmic transparency, personalization, and user control. While the empirical scope is context-specific, the underlying behavioral mechanisms explored in this study, such as trust formation, cognitive load, and attribute trade-offs, are grounded in widely established theoretical frameworks. These mechanisms may therefore offer insights applicable to other markets, subject to institutional and cultural differences. Future research should expand this analysis through cross-national comparative studies to evaluate the stability of the observed preference structures and to identify how regulatory regimes and cultural factors shape consumer responses to AI-driven financial services.

Third, although isolating intrinsic attributes enhances internal validity, it inherently limits external validity in relation to real-world market dynamics. Excluding extrinsic factors prevents the analysis of potential interactions between environmental cues and AI design features. For example, an established brand's reputation may serve as a trust heuristic that compensates for lower algorithmic transparency. In addition, omitting financial performance restricts the ability to examine how market volatility influences consumer priorities, such as whether demand for user control increases during bear markets. The lack of cost structures also impedes the assessment of price sensitivity toward premium AI features. Future research should consider incorporating price sensitivity, brand labels, and financial performance constructs into the experimental design to offer a more comprehensive understanding of RA adoption across varied economic contexts.

Finally, algorithmic transparency was defined specifically in terms of the level of explanation provided. However, transparency is a multidimensional concept. Future research should expand this framework by directly incorporating additional dimensions

such as algorithmic fairness and governance structures, as recommended by Guidotti et al. [27] and Ananny and Crawford [82].

6. Conclusions

This study investigates consumer choice behavior in RA services as a form of AI-based financial e-commerce. The findings indicate that adoption is influenced not by the isolated effects of individual service attributes, but by their combined structure and by systematic consumer heterogeneity. Through a DCE and an LCL model, this research identifies two distinct consumer segments: selective high-expertise investors, who prioritize the functional capability of RA through personalization and user control to align with their internal evaluative standards, and receptive general consumers, who demonstrate algorithm appreciation by relying on transparency and warm communication as heuristics to reduce cognitive effort.

Simulation analyses further demonstrate how this heterogeneity affects market outcomes. While a regulation-compliant, uniform service design may suffice for initial market entry among receptive novices, it limits market expansion by failing to engage more sophisticated segments. In contrast, a segmented service portfolio tailored to the distinct cognitive profiles of each group significantly increases overall adoption. This study concludes that algorithmic transparency is not a universally dominant design feature, but rather a contingent signal whose value must be balanced against functional utility and cognitive effort. Aligning attribute bundling with segment-based service design enables financial institutions and policymakers to promote more sustainable and inclusive diffusion of AI-based services within the digital commerce landscape.

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Institutional Review Board Statement: Ethical review and approval were not required for this study in accordance with the national legislation (Bioethics and Safety Act https://elaw.klri.re.kr/eng_mobile/viewer.do?hseq=52559&type=part&key=36 and Personal Information Protection Act https://elaw.klri.re.kr/eng_service/lawView.do?hseq=53044&lang=ENG accessed on 28 February 2026). The research was conducted through an anonymous online survey administered by a professional survey agency (Embrain) using its registered panel, which ensured that the researchers remained blinded to any personally identifiable information. Since the study utilized a de-identified dataset and involved no intervention or risk to participants, it falls outside the scope of mandatory institutional review. All participants were fully informed of the study's purpose and their anonymity by the survey agency prior to participation.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial intelligence
RA	Robo-advisor
RQ	Research question
DCE	Discrete choice experiment
TAM	Technology acceptance model
PU	Perceived usefulness
PEOU	Perceived ease of use
TRA	Theory of reasoned action
MNL	Multinomial logit
LCL	Latent class logit
KRW	Korean won
USD	US dollar
BIC	Bayesian Information Criteria
CAIC	Consistent Akaike Information Criterion

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