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Adoption of Robo-Advisors: The Mediating Role of Experiential Value and the Moderating Effect of User Involvement

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The rise of robo-advisors-automated, algorithm-driven investment services—has transformed the financial service landscape by offering low-cost, data-driven solutions tailored to individual users. While prior research has examined factors influencing the adoption of FinTech tools, limited attention has been paid to how users' experiential value and involvement interact with perceived innovation attributes to shape behavioral intention. This study integrates Innovation Diffusion Theory, Experiential Value Theory, and Involvement Theory to propose a comprehensive research model. Using data from 565 valid responses collected in Taiwan, the model is tested via partial least squares structural equation modeling (PLS-SEM). The results indicate that innovation attributes-particularly usability, relative advantage, and observability-positively influence multiple dimensions of experiential value, including investment return, hedonic value, aesthetics, and playfulness. In turn, experiential value significantly predicts users' behavioral intention to adopt robo-advisory services, with investment return and hedonic value emerging as the strongest predictors. Interestingly, user involvement negatively moderates the relationship between playfulness and behavioral intention, suggesting that highly involved users prioritize functionality over entertainment. This study contributes to the FinTech adoption literature by identifying experiential value as a critical mediating mechanism and reframing the role of user involvement. The findings provide theoretical insights and practical guidance for designing personalized, user-centric robo-advisory platforms.

Keywords: Robo-advisors, Experiential value, Innovation attributes, Involvement, FinTech adoption

1. Introduction

Since the 2008 global financial crisis, the financial services industry has been undergoing rapid digital transformation. Advances in technology, particularly in artificial intelligence(AI), big data analytics, and algorithmic decision-making, have enabled banks and investment firms to streamline

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services through automation and personalization[1]. The rise of financial technology(FinTech) has accelerated the shift from traditional human-centered advisory services to digital platforms, with robo-advisors emerging as a significant innovation in this domain[2].

Robo-advisors, broadly defined, encompass a range of AI-driven financial tools. However, with the launch of generative AI applications in 2022, the scope of robo-advisors has significantly broadened. For this study, robo-advisors are defined specifically as algorithm-based investment advisory services offered by licensed financial institutions. These platforms provide automated portfolio recommendations, risk assessments, and personalized financial planning through data analytics-differentiating them from basic AI chatbots or general-purpose banking apps.

In Taiwan, the Financial Supervisory Commission formally introduced regulatory guidelines for robo-advisory services in 2017. By mid-2023, 16 firms were offering such services, collectively managing NT$7.325 billion in assets-marking a 32% annual growth. This development reflects global trends where digital tools increasingly fulfill consumers' evolving expectations for convenience, personalization, and data-informed investment strategies.

Existing literature highlights that innovation characteristics such as usability, compatibility, and relative advantage play a critical role in consumers' adoption of new financial technologies[3~5]. In parallel, the concept of experiential value-capturing users' emotional, cognitive, and aesthetic experiences-has gained attention as a determinant of digital service adoption[6,7]. Studies have shown that well-designed, interactive, and intuitive financial platforms can enhance user satisfaction, trust, and engagement[8].

However, most prior research examines these dimensions in isolation. Few studies have integrated innovation attributes and experiential value into a unified framework. Moreover, the role of user involvement-defined as the degree of personal relevance or interest toward a service has rarely been tested as a moderator in this context. Understanding how involvement interacts with users' perceptions could provide deeper insights into behavior across different engagement levels.

To address this gap, this study aims to investigate:

1.How innovation attributes influence experiential value,

2.How experiential value affects users' behavioral intention to adopt robo-advisors, and

3.whether user involvement moderates these relationships.

The research contributes to the literature by integrating constructs from Innovation Diffusion Theory(IDT), Experiential Value Theory, and Involvement Theory into a comprehensive model. The findings offer theoretical and

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managerial implications for the design and promotion of AI-based financial services.

2. Literature Reviewand Hypothesis Development

2.1 Artificial Intelligence and Robo-Advisors

Advances in high-performance information technology and communication networks have propelled AI forward, encompassing technologies like neural networks and intelligent agents. Current AI applications in investment include customer service, investor tools, product and allocation recommendations, and active investment management. Robo-advisors, driven by algorithms and machine learning, act as automated financial advisors through online banking platforms[5]. These robo-advisors have gained consumer favor by optimizing investment decisions and offering personalized advice[9].

Recent studies show they provide professional advice comparable to that of human advisors while reducing the time consumers spend selecting financial products . Users of robo-advisors tend to be younger, more confident in these technologies, and less trusting of traditional financial advisory methods[10,11]. The proliferation of financial information and reduced transaction costs have facilitated their rapid adoption, making it easier for small investors to participate in the market[12]. These advantages have made robo-advisors increasingly attractive due to their convenience and cost-effectiveness.

2.2 Innovation Attributes

Rogers explores how innovation attributes affect the diffusion of innovations within social systems, emphasizing the crucial role of communication in achieving consensus and adoption. Previous studies underscore the importance of innovation attributes in the adoption of information system innovations.

The awareness of these attributes influences adopter behavior, with the diffusion rate dependent on perceptions of these attributes, particularly their role in facilitating faster adoption[13]. Previous research has categorized innovation attributes into five key elements: (1) Relative advantage, which refers to the perceived benefits of adoption[14]; (2) Compatibility, which concerns the alignment with existing needs, values, past experiences, and infrastructure [15]; (3) Complexity, the degree to which an innovation is perceived as difficult to understand and use, where lower complexity (higher usability) fosters positive attitudes[16]; (4) Observability, the clarity with which the results and benefits of

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the innovation can be perceived[17]; and (5) Trialability, which refers to the testability of the innovation[18]. Higher trialability helps to reduce uncertainty and accelerates adoption.

2.3 Experiential Value

Holbrook defines experiential value as encompassing consumers' preferences and overall feelings following the use of a product or service, emphasizing the direct interactions that shape perceived value[9]. Mathwick et al. further elaborates that experiential value is shaped by individual behaviors, incorporating both immediate utility and long-term appreciation. With the rise of the experience economy, the importance of experiential value has grown, spanning dimensions such as experience quality, perceived value, and satisfaction[7].

Wu et al. highlight that experiential value focuses on the residual value derived from experiences, which impacts behavioral intention, satisfaction, and loyalty in various fields, including tourism and marketing[19,20]. It is closely linked to experience quality, emotional responses, and social stimuli, all of which influence consumer perceptions and behaviors[21]. Furthermore, experiential value has been shown to moderate the relationship between experiential marketing and customer satisfaction across different contexts[22].

In the context of FinTech development, robo-advisors leverage advanced technologies and AI algorithms to enhance their offerings[23]. Belanche et al. emphasize that individuals' backgrounds and social environments significantly influence the acceptance of robo-advisors. These AI-driven tools provide 24/7 availability, eliminate human biases, and improve decision-making accuracy, thereby enhancing users' overall service experience[24].

Mathwick et al. categorizes experiential value into four primary dimensions: consumer investment return, service excellence, aesthetics, and playfulness. By considering these dimensions, we gain a comprehensive understanding of consumers' intrinsic value, including financial knowledge, emotional responses, and prior interactions with FinTech tools such as robo-advisors. Recent evidence suggests that well-crafted UX design can significantly elevate users' satisfaction and trust in robo-advisors[7]. Komatireddy et al. found that a thoughtful user interface plays a pivotal role in improving user perception and engagement, especially in competitive FinTech environments. This multidimensional perspective reveals how various experiential processes influence consumers' willingness to adopt robo-advisors[8].

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2.4 Involvement

Involvement-a psychological state that reflects an individual's level of interest or personal relevance in a subject-is central to consumer behavior research. It describes how the relevance of a subject to personal needs, values, and goals affects cognitive self-relevance and subsequent behaviors. Zaichkowsky refined the concept as a measure of the importance consumers place on a product or service[25].

Involvement significantly influences the consumer decision-making process, as higher product importance leads to stronger motivation for information search and decision-making[26]. Consumers' attention spans also vary, with highly involved consumers more likely to actively process information[27].

Specifically, high-involvement users tend to scrutinize product or service attributes more thoroughly, while low-involvement users often rely on heuristic cues or simplified decision rules[25].

Adomaviciute et al., explored how product involvement moderates the impact of purchase motives on related product intentions, emphasizing the importance of business involvement[28]. Product involvement has been shown to significantly influence investment intention and moderate the relationship between attitude and purchase intention[29,30].

This study investigates the role of involvement in the relationship between experiential value and usage intention of robo-advisors, emphasizing its interaction with other variables, such as innovation attributes and experiential value. The aim is to provide deeper insights for academic research and practical applications in consumer behavior, as high-involvement users may place greater emphasis on detailed functionalities and risk assessments when evaluating robo-advisors, whereas low-involvement users might prioritize convenience and ease of use.

2.5 Hypotheses Development

2.5.1 Innovation Attributes and Experiential Value

Relative Advantage refers to the extent to which an innovative technology outperforms existing technologies[3]. Davis posits that relative advantage is a primary determinant of innovation adoption, primarily influencing users' attitudes[31]. Numerous studies have found that relative advantage affects consumers' attitudes toward using innovations[32,33]. Fisch et al., suggests that robo-advisors, as an innovative technology, can enhance consumers' experiential value[5]. Many studies indicate that early adopters of innovative products often seek novelty, making them more influenced by product experiences and more

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likely to purchase[34]. This study posits that robo-advisors are more competitive than traditional financial advisors because they enhance user engagement through online operations, thereby increasing consumers' perceived experiential value. Thus, the following hypotheses are proposed:

- **H1a~H1d:** The relative advantage of robo-advisors has a significant positive impact on consumer investment return, service excellence, aesthetics, and playfulness.

Compatibility refers to the extent to which robo-advisors align with consumers' existing financial concepts, values, investment methods, and personal needs[35]. When consumers encounter new technology, they integrate it into their lifestyles, behaviors, thoughts, and values, continuing to use it through product experience[36]. Therefore, the compatibility of new technology is crucial for consumers. Many researchers have found that compatibility positively influences consumers' attitudes toward new technologies[37,38]. Numerous studies also suggest that compatibility significantly impacts program design, especially when consumer feedback after product experience guides improvements[37]. Consumers are more likely to positively evaluate products compatible with their current lifestyle, behavior, and financial concepts. Compatibility is often considered the first and most important factor in consumer experiential value. Thus, the following hypotheses are proposed:

- **H2a~H2d:** The compatibility of robo-advisors has a significant positive impact on consumer investment return, service excellence, aesthetics, and playfulness.

Usability refers to how easy robo-advisors are to understand and use. Many scholars consider usability a primary factor in technology adoption. The usability of an innovation directly affects users' attitudes and perceptions, influencing their overall experiential value. Oh et al., confirm in the Technology Acceptance Model that perceived usability significantly impacts the willingness to adopt technology, emphasizing its direct impact on user experiential value[39,40]. Usability is a key driver of technology adoption, enhancing consumer experiential value and promoting positive behavioral intentions. Consumers have various thoughts about using robo-advisors[41]. Enthusiastic consumers find these advisors easier to operate, thereby perceiving higher experiential value. Thus, this study posits that usability will enhance experiential value in the development of innovative technology. Therefore, the following hypotheses are proposed:

- **H3a~H3d:** The usability of robo-advisors has a significant positive impact on consumer investment return, service excellence, aesthetics, and playfulness.

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Trialability refers to the extent to which consumers can experiment with a new technology before fully adopting it[16]. Studies in innovation diffusion suggest that trial experiences positively influence user attitudes toward new systems[42]. For example, Belanche et al. note that providing users with a chance to try a service in advance reduces perceived risk and enhances experiential value[4]. In practice, allowing people to engage in a risk-free trial of a robo-advisor lets them explore its features while minimizing investment uncertainty. By testing different investment models and directly experiencing the advisor's benefits without commitment, users become more familiar and confident. Therefore, we hypothesize that increased trialability will strengthen users' experiential value. Specifically:

■ **H4a~H4d:** The trialability of robo-advisors has a significant positive impact on consumer investment return, service excellence, aesthetics, and playfulness.

Observability is the degree to which the use and results of robo-advisors can be noticed by others[3]. It involves whether the behaviors and outcomes generated by consumers while using robo-advisors are noticeable to external parties. Moore & Benbasat explain that observability includes the demonstrability and visibility of these results-that is, how users can showcase the effects of their product use to others. This characteristic allows consumers to learn how to operate robo-advisors more effectively by observing others' usage [43].

The observability of robo-advisors enhances their transparency, enabling consumers to understand investment methods more clearly. By observing others' experiences and outcomes, consumers can learn new strategies or avoid mistakes. This observational learning enhances the perceived experiential value as consumers engage in continuous learning and improvement. Therefore, the following hypotheses are proposed:

■ **H5a~H5d:** The observability of robo-advisors has a significant positive impact on consumer investment return, service excellence, aesthetics, and playfulness.

2.5.2 Experiential Value and Behavioral Intention

Experiential value is regarded as a personal relative preference derived from the intrinsic (tangible and intangible) qualities of product or service interactions, whether face-to-face or remote[7]. Helkkula et al. views experiential value as an assessment method for digital interactions[44]. Varshneya & Das identify dimensions such as cognitive value, hedonic value, social value, and moral value, which transcend culture, product, and channel[45]. Experiential value is central to service research, particularly for its predictive power on usage intention[46,47].

Adhikari & Bhattacharya found that customer satisfaction during the consumption process enhances purchase intention. Consequently, as consumers experience robo-advisors more frequently, their experiential value increases, leading to higher usage intentions[48]. Similarly, Cahyadi et al. found that trust, perceived usefulness, and user satisfaction significantly influence the continued use of robo-advisors, supporting the notion that experiential value plays a central role not only in initial adoption but also in long-term engagement[49].Thus, the following hypotheses are proposed:

- **H6:** The investment return provided by robo-advisors has a positive impact on behavioral intention.
- **H7:** The service excellence provided by robo-advisors has a positive impact on behavioral intention.
- **H8:** The aesthetics provided by robo-advisors have a positive impact on behavioral intention.
- **H9:** The playfulness provided by robo-advisors has a positive impact on behavioral intention.

2.5.3 Involvement as a Moderator

Zaichkowsky defines involvement as the degree to which an individual is concerned about a matter based on personal needs, values, and interests[25]. Prebensen et al. found that higher levels of involvement correlate with increased purchase intention after product experience[34]. Low involvement leads to reliance on situationally induced long-term memory, indicating that information is not carefully considered due to perceived irrelevance to outcomes, behaviors, or objects. Thus, under low-involvement conditions, consumers invest less mental effort and attention. Purchase intention varies with context, including product involvement, leading to different behaviors[50]. Studies suggest that involvement generates specific behaviors that aid in purchase decisions; when a decision or activity is highly relevant, its importance increases[51]. In rational decision-making, consumers spend more time gathering information, indicating that high involvement positively affects purchase decisions. Playfulness derived from product experiences motivates consumers to seek product-related information and proceed with purchases if expectations are met[51].

The rise of FinTech has led banks to introduce robo-advisors to meet various investor needs. Literature reviews show that involvement as a moderating variable generally positively impacts usage behavior across contexts. Moreover, experiential value (investment return, service excellence, aesthetics, and playfulness) from media interaction can have both positive and negative

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effects on user behavior. However, research on involvement as a moderator between experiential value and usage intention in robo-advisors is scarce. For instance, aesthetics may not directly relate to usage intention but can be strengthened by higher involvement. This study examines the moderating role of involvement between experiential value and usage intention, leading to the following hypotheses:

- **H10a:** Involvement moderates the relationship between investment return and behavioral intention; the higher the involvement, the stronger the relationship.
- **H10b:** Involvement moderates the relationship between service excellence and behavioral intention; the higher the involvement, the stronger the relationship.
- **H10c:** Involvement moderates the relationship between aesthetics and behavioral intention; the higher the involvement, the stronger the relationship.
- **H10d:** Involvement moderates the relationship between playfulness and behavioral intention; the higher the involvement, the stronger the relationship.

3. Research Model

The study primarily explores the factors influencing users' intention to use robo-advisors, aiming to understand the interrelationships among various variables. A comprehensive literature review led to the development of the research framework illustrated in Fig. 1. Rogers categorizes innovation attributes into relative advantage, compatibility, usability, trialability, and observability, which are applied to robo-advisors in this study[3]. Mathwick et al., divides experiential value into four dimensions: investment return, service excellence, aesthetics, and playfulness. This study investigates these factors through users' experiences and behaviors with robo-advisors. According to the research framework, innovation attributes, involvement, and experiential value all impact usage intention[7].

3.1 Data and Sample

A quantitative survey was used to collect data. At the outset of the questionnaire, participants were informed about the study's purpose. The questionnaire was divided into three sections: demographics (gender, age, education level, occupation), perceptions of robo-advisors (innovation attributes, experiential value, involvement, usage intention), and usage experience. To assess the feasibility and clarity of the questionnaire, a pilot online survey was conducted from June to August 2024 via the MySurvey platform, collecting 121

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preliminary responses. The main survey was administered from October to November 2024 through the same platform, employing a snowball sampling technique. This study focused on participants in Taiwan with actual experience using bank robo-advisors. We did not classify respondents by region in the sampling process. Consequently, a total of 582 responses were collected, of which 565 were deemed valid for analysis.

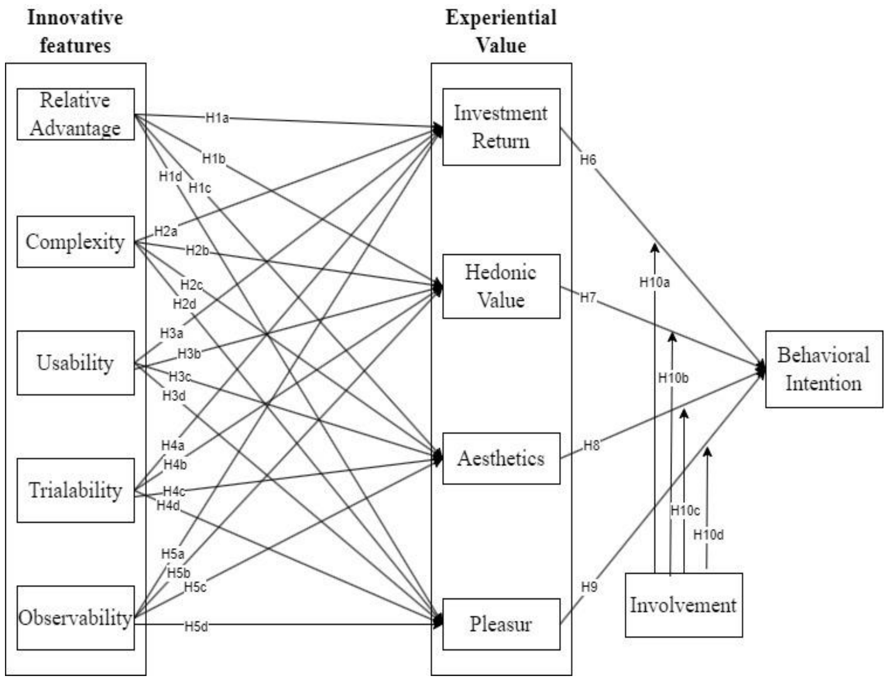

Fig. 1 Research framework

3.2 Measurement

The study is grounded in the diffusion of innovation theory. The questionnaire comprises eight dimensions designed to understand the factors determining consumers' usage intentions of robo-advisors. All respondents were required to have prior experience with robo-advisors. A 7-point Likert scale (1= strongly disagree, 7=strongly agree) was employed to rate each item within these dimensions.

The innovation attributes scale, based on the classifications by Moore & Benbasat[43]; Venkatesh et al. includes five dimensions: relative advantage, compatibility, usability, trialability, and observability[52]. The experiential value

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scale, following the work of Mathwick et al. encompasses four dimensions: hedonic value, investment return, playfulness, and aesthetics[7]. The involvement scale is derived from Varki & Wong[53]; Zaichkowsky[25], while the usage intention scale is adapted from Yang[54]. Each construct was measured by 3–5 items adapted from validated scales.

4. Results and Discussion

4.1Descriptive Statistical Analysis

The study utilized SPSS and SmartPLS 3.0 for data analysis. Table 1 indicates that the majority of participants were women aged 31–40 with higher education levels.

Table 1 Descriptive statistics of participants' demographic information

Characteristics		*N*	%	Mean	SD
Gender	Male	221	39.2	1.608	0.489
	Female	343	60.8		
Age (years)	20≤	3	1.1	3.193	0.855
	21~30	110	19.5		
	31-40	251	44.5		
	41-50	163	28.9		
	≥51	34	6.0		
Education	Below Junior High	2	4	2.947	0.520
	High School/Vocational	86	15.2		
	College/Associate Degree	416	73.8		
	Masters and Above	60	10.6		
Industry	Student	19	3.4	3.491	1.122
	Government/Military	59	10.5		
	Service Industry	234	41.5		
	Manufacturing	176	31.2		
	Financial Sector	30	5.3		
	Other	46	8.2		

The paper used Harman's single-factor test to detect common method bias[55]. The first factor accounted for 23% of the variance, well below the 50% threshold, indicating no significant common method bias. Further checks for data normality showed that the univariate skewness and kurtosis values were within acceptable limits (±1 and ±7, respectively). However, the multivariate data exhibited a non-normal distribution. Consequently, we used bootstrapping in SmartPLS for the subsequent analysis.

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4.2Construct Validity and Reliability

The study employs Confirmatory Factor Analysis (CFA) to validate the scales of each construct. One advantage of CFA is that it allows researchers to predefine the measurement model based on theoretical foundations, thereby testing both convergent and discriminant validity. However, CFA requires a sufficiently large sample size and assumes near-normal data distribution; otherwise, estimation stability may be compromised. Given that the constructs in this study derive from established theories, the sample size is adequate, and Partial Least Squares (PLS) with bootstrapping is used to address non-normality, this approach effectively verifies the multidimensional innovation attributes and experiential value constructs and aligns with the study’s objective of examining usage intentions.

The reliability and validity of the measurement items were examined, and the results are presented in Table 2. The measurement model includes 11 constructs, and the evaluation metrics comprise model fit indices, standardized factor loadings(λ), Cronbach’s alpha(α), Average Variance Extracted(AVE), Composite Reliability(CR), and Variance Inflation Factor(VIF).

All standardized factor loadings (λ) exceeded the recommended threshold of 0.5, indicating acceptable validity[56]. Cronbach's alpha values for all constructs surpassed the generally accepted standard of 0.7, demonstrating good reliability[57]. The AVE values for all constructs were above 0.5, confirming convergent validity[58].

The overall composite reliability(CR) for all constructs ranged between 0.833 and 0.930, exceeding the acceptable threshold of 0.7. Additionally, the VIF values were below the recommended threshold of 5, avoiding issues of multicollinearity[59]. Overall, the measurement model in this study exhibits satisfactory convergent validity.

Cronbach’s alpha values were used to assess the internal consistency of each construct. As shown in Table 3, all Cronbach's alpha values ranged between 0.729 and 0.886, exceeding the threshold of 0.7[60]. The composite reliability (CR) values ranged from 0.833 to 0.922, all above the threshold of 0.7, indicating good internal consistency. The rho_A values ranged from 0.705 to 0.890, with each construct exceeding the threshold of 0.7. These results confirm the reliability and validity of each construct.

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Table 2 Construct reliability and validity

	Cronbach's alpha	rho_A	Composite reliability	Average variance extracted
AES	0.886	0.887	0.922	0.746
BI	0.885	0.890	0.921	0.744
COM	0.809	0.827	0.887	0.725
USAB	0.839	0.840	0.903	0.757
IR	0.876	0.891	0.911	0.674
HV	0.878	0.885	0.911	0.673
INVO	0.899	0.901	0.930	0.767
OBS	0.865	0.867	0.908	0.712
PL	0.853	0.871	0.900	0.693
RA	0.826	0.827	0.885	0.658
TRL	0.729	0.705	0.833	0.625

Note: AES : Aesthetics, BI: Behavioral Intention, USAB: Usability, COM: Complexity, IR: Investment Return, HV: Hedonic Value, INVO: Involvement, OBS: Observability, PL: Playfulness, RA: Relative Advantage, TRL: Trialability.

Table 3 employs the Fornell-Larcker criterion to assess discriminant validity, ensuring that each construct is distinct from the others in the model[61].

Table 3 Fornell-Larcker criterion

	AES	BI	COM	USAB	IR	HV	INVO	OBS	PL	RA	TRL
AES	0.864										
BI	0.678	0.862									
COM	0.626	0.629	0.851								
USAB	0.652	0.716	0.739	0.870							
IR	0.738	0.773	0.744	0.771	0.821						
HV	0.728	0.768	0.702	0.760	0.837	0.821					
INVO	0.714	0.827	0.677	0.729	0.782	0.774	0.876				
OBS	0.703	0.683	0.726	0.739	0.805	0.806	0.723	0.844			
PL	0.728	0.688	0.641	0.666	0.762	0.764	0.760	0.700	0.832		
RA	0.646	0.682	0.774	0.775	0.781	0.760	0.688	0.727	0.646	0.811	
TRL	0.566	0.621	0.608	0.658	0.680	0.666	0.613	0.680	0.535	0.654	0.791

This method involves comparing the square root of the Average Variance Extracted (AVE) for each construct with the cross-loadings (correlation coefficients) between constructs. As shown in Table 2, the square root of the AVE for each construct is greater than the correlation coefficients with other constructs, satisfying the requirements for discriminant validity.

Furthermore, as shown in Table 4 and Table 5, each indicator's loading on its corresponding construct is greater than its loadings on other constructs, satisfying the requirements for discriminant validity. This indicates that each

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construct is empirically distinct and that the measurement items are appropriately assigned. Additionally, the proposed framework demonstrates strong internal consistency among the constructs, further confirming the reliability and validity of the measurement model.

Table 4 Cross loadings

	AES	BI	COM	USAB	IR	HV	INVO	OBS	PL	RA	TRL
AES1	0.851	0.598	0.513	0.585	0.610	0.612	0.597	0.590	0.601	0.560	0.491
AES2	0.881	0.556	0.507	0.542	0.605	0.624	0.601	0.577	0.636	0.532	0.461
AES3	0.880	0.597	0.548	0.567	0.653	0.647	0.658	0.626	0.646	0.561	0.501
AES4	0.842	0.589	0.591	0.557	0.676	0.631	0.610	0.632	0.630	0.576	0.501
BI1	0.603	0.881	0.585	0.637	0.708	0.691	0.753	0.616	0.596	0.625	0.569
BI2	0.597	0.903	0.565	0.673	0.701	0.711	0.753	0.612	0.631	0.638	0.564
BI3	0.616	0.843	0.510	0.596	0.655	0.638	0.718	0.583	0.630	0.542	0.483
BI4	0.518	0.819	0.503	0.559	0.594	0.601	0.617	0.541	0.507	0.542	0.525
COM1	0.470	0.469	0.788	0.587	0.535	0.534	0.480	0.523	0.433	0.623	0.491
COM2	0.587	0.584	0.904	0.692	0.714	0.665	0.647	0.704	0.623	0.722	0.541
COM3	0.534	0.543	0.858	0.602	0.634	0.584	0.588	0.612	0.563	0.626	0.521
USAB1	0.585	0.648	0.681	0.846	0.708	0.678	0.663	0.689	0.622	0.696	0.580
USAB2	0.557	0.624	0.639	0.888	0.641	0.633	0.626	0.627	0.550	0.673	0.558
USAB3	0.557	0.595	0.604	0.876	0.659	0.669	0.610	0.607	0.561	0.650	0.577
IR1	0.586	0.649	0.600	0.619	0.815	0.699	0.625	0.647	0.581	0.626	0.598
IR2	0.598	0.718	0.627	0.669	0.865	0.763	0.683	0.678	0.639	0.715	0.614
IR3	0.625	0.680	0.668	0.660	0.872	0.718	0.690	0.696	0.650	0.676	0.547
IR4	0.671	0.673	0.650	0.696	0.876	0.704	0.682	0.712	0.665	0.671	0.588
IR5	0.553	0.402	0.493	0.503	0.854	0.529	0.509	0.565	0.605	0.497	0.427
HV1	0.657	0.664	0.638	0.664	0.735	0.849	0.677	0.716	0.692	0.674	0.572
HV2	0.547	0.517	0.479	0.539	0.576	0.728	0.568	0.554	0.614	0.499	0.470
HV3	0.607	0.651	0.573	0.618	0.705	0.854	0.658	0.673	0.645	0.634	0.546
HV4	0.610	0.684	0.630	0.685	0.734	0.859	0.658	0.697	0.634	0.685	0.546
HV5	0.561	0.617	0.545	0.599	0.671	0.805	0.609	0.652	0.550	0.609	0.594
Invo	0.638	0.722	0.605	0.651	0.680	0.674	0.869	0.651	0.661	0.625	0.520
Invo	0.611	0.669	0.556	0.611	0.665	0.650	0.869	0.592	0.673	0.550	0.477
Invo	0.637	0.745	0.583	0.642	0.685	0.690	0.878	0.623	0.661	0.624	0.569
Invo	0.617	0.756	0.626	0.647	0.707	0.696	0.887	0.663	0.669	0.608	0.573
OBS1	0.632	0.586	0.621	0.632	0.665	0.697	0.644	0.854	0.624	0.612	0.595
OBS2	0.592	0.570	0.621	0.607	0.697	0.662	0.598	0.860	0.598	0.599	0.556
OBS3	0.558	0.560	0.584	0.573	0.656	0.645	0.545	0.800	0.527	0.601	0.592
OBS4	0.589	0.590	0.625	0.678	0.699	0.714	0.649	0.861	0.608	0.643	0.555
PL1	0.512	0.407	0.416	0.422	0.505	0.488	0.498	0.466	0.785	0.378	0.295
PL2	0.557	0.520	0.502	0.538	0.615	0.608	0.598	0.558	0.811	0.564	0.421
PL3	0.670	0.663	0.616	0.615	0.705	0.697	0.707	0.659	0.872	0.605	0.513
PL4	0.656	0.647	0.566	0.607	0.677	0.709	0.689	0.614	0.858	0.564	0.508

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Table 5 Cross loadings(cont.)

	AES	BI	COM	USAB	IR	HV	INVO	OBS	PL	RA	TRL
RA1	0.531	0.554	0.655	0.586	0.637	0.589	0.579	0.597	0.545	**0.793**	0.507
RA2	0.540	0.602	0.657	0.658	0.687	0.643	0.585	0.609	0.522	**0.860**	0.563
RA3	0.502	0.500	0.594	0.661	0.591	0.606	0.536	0.575	0.491	**0.788**	0.522
RA4	0.521	0.553	0.602	0.610	0.616	0.628	0.530	0.577	0.538	**0.801**	0.529
TRL1	0.452	0.492	0.496	0.534	0.541	0.478	0.480	0.525	0.420	0.491	**0.778**
TRL2	0.441	0.546	0.534	0.592	0.577	0.600	0.539	0.574	0.469	0.586	**0.838**
TRL3	0.453	0.430	0.407	0.426	0.492	0.495	0.428	0.511	0.377	0.468	**0.753**

4.4 Path Analysis

Table 6 and Table 7 present the results of the structural model analysis. This study examines how different attributes of robo-advisors-specifically, relative advantage, compatibility, usability, trialability, and observability-influence users' behavioral intention to use these services through various dimensions of experiential value(investment return, service excellence, aesthetics, and playfulness). The results indicate that most of the hypothesized paths are supported, demonstrating that the core innovation attributes of robo-advisors significantly enhance usage intention.

Specifically, relative advantage and observability exhibit strong positive effects across all tested mediating paths, underscoring their critical role in enhancing users' experiential value. Relative advantage significantly boosts behavioral intention by improving users' perceptions of investment return, service excellence, aesthetics, and playfulness. Observability similarly drives behavioral intention through these mediating paths.

Table 6 Path analysis results

		β	SE	z-value	p-value	Support
H1a	RA→HV	0.251	0.047	5.386	< **.001**	Yes
H1b	RA→CROI	0.247	0.045	5.530	< **.001**	Yes
H1c	RA→PL	0.127	0.062	2.038	**0.042**	Yes
H1d	RA→AES	0.155	0.060	2.588	**0.010**	Yes
H2a	COM→HV	0.020	0.040	0.496	0.620	No
H2b	COM→CROI	0.112	0.039	2.916	**0.004**	Yes
H2c	COM→PL	0.122	0.054	2.278	**0.023**	Yes
H2d	COM→AES	0.094	0.052	1.805	0.071	No
H3a	USAB→HV	0.212	0.041	5.224	< **.001**	Yes
H3b	USAB→CROI	0.187	0.039	4.807	< **.001**	Yes
H3c	USAB→PL	0.219	0.054	4.046	< **.001**	Yes
H3d	USAB→AES	0.162	0.052	3.107	**0.002**	Yes

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Table 7 Path analysis results(cont.)

		β	SE	z-value	p-value	Support
H1a	RA→HV	0.251	0.047	5.386	< **.001**	Yes
H1b	RA→CROI	0.247	0.045	5.530	< **.001**	Yes
H1c	RA→PL	0.127	0.062	2.038	**0.042**	Yes
H1d	RA→AES	0.155	0.060	2.588	**0.010**	Yes
H2a	COM→HV	0.020	0.040	0.496	0.620	No
H2b	COM→CROI	0.112	0.039	2.916	**0.004**	Yes
H2c	COM→PL	0.122	0.054	2.278	**0.023**	Yes
H2d	COM→AES	0.094	0.052	1.805	0.071	No
H3a	USAB→HV	0.212	0.041	5.224	< **.001**	Yes
H3b	USAB→CROI	0.187	0.039	4.807	< **.001**	Yes
H3c	USAB→PL	0.219	0.054	4.046	< **.001**	Yes
H3d	USAB→AES	0.162	0.052	3.107	**0.002**	Yes
H4a	TRL→HV	0.098	0.035	2.769	**0.006**	Yes
H4b	TRL→CROI	0.108	0.034	3.188	**0.001**	Yes
H4c	TRL→PL	-0.037	0.047	-0.785	0.432	No
H4d	TRL→AES	0.073	0.046	1.599	0.110	No
H5a	OBS→HV	0.443	0.041	10.923	< **.001**	Yes
H5b	OBS→CROI	0.395	0.039	10.179	< **.001**	Yes
H5c	OBS→PL	0.404	0.054	7.465	< **.001**	Yes
H5d	OBS→AES	0.403	0.052	7.712	< **.001**	Yes
H6	HV→BI	0.277	0.052	5.296	< **.001**	Yes
H7	CROI→BI	0.196	0.055	3.538	< **.001**	Yes
H8	PL→BI	0.059	0.041	1.443	0.149	No
H9	AES→BI	0.133	0.040	3.290	**0.001**	Yes

4.4.1Mediation analysis

Table 8 and Table 9 examine the impact of Relative Advantage(RA), Compatibility(COM), Usability(USAB), Trialability(TRL), and Observability (OBS) on Behavioral Intention(BI), considering Hedonic Value(HV), Investment Return(CROI), Playfulness(PL), and Aesthetics(AES) as potential mediators. The findings reveal significant pathways, summarized as follows:

1. **Relative Advantage:** RA significantly enhances BI through multiple pathways. It increases BI by enhancing users' HV(β=0.070, p<0.01), boosting perceptions of CROI (β=0.048, p=0.003), and increasing AES (β=0.021, p=0.042).
2. **Compatibility:** COM primarily impacts BI through increased CROI. Alignment with users' existing systems or values significantly elevates behavioral intention via a positive perception of investment return (β=0.220, p=0.0024).
3. **Usability:** USAB enhances BI through multiple dimensions. It directly affects HV (β=0.059, p<0.01), boosts CROI(β=0.037, p=0.004), and improves AES

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(β=0.022, p=0.024).

4.Trialability: TRL significantly impacts BI by enhancing HV(β=0.027, p=0.014) and increasing CROI(β=0.021, p=0.018).

5.Observability: OBS significantly enhances BI by increasing HV(β=0.123, p<0.01), boosting CROI (β =0.078, p<0.01), and improving AES(β=0.054, p=0.002).

These results demonstrate that relative advantage, compatibility, usability, trialability, and observability significantly influence behavioral intention through mediating variables such as hedonic value, investment return, and aesthetics. The findings underscore the importance of these innovation attributes in shaping positive user perceptions and behavioral intentions. For example, relative advantage boosts BI by enhancing hedonic value and perceptions of investment return, while usability increases BI through improvements in aesthetics and playfulness.

Table 8 Mediation analysis

Path	β	SE	z-value	p-value
RA→HV→BI	0.070	0.018	3.777	< .001
RA→CROI→BI	0.048	0.016	2.980	0.003
RA→PL→BI	0.008	0.006	1.178	0.239
RA→AES→BI	0.021	0.010	2.034	0.042
COM→HV→BI	0.006	0.011	0.494	0.621
COM→CROI→BI	0.022	0.010	2.250	0.024
COM→PL→BI	0.007	0.006	1.219	0.223

Table 9 Mediation analysis-cont

Path	β	SE	z-value	p-value
COM→AES→BI	0.012	0.008	1.582	0.114
USAB→HV→BI	0.059	0.016	3.719	< .001
USAB→CROI→BI	0.037	0.013	2.849	0.004
USAB→PL→BI	0.013	0.010	1.359	0.174
USAB→AES→BI	0.022	0.010	2.259	0.024
TRL→HV→BI	0.027	0.011	2.454	0.014
TRL→CROI→BI	0.021	0.009	2.368	0.018
TRL→PL→BI	-0.002	0.003	-0.690	0.490
TRL→AES→BI	0.010	0.007	1.438	0.150
OBS→HV→BI	0.123	0.026	4.766	< .001
OBS→CROI→BI	0.078	0.023	3.342	< .001
OBS→PL→BI	0.024	0.017	1.417	0.157
OBS→AES→BI	0.054	0.018	3.026	0.002

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4.4.2 Moderate analysis

Table 10 illustrates how involvement(INVO) moderates the relationship between specific experiential values of robo-advisors-namely, hedonic value(HV), investment return(CROI), playfulness(PL), and aesthetics(AES) and behavioral intention(BI). This section aims to explore whether involvement, as a potential moderating factor, alters the strength of these experiential values' effects on behavioral intention.

Table 10 Moderation analysis results

		β	SE	*t*	*p*	Support
H10a	HV*INVO→BI	-0.008	0.014	-0.592	0.554	No
H10b	CRO*INVO→BI	-0.022	0.015	-1.493	0.136	No
H10c	PL*INVO→BI	-0.035	0.016	-2.212	0.027	Yes
H10d	AES*INVO→BI	-0.009	0.017	-0.543	0.587	No

The analysis indicates that involvement does not significantly moderate the relationships between hedonic value(HV) (β=-0.008, p=0.554), investment return (CROI) (β=-0.022, p=0.136), and aesthetics(AES) (β=-0.009, p=0.587) with behavioral intention. This suggests that the effects of these experiential values on behavioral intention remain stable regardless of user involvement levels. However, involvement significantly moderates the relationship between playfulness(PL) and behavioral intention(β=-0.035, p=0.027), indicating that in contexts of high involvement, the influence of playfulness on behavioral intention is diminished. In such scenarios, factors like functionality and reliability may become more pivotal in shaping usage intentions. These insights are critical for refining product positioning and marketing strategies, emphasizing the need to focus on core functional attributes for highly involved users.

5. Discussion

The study developed an integrated model to examine how innovation attributes affect the adoption of robo-advisors through the mediation of experiential value, and how user involvement moderates these effects. The results confirm that innovation attributes (relative advantage, usability, and observability) significantly enhance key experiential dimensions—namely hedonic value, investment return, aesthetics, and playfulness-which in turn influence behavioral intention. These findings are consistent with prior research showing that innovation characteristics play a critical role in shaping consumer attitudes toward digital financial technologies[3,4,9].

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Among the innovation attributes, observability demonstrated the strongest impact across experiential dimensions. This supports prior findings that transparency and visibility in system performance-particularly in algorithmic services—build trust and increase perceived usefulness[62]. Likewise, relative advantage and usability align with the Technology Acceptance Model, where perceived usefulness and ease of use are core determinants of adoption [63].

Unexpectedly, the moderating role of user involvement did not align fully with theoretical predictions. While involvement is generally associated with deeper information processing and stronger behavioral responses[27,35], this study found that involvement only moderated the relationship between playfulness and behavioral intention, and that this moderation was negative. This suggests that high-involvement users prioritize functionality over emotional gratification, where elaborative processing may reduce reliance on hedonic cues. Conversely, low-involvement users may be more susceptible to surface-level experiential features like fun or aesthetics[34].

These findings enrich our understanding of user segmentation in FinTech adoption and challenge the assumption that higher involvement always amplifies positive experiential effects.

5.1 Theoretical Contributions

The study provides several important theoretical contributions to the literature on technology adoption, experiential value, and consumer involvement within the FinTech context.

1. **Integration of Multiple Theoretical Frameworks:** By synthesizing constructs from Innovation Diffusion Theory (IDT), Experiential Value Theory, and Involvement Theory, the research offers a novel conceptual framework that explains the adoption of robo-advisors through both functional attributes and subjective experiences. This multidimensional integration addresses a gap in existing FinTech literature, which tends to examine these theories in isolation.
2. **Establishing Experiential Value as a Mediator:** The study confirms the mediating role of experiential value in translating innovation attributes (e.g., usability, observability) into behavioral intention. While earlier models (e.g., TAM, UTAUT) emphasized cognitive beliefs such as perceived usefulness and ease of use, this study highlights the importance of emotional, aesthetic, and hedonic experiences. It demonstrates that experiential value is not just a by-product of system design, but a core explanatory mechanism for user engagement and adoption.
3. **Reframing the Role of User Involvement**: Contrary to conventional assumptions that higher involvement always strengthens adoption outcomes,

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this study reveals that involvement can weaken the influence of certain experiential factors-specifically, playfulness-on behavioral intention. This negative moderation suggests that highly involved users are more functionally driven and less influenced by gamified or hedonic elements. These findings refine our theoretical understanding of how involvement operates in digital service contexts and call for a more nuanced application of involvement theory in FinTech adoption research.

5.2 Managerial Implications

In addition to theoretical advancements, the study yields practical insights for financial institutions, FinTech developers, and policy makers aiming to improve the design and promotion of robo-advisory services.

1.**Design for Observability and Usability:** The strong impact of observability and usability implies that transparency and ease of use are central to enhancing user value and adoption. Firms should prioritize clear performance indicators, intuitive user interfaces, and demo-based onboarding experiences to build user trust and reduce perceived complexity.

2.**Segment by User Involvement Level:** The moderating effect of user involvement indicates the importance of tailoring robo-advisor features to different user types. Highly involved users are more likely to seek advanced analytics, personalization, and reliability, while low-involvement users respond better to aesthetics, gamified features, and emotional engagement. Designing differentiated user paths and marketing messages based on involvement profiles can enhance relevance and effectiveness[64].

3.**Promote Trialability Through Structured Experiences:** Trialability was shown to significantly influence perceived value dimensions such as investment return and hedonic value. Financial institutions should offer structured trial programs—such as risk-free simulation portfolios or time-limited demos—to allow users to experience the benefits before committing. These programs reduce psychological and financial barriers to adoption.

4.**Enhance Long-term Engagement Through UX Personalization:** Given that different experiential components influence users differently, especially under varying involvement levels, implementing AI-driven adaptive interfaces that adjust based on user behavior and preferences can increase satisfaction and retention. Such dynamic personalization aligns with emerging best practices in FinTech UX design [65].

By leveraging these strategies, firms can not only increase initial adoption but also foster sustained engagement, trust, and loyalty in the rapidly evolving robo-advisory landscape.

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5. Conclusion

The study provides a comprehensive analysis of the factors influencing the adoption of robo-advisors, integrating innovation attributes, experiential value, and user involvement into a unified framework. Drawing from Innovation Diffusion Theory, Experiential Value Theory, and Involvement Theory, the research demonstrates that innovation attributes-particularly usability, relative advantage, and observability-significantly enhance various dimensions of experiential value, which in turn positively influence users' behavioral intention to adopt robo-advisors.

Among experiential value components, investment return and hedonic value emerged as the most influential predictors of behavioral intention, underscoring the importance of both functional performance and emotional gratification in digital financial service design. Interestingly, while involvement was expected to amplify these effects, it negatively moderated the impact of playfulness. This suggests that high-involvement users prioritize instrumental features over affective elements. This insight calls into question simplistic assumptions about user engagement and highlights the importance of user segmentation strategies in FinTech service delivery.

The study contributes both theoretically and practically by offering a validated framework that captures the complex interplay between system design, user experience, and personal relevance in digital investment contexts. It informs product developers, marketers, and policy makers on how to optimize robo-advisory systems to meet the differentiated needs of their users, and provides a robust platform for further research in this emerging domain.

While the findings offer valuable insights, several limitations open opportunities for future investigation:

1. **Cross-cultural Generalizability:** The data were collected exclusively from users in Taiwan, which limits the cultural generalizability of the findings. Future research should examine whether the proposed framework holds across countries with different financial regulations, digital infrastructure maturity, and investment behavior norms.
2. **Longitudinal and Behavioral Data:** The study employed a cross-sectional self-report survey, which restricts causal inference. Future research should use longitudinal designs or behavioral tracking data to capture how user perceptions, experiential value, and involvement evolve over time, particularly as users transition from initial trial to sustained usage.
3. **Broader Psychographic Profiling:** The current model does not account for user-level psychological traits such as financial literacy, risk tolerance, trust

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propensity, or technology readiness. Integrating these variables may improve the model's predictive power and explain heterogeneity in adoption behavior.

4. **Emerging Technologies and Ethical Considerations:** As robo-advisors increasingly leverage AI, machine learning, and generative technologies, future research should examine their impact on user autonomy, transparency, and ethical trust. Furthermore, investigating the regulatory and societal implications of algorithmic financial advice-especially in light of data privacy and explainability-can enrich the conversation on responsible innovation.
5. **User Segmentation by Involvement Trajectories:** Building on this study's findings, future research could explore how involvement levels change dynamically over time and how these changes affect experiential value perceptions and usage patterns. This would allow for more adaptive personalization in robo-advisor platforms and provide a foundation for real-time UX optimization.

By addressing these research avenues, future studies can deepen our understanding of digital financial service adoption and contribute to the design of more inclusive, adaptive, and trustworthy robo-advisory systems in a global context.

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