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Exploring Factors Affecting User Intention to Accept Explainable Artificial Intelligence

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Abstract. Explainable Artificial intelligence (XAI) represents a pivotal innovation aimed at addressing the "black box" problem in AI, thereby enhancing users' understanding of AI reasoning processes and outcomes. The implementation of XAI is not merely a technological endeavor but also involves various individual factors. As XAI remains in its early developmental stages and exhibits unique characteristics, identifying and understanding the factors influencing users' intention to adopt XAI is essential for its long-term success. This study develops a research model grounded in the characteristics of XAI and prior technology acceptance studies that consider individual factors. The model was evaluated using data collected from 252 potential XAI users. The validated model exhibits strong explanatory power, accounting for 45% of the variance in users' intention to use XAI. Findings indicate that perceived value and perceived need are key determinants of users' intention to adopt XAI. These results provide empirical evidence and deepen the understanding of user perceptions and intentions regarding XAI adoption.

Keywords: explainable artificial intelligence, artificial intelligence, user acceptance, individual differences, intention to use.

1. Introduction

Advancements in computing capabilities and algorithms have driven the rapid progress and widespread adoption of Artificial Intelligence (AI) [1],[2],[3]. AI encompasses a wide array of techniques, algorithms, machines, and software capable of learning, reasoning, self-correcting, and executing instructions or actions [4],[5]. As AI performance and applications expand, it increasingly integrates into daily life, replacing human roles across various professional fields such as healthcare, public safety, inspections, and finance.

Historically, AI development prioritized effectiveness and performance, often overlooking the transparency of reasoning processes and the interpretability of results.

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Users have typically aware only of the inputs and outputs, lacking insight into the underlying decision-making processes of AI systems. This opacity has led to AI being referred to as a "black box" [6],[7]. The growing importance of AI applications has heightened concerns about privacy, fairness, ethics, and the potential for deception [8],[9]. The lack of transparency in AI systems raises questions regarding the fairness and accountability of AI-generated decisions, as well as potential biases and unintended consequences.

Explainable AI (XAI) seeks to address these concerns by prioritizing interpretable and transparent AI models. This approach has garnered increasing attention and expectations from various fields [10]. XAI involves three key elements: a new machine learning process, an explainable model, and an interactive interface [11]. Unlike traditional AI, XAI emphasizes performance, reasoning transparency, and interpretability equally. This dual focus presents significant development challenges, necessitating innovative technologies and resources. Furthermore, implementing XAI extends beyond technological considerations, encompassing individual user factors. As XAI remains in its early stages and exhibits unique characteristics, understanding the factors influencing users' intention to adopt XAI is crucial for its long-term success. By exploring these factors, researchers and practitioners can develop user-centric XAI systems that address users' needs and expectations while ensuring transparency, trustworthiness, and effective decision-making.

Drawing from the unique attributes of XAI and prior technology acceptance studies, this study develops a model to investigate the factors influencing users' intention to adopt XAI. The findings aim to provide empirical evidence and deepen understanding of user perceptions and intentions regarding XAI adoption.

The remainder of this paper is structured as follows: Section 2 introduces XAI and outlines its theoretical foundations. Section 3 presents the research model and hypotheses derived from the literature. Section 4 describes the research methods, including the data collection and measurement of constructs. Section 5 details the data analysis techniques and findings. Finally, Sections 6 and 7 discuss the implications of the results and offer conclusions based on the study's findings.

2. Literature Review

2.1. Explainable AI

The widespread application of Artificial Intelligence (AI) in various aspects of human life, both commercially and industrially, has become increasingly prevalent. Over the past decade, significant advancements in AI technology, particularly in machine learning, have facilitated the integration of AI into critical decision-making processes, including credit scoring, criminal justice, job recruitment, and teaching evaluation [10]. The demand for AI arises from the human need for effective decision-making. Bucincai et al. [12] emphasized that decision-making is a fundamental cognitive process through which individuals select a choice or action plan from a range of alternatives. While humans often rely on mental shortcuts or heuristic methods to make decisions, these methods, although efficient, can sometimes lead to systematic errors. To support reliable and sound decision-making, various fields, including management and medicine, have employed computer-based decision support systems [13],[14]. With recent advancements in AI, these systems have achieved high levels of precision, leading to the adoption of AI in an increasing number of domains for decision support purposes [12].

However, Hind et al. [10] highlight the growing concern about the trustworthiness of AI systems' decision-making processes in society. As AI use becomes more widespread, there is a strong demand for AI systems to provide explanations for their decisions. Paradoxically, as AI systems becomes more effective, they also grow increasingly complex, making it difficult to understand their inner workings. Hind et al. [10] specifically note that certain technologies, such as deep neural networks and large random forests, are challenging to explain even for experts, resulting in AI models functioning as “black boxes”. This lack of transparency introduces significant risks. Liao et al. [15] further support this assertion, highlighting the adoption of machine learning technology, particularly those utilizing opaque deep neural networks, across various practical fields. This trend has sparked significant interest in XAI within both academic and practical communities, emphasizing the need for greater transparency and interpretability in AI systems.

Bucinca et al. [12] emphasize the importance of evaluating interpretable systems within XAI-driven decision support systems. They argue for user-centered methods and interdisciplinary research to align technological advancements with user needs. Liao et al. [15] support this perspective, noting the diversity and their ability to incorporate multiple styles of interpretation to enhance user experience. Hoffman et al. [6] stress that XAI is a dynamic process, requiring continuous user experience evaluation to foster trust and dependence. Doshi-Velez and Kim [16] propose a taxonomy for evaluating XAI systems, focusing on domain experts, non-professionals, and agency tasks, and stress the importance of selecting appropriate evaluation indicators [17].

Hoffman et al. [18] suggest subjective evaluation measures, such as user trust and satisfaction, as key indicators for interpretable systems. However, Lakkaraju and Bastani [19] caution that subjective measures may fail to reliably predict user performance, potentially leading to biases or dependence on flawed interpretations. Therefore, it is necessary to consider multiple dimensions and comprehensive evaluation indicators when assessing XAI systems. This approach goes beyond subjective measures and aims to provide a more complete understanding of the system's performance and effectiveness [12].

Casimir Wierzynski [7] and Hani Hagras [20] were pioneers in developing a comprehensive evaluation index for XAI needs from a user perspective. Wierzynski [7] emphasized that interpretability is a subject of great scientific fascination and societal significance, as it resides at the convergence of various actively researched domains in machine learning and AI. The key areas of focus encompass the following elements [7],[20]:

- Bias: Ensure the AI system avoids biases from training data, models, or objective functions. Curate diverse and representative data, use techniques like augmentation and balancing, and regularly evaluate performance on different subgroups.

- Fairness: Verify fairness in AI-based decisions. Define fairness and identify whom it should be fair to. Assess decision-making processes for bias and ensure equal treatment.
- Transparency: Users should have the right to understand how AI affects decision-making. Seek explanations in understandable terms, formats, and language. Establish grounds for appealing decisions.
- Security: A lack of explanation may undermine confidence in AI reliability. Relate this to generalization in statistical learning. Address the challenge of tying errors to unseen data.
- Causality: Learn from data and obtain accurate inferences and explanations for underlying phenomena. Seek a mechanical understanding from the learned model.
- • Engineering: Debug incorrect output from trained models. Identify and rectify errors through thorough analysis and troubleshooting.

Addressing the technical aspects of XAI methods, the recent introduction of Shapley Additive Explanations (SHAP) by Lundberg and Lee [21] has gained widespread adoption in AI research applications [22-29]. SHAP addresses a critical challenge in interpreting tree-based and ensemble models by directly uncovering the contribution of features to predictions [27]. It provides a significant advantage over traditional feature importance analysis by accurately reflecting the impact of features on individual samples, capturing both positive and negative influences [27]. Antwarg et al. [22] and Jabeur et al. [23] emphasize SHAP's superiority over other statistical methods in interpreting machine learning model outputs. Rizk-Allah et al. [30] proposed a model utilizing Local Interpretable Model-Agonistic Explanation (LIME), based on XAI, to identify the critical factors influencing the accuracy of the power generation forecasts in smart solar systems. Similarly, Rajabi and Etminani [31] conducted a systematic review of knowledge graphs (KGs) in XAI systems. Their findings revealed that KGs are primarily used in pre-model XAI for feature and relationship extraction and in post-model XAI for reasoning and inference. The review also highlighted several studies employing KGs to explain XAI models in the healthcare domain.

In exploring the subjective and behavioral aspects of XAI, Chinu and Bansal [32] conducted a literature review that identified several key issues with AI systems, including unfair or biased decisions, poor accuracy, insufficient reliability, and the absence of evaluation metrics for assessing the effectiveness of explanations and data security. These findings underscore the challenges, and opportunities in advancing the field of XAI. In practical applications, Wang, Bian, and Chen [33] proposed and validated the use of XAI to address the interpretability challenges of deep learning models in classroom dialogue analysis. Their results indicated that XAI enhances teachers' trust in and acceptance of AI models for classroom dialogue analysis without increasing cognitive load. Additionally, Sano, Shi, and Kawabata [34] employed gradient-weighted class activation mapping, an XAI technique, to extract key features for each impression based on facial images and impression evaluation results. Their findings indicated that this computational method using XAI could independently identify the determinants of facial impressions without relying on visual attention captured by eye-tracking devices. Ebermann, Selisky, and Weibelzahl [35] explored the impact on user acceptance when the decisions made by an AI system and their associated explanations contradict the user's decisions. They found that in decision scenarios with cognitive misfit, users are significantly more likely to experience negative emotions and provide unfavorable evaluations of the AI system's support.

2.2. Theoretical Bases

The Technology Acceptance Model (TAM) is widely utilized in research on technology adoption. TAM proposes a causal chain involving external factors (stimulus) $\rightarrow$ beliefs (cognitive response) $\rightarrow$ intention $\rightarrow$ behavior [36]. Building on TAM, Agarwal and Prasad [37] incorporated five individual differences as external factors, arguing that these differences influence the behavioral intention to adopt new information technology through beliefs. Additionally, Agarwal and Prasad [37] suggested that cross-sectional research, where beliefs and intention are measured simultaneously, might exclude usage as a research variable.

Hong et al. [38] made a significant contribution by emphasizing the impact of individual differences on technology adoption, particularly in the context of digital libraries. They introduced a model examining the factors influencing user acceptance of digital libraries, incorporating system characteristics as a variable and proposing causal relationships: individual differences and system characteristics influence beliefs, which in turn influence intention. Furthermore, Hong et al. [38] highlighted the significance of computer anxiety and computer self-efficacy as potential individual differences. They suggested that future studies should include these constructs in research models to further explore their influence on technology adoption.

Drawing from the aforementioned studies and existing literature on IT acceptance, Wang and Wang [39] developed a research model examining causal relationships in technology adoption. In their model, they posited that individual differences and system characteristics influence beliefs, which subsequently impact intention. Wang and Wang [39] departed from conventional approaches by introducing perceived playfulness as the variable representing beliefs, differing from the commonly used constructs in previous studies. Additionally, they incorporated computer anxiety and computer self-efficacy as individual difference variables in their research model.

Wang et al. [40] built on the theoretical model proposed by Wang and Wang [39] to investigate the acceptance of hedonic information systems. They utilized the same model and variables, including computer anxiety and computer self-efficacy as individual differences, and perceived playfulness as the variable representing beliefs. Using this model, they analyzed the factors influencing the acceptance of hedonic information systems.

Wang et al. [41] provided further support for the arguments by Hong et al. [38] and Wang and Wang [39], emphasizing the significance of individual differences in shaping behavioral intentions through beliefs about IT usage. They introduced a research model positing causal relationships: individual differences influence beliefs, which subsequently influence intention. In their model, Wang et al. [40] incorporated perceived enjoyment as the variable representing beliefs. They categorized individual differences into two groups: personality traits and computer skills-related individual differences, including computer self-efficacy and personal innovativeness. By considering these variables, they examined how individual differences impact the formation of beliefs and subsequently influence behavioral intention in the context of technology adoption.

Based on the literature review, four key insights emerge. First, the causal chain linking external factors (individual differences and system characteristics) to beliefs and then to intention is a powerful framework for analyzing technological innovations. This chain provides a solid foundation for constructing the research model in this study. Second, as XAI represents an innovative category rather than a specific system, system characteristics are excluded in the research model of this study. Third, individual differences can be categorized as AI-related and AI-unrelated. Anxiety and self-efficacy are important AI, whereas personality traits are significant individual differences that are independent of AI. Lastly, belief variables should align with the characteristics of the technology under study. In the context of XAI adoption, this research model includes perceived value and perceived need as belief variables. Perceived value, proposed by Kim et al. [42], has been highlighted in previous technology adoption research [3],[43],[44]. It reflects users' preferences and evaluations of whether innovation attributes can meet their needs [45]. Considering that XAI is developed based on people's perceptions of AI's shortcomings and deficiencies, perceived need for XAI is included in the research model. This construct reflects the level of demand potential users have for XAI.

3. Research Model and Hypotheses

The research model is depicted in Fig. 1, illustrating the proposed framework. The dependent variable in this study is the "intention to use." Drawing from the characteristics of XAI and previous IT acceptance research, two belief constructs—perceived value and perceived need—are incorporated as antecedents of intention. Furthermore, the interrelationships between these constructs are integrated into the research model. Additionally, three individual differences—personality, AI anxiety, and AI self-efficacy—are identified as significant external factors that influence intention, mediated by the two beliefs.

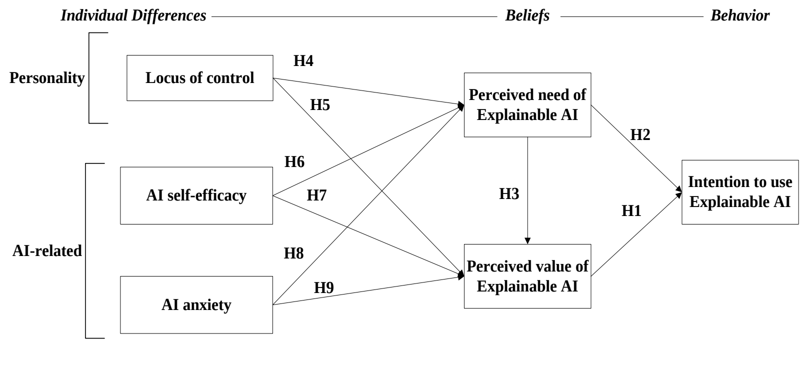

Fig. 1. The research model

3.1. Perceived Value, Perceived Need, and Intention to Use

Perceived value, as defined by Zeithaml [46], refers to the overall assessment made by potential users regarding the utility of an innovative product or service. Numerous studies have consistently demonstrated that perceived value significantly and positively influences adoption intention or behaviors. Empirical evidence supporting the impact of perceived value has been observed across various domains of innovative technologies and applications. For instance, perceived value play a crucial role contexts such as of mobile commerce [27], online gaming [47], Internet protocol television [48], online content services [49], mobile GPS applications [44], mobile catering applications [50], AI technology [51], and XAI [52]. In the XAI environment, when potential users perceive XAI as valuable, they are more likely to exhibit a greater willingness to adopt and utilize it. Therefore, the following hypothesis is proposed:

H1: Perceived value has a positive effect on the intention to use XAI.

Perceived need refers to an individual's personal assessment of the necessity or benefits associated with a particular innovation or change [53],[54],[55]. When potential users perceive a strong need for a specific innovation, they are more likely to attribute higher perceived value to it and demonstrate greater eagerness to adopt the innovation. Numerous studies support the positive impact of perceived need on perceived value and emphasize its significance as a facilitator of behavioral intention [56],[57],[58]. In light of the above, the following hypotheses are proposed:

H2: Perceived need has a positive effect on the intention to use XAI.

H3: Perceived need has a positive effect on perceived value.

3.2. Individual Differences—Personality

Personality is recognized as a significant individual difference influencing innovations adoption through beliefs [37],[41]. Among various personality traits, locus of control has garnered considerable attention and is commonly employed in IT acceptance analyses [59],[60]. Locus of control refers to the extent to which individuals believe they can control events that affect them [61]. Individuals who perceive events as within their control are referred to as having an internal locus of control (internals), while those who attribute events to external factors are characterized as having an external locus of control (externals) [62].

Individuals with a high internal locus of control are more inclined to adopt innovative technologies due to their greater confidence in controlling outcomes compared to individuals with a high external locus of control [63]. Internals, being predisposed to exert control and mastery over their environment, are more likely to perceive the needs and value of XAI, which offers a comprehensible and self-controlled usage environment. Thus, the following hypotheses are proposed:

H4: Internal locus of control has a positive effect on the perceived need of XAI.

H5: Internal locus of control has a positive effect on the perceived value of XAI.

3.3. Individual differences—Self-efficacy and Anxiety

Numerous studies [39],[64],[65] indicate that self-efficacy and anxiety related to specific technology or innovations are crucial individual differences influencing beliefs about using technologies. Self-efficacy refers to an individual's confidence in their ability to execute a specific task or master a new technology [66],[67]. This construct significantly affects perceptions, needs, and the desirability of an innovation or technology [67],[68],[69].

Individuals with high levels of AI self-efficacy are more likely to feel confident and willing to use AI. Consequently, they tend to perceive higher levels of value and need for explainable AI (XAI) because it is viewed as clearer and easier to operate compared to traditional AI. Based on this reasoning, the following hypotheses are proposed:

H6: AI self-efficacy has a positive effect on the perceived need of XAI.

H7: AI self-efficacy has a positive effect on the perceived value of XAI.

Anxiety is another crucial individual difference that has negatively influences IT adoption [39]. Researchers such as Hong et al. [70] emphasize the importance of investigating anxiety in the context of IT adoption. AI anxiety specifically refers to feelings of fear or agitation about AI being out of control [71]. Wang and Wang [72] define AI anxiety as an overall affective response of fear or discomfort that hinders individuals from engaging with AI.

XAI, designed to be more transparent and understandable than traditional AI, can mitigate concerns among individuals with AI anxiety. The enhanced transparency and interpretability of XAI can help alleviate anxiety, making such individuals more likely to perceive XAI as valuable and necessary. Based on this rationale, the following hypotheses are proposed:

H8: AI anxiety has a positive effect on the perceived need of XAI.

H9: AI anxiety has a positive effect on the perceived value of XAI.

4. Research Methodology

4.1. Construct Measures

To ensure the content validity of the construct measures in this study, initial items were developed based on existing instruments from the fields of IT/innovation adoption, AI anxiety, and XAI. These items were subsequently revised and adapted to fit the specific context of XAI. The wording, completeness, and appropriateness of the items were reviewed and confirmed by five experts specializing in information management and AI. Ultimately, a total of 29 items were used to measure the six constructs outlined in the research model. All measurement items were evaluated using a five-point Likert scale ranging from "1 - strongly disagree" to "5 - strongly agree." The specific measurement items and their corresponding references for each construct are summarized in Table 1.

Table 1. Measurement items used in the study

Construct	Items	References
Locus of Control (LC)	LOC1. People's misfortunes result from the mistakes they make. LOC2. In the long run, people get the respect they deserve in this world. LOC3. Capable people who fail to become leaders have not taken advantage of their opportunities. LOC4. Becoming a success is a matter of hard work; luck has little or nothing to do with it. LOC5. What happens to me is my own doing. LOC6. When I make plans, I am almost certain that I can make them work. LOC7. In my case, getting what I want has little or nothing to do with luck. LOC8. Getting people to do the right thing depends upon ability; luck has little or nothing to do with it. LOC9. There is really no such thing as "luck." LOC10. Most misfortunes are the result of lack of ability, ignorance, laziness, or all three. LOC11. It is impossible for me to believe that chance or luck plays an important role in my life.	[59]
AI Self-Efficacy (ASE)	ASE1. I am confident in my ability to effectively utilize an AI technique/product. ASE2. I have confidence in my capacity to proficiently use an AI technique/product independently. ASE3. Based on my knowledge and skills, I am confident that I can readily employ an AI technique/product.	[73] ,[74]
AI Anxiety (AIA)	AIA1. Learning how an AI technique/product works makes me anxious. AIA2. I am afraid that an AI technique/product may replace humans. AIA3. I am afraid that an AI technique/product may get out of control and malfunction. AIA4. I find humanoid AI techniques/products (e.g., humanoid robots) scary.	[72]
Perceived Need of XAI (PN)	PN1. Transparency: XAI is capable of providing me with explanations that I can comprehend if it makes a decision that affects me. PN2. Causality: XAI not only offers accurate inferences but also provides me with explanations when it learns a model from data. PN3. Bias: It is essential for an AI technique/product to ensure that forecasts and recommendations are based on objective and comprehensive data rather than problematic, defective, or biased data. PN4. Fairness: XAI should guarantee that decisions made by an AI technique/product that impact me are conducted in a fair manner. PN5. Safety: Even without an explanation of how it reaches conclusions, I can have confidence in the reliability of an AI technique/product. PN6. Engineering: I possess the capability to identify and rectify incorrect outputs generated by an AI technique/product.	[7], [35]
Perceived Value of XAI (PV)	PV1. I think the development towards XAI is worthwhile. PV2. I think the development towards XAI is important. PV3. I think the development towards XAI is valuable.	[42],[75],[76]
Behavioral Intention (BI)	BI1. I am willing to use XAI products/services in the future. BI2. I expect I will use XAI products/services in the future	[77]

4.2. Data Collection and Sample Characteristics

The survey methodology was chosen for this study because it allows for the generalization of results [78]. To collect empirical data and validate the research model, a web-based survey platform was developed. A total of 265 responses were obtained for this study. Of these, thirteen were excluded because the respondents either did not complete the questionnaire in its entirety or reported no prior knowledge of AI. Consequently, 252 valid responses were considered for subsequent analysis. The demographic characteristics of the sample are presented in Table 2. Among the respondents, 95 (37.7%) were male and 157 (62.3%) were female. The distribution of respondents' ages was as follows: 20 years or younger: (8.3%), 21-30 years: (28.6%), 31-40 years: (20.2%), 41-50 years: (23.0%), and 51 years or older: (19.9%). Regarding educational attainment, approximately 45.6% of respondents had completed a college education, while 44.8% held a master's degree or higher, reflecting a high level of education among the majority of participants. The sample demonstrated considerable diversity, as evidenced by the wide range of ages and income levels represented.

Table 2. Respondent profiles

Demographics	Frequency
Gender	
Male	37.7%
Female	62.3%
Age	
≦ 20	8.3%
21-30	28.6%
31-40	20.2%
41-50	23.0%
≧ 51	19.9%
Education	
Senior high school	9.6%
College	45.6%
Graduate school or above	44.8%
Monthly income (NT$)	
Less than 10,000	23.4%
10,001-30,000	9.9%
30,001-60,000	36.1%
60,001-100,000	16.7%
Over 100,000	13.8%

5. Data Analysis and Results

The SmartPLS software, utilizing the partial least squares-structural equation modeling (PLS-SEM) approach, was chosen for data analysis in this study. PLS-SEM was selected for its strengths in exploratory research and its ability to handle non-normal data distributions. Following the guidelines of Hair et al. [79], data analysis was conducted in two stages. In the first stage, the measurement model was assessed to evaluate the relationships between constructs and their corresponding measurement items. This included an examination of the reliability and validity of the measurement items, as well as the overall fit of the measurement model. The second stage involved assessing the structural model, focusing on the hypothesized relationships between constructs. This stage aimed to evaluate the significance and strength of these relationships. By adopting this two-stage approach, the study ensured a comprehensive evaluation of both the measurement and structural models to derive insights into the relationships among the constructs under investigation.

5.1. Measurement Model

The measurement model was assessed using four criteria: indicator reliability, internal consistency reliability, convergent validity, and discriminant validity.

Indicator Reliability. Indicator reliability was evaluated by analyzing the outer loadings of the measurement items. Items with outer loadings below 0.6 and insufficient content validity were considered for removal to enhance the model's robustness. Consequently, five items (LC1, LC2, LC6, PN5, and PN6) were excluded. Table 3 demonstrates that most items have outer loadings above 0.7, indicating strong reliability. For items with outer loadings exceeding 0.4—the minimum threshold for exploratory research—all constructs displayed satisfactory indicator reliability.

Internal Consistency Reliability. Internal consistency reliability was assessed using the rho_A and Cronbach's Alpha coefficients, as recommended by Wong [80]. Table 3 shows that all rho_A and Cronbach's Alpha values surpassed the threshold of 0.7, indicating strong internal consistency reliability for each construct. This indicates that the constructs were measured consistently across items.

Convergent Validity. Convergent validity was assessed using the Average Variance Extracted (AVE). Table 3 reveals that all constructs, except locus of control, have AVE values exceeding 0.5, supporting their convergent validity. As suggested by Cheung and Wang [81], Fornell and Larcker [82], and Lam [83], convergent validity can still be acceptable if the AVE is below 0.5, provided the composite reliability is above the recommended level and all factor loadings are greater than 0.5. For the locus of control construct, all outer loadings exceeded 0.5, and its composite reliability was 0.85. Therefore, despite its AVE being below 0.5, the convergent validity of this construct was deemed adequate. Overall, the measurement model demonstrated satisfactory convergent validity based on AVE values and additional criteria.

Discriminant Validity. Discriminant validity was assessed using the heterotrait-monotrait ratio (HTMT), which compares the average correlation between items across different constructs to the average correlation between items within the same construct [84]. A threshold value of 0.85 is typically used to indicate discriminant validity. As shown in Table 4, all HTMT ratios were below this threshold, confirming discriminant validity. This indicates that the constructs were sufficiently distinct, as inter-construct correlations were lower than intra-construct correlations.

In summary, the measurement model demonstrated satisfactory reliability and validity, as evidenced by the assessment of indicator reliability, internal consistency reliability, convergent validity, and discriminant validity.

Table 3. Construct reliabilities and validities

Constructs	Items	Outer Loading	rho_A	Cronbach's Alpha	AVE
LC	LC3	0.66	0.86	0.83	0.41
	LC4	0.59			
	LC5	0.76			
	LC7	0.70			
	LC8	0.71			
	LC9	0.53			
	LC10	0.63			
	LC11	0.54			
ASE	ASE1	0.93	0.96	0.89	0.81
	ASE2	0.88			
	ASE3	0.89			
AIA	AIA1	0.81	0.81	0.77	0.55
	AIA2	0.80			
	AIA3	0.78			
	AIA4	0.57			
PN	PN1	0.84	0.91	0.90	0.76
	PN2	0.91			
	PN3	0.86			
	PN4	0.89			
PV	PV1	0.92	0.90	0.90	0.84
	PV2	0.94			
	PV3	0.88			
BI	BI1	0.96	0.92	0.91	0.92
	BI4	0.96			

Table 4. Heterotrait-Monotrait ratio (HTMT)

	LC	PBC	AIA	PN	PV
PBC	0.15				
AIA	0.19	0.53			
PN	0.32	0.25	0.20		
PV	0.39	0.34	0.22	0.75	
BI	0.27	0.34	0.41	0.64	0.69

5.2. Structural Model (Hypotheses Testing)

The structural model was analyzed using the bootstrapping technique with 5,000 resamples to evaluate the significance and predictive power of the hypothesized relationships within the research model. Table 5 presents the path coefficients (β), t-values, p-values, f-square, variance inflation factor (VIF), and coefficients of determination (R^2) for each dependent variable, while Table 6 summarizes the total effects of each independent variable on the dependent variables.

The coefficient of determination (R^2) measures the proportion of variance in a dependent variable that is explained by the independent variables in the research model [84]. It is a critical metric for assessing the model's predictive power [85]. According to Falk and Miller [86] and Weidich and Bastiaens [87], an R^2 value exceeding 0.1 is considered indicative of an adequate level of explanation for the dependent variables.

The path coefficients (β) reflect the strength, direction, and significance of the relationships between independent and dependent variables, indicating the magnitude of the effects within the research model. The f-square values indicate the effect size of the independent variables on the dependent variables, while the VIF values assess multicollinearity issues among the independent variables.

Table 5. The results of the structural model

Dependent variable	Independent variable	Path coefficient	t-value	p-value	f-square	VIF	R^2
BI	PN	0.30	2.83	0.005*	0.089	1.887	0.45
	PV	0.43	4.05	0.000*	0.567	1.887	
PN	LC	0.37	6.57	0.000*	0.153	1.026	0.22
	ASE	0.11	1.63	0.102	0.013	1.283	
	AIA	0.16	2.17	0.030*	0.022	1.254	
PV	PN	0.57	10.87	0.000*	0.166	1.238	0.54
	LC	0.19	3.72	0.000*	0.062	1.182	
	ASE	0.15	2.84	0.005*	0.036	1.299	
	AIA	0.02	0.27	0.788	0.000	1.282	

* $p < 0.05$

Table 6. The results of total effect

Dependent variable	Independent variable	Total effect	t-value	p-value
BI	PN	0.55	9.82	0.000*
	PV	0.43	4.12	0.000*
	LC	0.28	6.93	0.000*
	ASE	0.12	2.88	0.004*
	AIA	0.10	2.21	0.027*
PN	LC	0.37	6.87	0.000*
	ASE	0.11	1.63	0.102
	AIA	0.16	2.17	0.030*
PV	PN	0.57	10.80	0.000*
	LC	0.40	7.57	0.000*
	ASE	0.21	3.52	0.000*
	AIA	0.11	1.70	0.089

* $p < 0.05$

The results of the hypotheses testing are summarized in Fig 2, indicating the relationships between the variables and whether they are supported or not. The model explains a significant amount of variance in behavioral intention (45%), perceived need (22%), and perceived value (54%). Regarding the effects on behavioral intention, both perceived need ($\beta = 0.30$) and perceived value ($\beta = 0.43$) have positive and significant influences, supporting Hypotheses 1 and 2. In terms of perceived need, locus of control ($\beta = 0.37$) and AI anxiety ($\beta = 0.16$) are significant determinants, supporting Hypotheses 4 and 8. However, AI self-efficacy does not have a significant influence on perceived need, contradicting Hypothesis 6. For perceived value, perceived need ($\beta = 0.57$), locus of control ($\beta = 0.19$), and AI self-efficacy ($\beta = 0.15$) are significant predictors, supporting Hypotheses 3, 5, and 7. However, AI anxiety does not show a significant influence on perceived value, not supporting Hypothesis 9.

Overall, the results suggest that perceived need and perceived value are important factors influencing behavioral intention to use XAI. Locus of control and AI anxiety also play significant roles in shaping perceived need, while locus of control and AI self-efficacy contribute to perceived value. Furthermore, from Table 6, it can be observed that the strongest factor influencing perceived need is locus of control, while the strongest factor influencing perceived value is perceived need. Finally, the strongest factor affecting behavioral intention to use XAI is perceived need.

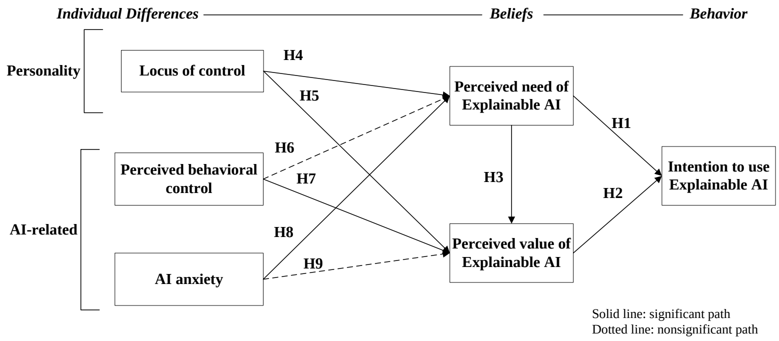

Fig. 2. Summary of hypotheses testing results

6. Discussion

6.1. The Influences of Perceived Needs and Perceived Value

The empirical findings of this study support Hypotheses 1 and 2, indicating that perceived value and perceived need for XAI positively influence the intention to use XAI, with perceived needs having the greatest total effect. Perceived need is recognized as a crucial determinant of user behavior and the intention to adopt innovations or change in the literature.

Perceived need refers to an individual's judgment regarding the necessity or benefits of a specific innovation or change. When individuals perceive a need for the innovation, they understand its potential benefits and view it as essential for themselves, which increases their intention to adopt it. This notion is supported by previous studies. Coulton and Frost [53], King and Teo [54], and Mukred and Singh [55] have emphasized the significance of perceived need as a driver of behavioral intention. In the context of XAI, perceived need addresses key concerns surrounding the opaque, "black-box" nature of AI algorithms, as well as the importance of transparency and interpretability. When users recognize the necessity of XAI in providing explanations and insights into AI decision-making processes, their intention to use XAI increases. Several studies further substantiate this perspective: Jeong et al. [56], Lee and Han [57], and Wang et al. [58] have all highlighted perceived need as critical to influencing user behavior. Similarly, Lin [88] demonstrated that users' intention to adopt mobile communication software is heightened when they perceive a need for it.

The findings of this study resonate with these insights, suggesting that users who appreciate the benefits and necessity of XAI—particularly in addressing transparency and interpretability concerns—exhibit a stronger intention to adopt it. This underscores the significant role perceived needs play in promoting the use of XAI as a solution to the challenges posed by complex AI systems.

Perceived value, as defined by Zeithaml [46], reflects the overall evaluation of the practicality and usefulness of an innovation from the user's perspective. When users perceive XAI as practically valuable and beneficial to them, it naturally increases their intention to use it. Dodds et al. [89] define perceived value as the ratio of perceived benefits to perceived sacrifices. If users perceive that the benefits of using XAI outweigh the sacrifices or costs associated with it, their perceived value of XAI increases. The findings align with the research of Liu et al. [52], which highlights that users with higher perceived value for XAI are more likely to demonstrate a stronger intention to adopt it. These results indicate that users' perceptions of the practicality, usefulness, and cost-benefit ratio of XAI significantly influence their behavioral intentions. When XAI is perceived as offering substantial benefits and a favorable cost-benefit ratio, users are more motivated to adopt it.

The empirical results of this study support Hypothesis 3, which suggests that perceived need for XAI positively impacts the perceived value of XAI, with the total effect being the greatest. While there is limited research specifically examining the relationship between perceived need and perceived value of innovations, existing empirical literature [56],[57],[58] suggests that perceived need does indeed positively influence perceived value. When potential users perceive a high need for a particular innovative product or service, they also tend to perceive it as having greater value and are more likely to adopt it. In the context of AI and algorithmic decision-making, the black-box nature and lack of transparency have been subjects of criticism and concern [91]. Users inherently desire to understand why and how AI systems or algorithms make decisions [92]. As AI systems and algorithms become more complex, they are often seen as "black boxes," which increases decision risks and requires expertise to comprehend their decisions or performance [90],[91].

This lack of transparency in complex AI systems hampers understanding and diminishes trust [91]. When trust in the outcomes of AI decreases, the need to understand AI decision-making or performance becomes more pronounced, thereby increasing the perceived value of XAI. In other words, when users demand XAI to trust the outcomes of AI, they perceive XAI as valuable. Therefore, the perceived need for XAI strongly and positively influences the perceived value of XAI. The perceived value, in turn, has a positive effect on the intention to use XAI, as evidenced by previous studies [42],[44],[50],[52],[91],[93].

6.2. The Influences of Locus of Control

The empirical results of this study provide support for Hypotheses 4 and 5, which propose that locus of control positively influences the perceived need and perceived value of XAI, with the greatest total effect on perceived need. Locus of control refers to individuals' beliefs about the extent to which they can control events in their lives [61],[94]. Individuals with a high degree of internal locus of control believe that they have control over events in their lives and can influence their surrounding environment [95]. When individuals with an internal locus of control consider whether to use AI, they are more inclined to seek an understanding of how AI makes decisions. They believe that they have the ability to comprehend and influence the outcomes, leading to a higher perceived need for XAI. These individuals perceive XAI as valuable because it aligns with their desire for control and understanding. Conversely, individuals with an external locus of control feel that they have little control their lives and are less likely to seek explanations for the decision-making process of AI. They may simply accept the use of AI without questioning or desiring explanations. As a result, their need for XAI is lower, and they are less likely to perceive XAI as valuable.

In summary, individuals with an internal locus of control have a higher need for explanations of AI results and perceive greater value in XAI compared to those with an external locus of control.

6.3. The Influences of AI Self-efficacy

The findings support for Hypothesis 7, indicating that AI self-efficacy has a significant positive impact on the perceived value of XAI. However, the results do not support Hypothesis 6, suggesting that AI self-efficacy does not significantly impact the perceived needs of XAI.

AI self-efficacy refers to an individual's belief and perception of their capability to perform specific tasks or master new technologies [66],[67],[96]. Individuals with high self-efficacy in AI have confidence in their abilities and resources related to AI manipulation and its outcomes. As a result, their demand for XAI may not be significant, as they possess the necessary knowledge and skills to navigate AI effectively. Nevertheless, these individuals place significant value on understanding how AI makes decisions. They appreciate the importance of explainability and transparency, as these features enable them to comprehend AI systems more effectively. Transparency, a core characteristic of XAI, facilitates user understanding by providing clear explanations of AI decision-making processes [91],[97].

The findings indicate that individuals with high AI self-efficacy perceive XAI as valuable because it aligns with their desire for understanding and control. Transparency offered by XAI further enhances their appreciation of AI systems, reinforcing their positive perception of XAI's value.

In summary, while individuals with high AI self-efficacy may not express a heightened need for XAI, they recognize its value in fostering understanding and transparency, which supports their confidence in engaging with AI technologies.

6.4. The Influences of AI Anxiety

The empirical results confirm Hypothesis 8, suggesting that AI anxiety increases perceived needs for XAI. However, the findings do not support Hypothesis 9, indicating that AI anxiety does not significantly influence the perceived value of XAI.

AI anxiety refers to the fear or agitation individuals experience regarding the control or lack thereof over AI [71]. It can lead people to reduce or avoid using AI due to their emotional response of anxiety or fear, which hinders their interaction with AI [72]. However, XAI addresses the black-box paradox of AI by providing transparency and explainability. XAI allows users to understand the inner workings of machine learning algorithms, even with limited technical knowledge [98].

The study aligns with prior research [98], demonstrating that XAI can enhance transparency, trust, and user adoption by addressing concerns about AI decision-making processes. Users with higher AI anxiety and lower trust in AI are more likely to perceive a need for XAI, as it provides the transparency they require to build confidence in AI systems. However, individuals with AI anxiety often view AI as a potential threat, associating it with fears of replacement or loss of control. These concerns may hinder their ability to recognize the value of XAI, as they perceive it as part of the broader AI ecosystem that evokes their apprehension. To address this, it is crucial to emphasize the benefits and transparency offered by XAI, helping users understand its role in reducing risks and increasing trust in AI systems.

In summary, individuals with AI anxiety perceive a strong need for XAI due to their desire for transparency and understanding. However, their concerns about AI as a whole may obscure their recognition of XAI’s value. Efforts to highlight the advantages of XAI and address their apprehensions are essential to encourage its adoption and use.

7. Conclusions

7.1. Conclusions

Understanding the factors that influence potential users' intention to adopt explainable AI (XAI) is essential for promoting its development and widespread acceptance. By identifying these factors, developers and researchers can design XAI systems that better meet user needs and preferences, thereby enhancing their acceptance and utilization.

This study developed a research model grounded in the characteristics of XAI and prior studies on technology acceptance, with a particular focus on individual factors. Using data from 252 potential XAI users, the model demonstrated strong explanatory power, accounting for 45% of the variance in users’ intention to adopt XAI. Key findings include:

Technology Acceptance Model (TAM) Validation. The study confirms the causal chain proposed by TAM, demonstrating that external stimuli influence beliefs, which in turn shape users' intention to adopt technology. For XAI, perceived value and perceived need emerged as critical determinants of adoption intentions. Additionally, the study extended the TAM framework by incorporating individual difference variables, including locus of control, AI self-efficacy, and AI anxiety.

Perceived Needs as a Driving Force. Among the determinants, perceived needs exerted the strongest influence on perceived value. When users recognize a significant need for XAI, their perception of its value is enhanced, ultimately driving their intention to adopt it.

Role of Internal Locus of Control. Individuals with an internal locus of control—those who believe they can influence events in their lives—exhibited higher perceived needs and perceived value for XAI. This suggests that their sense of agency fosters a stronger alignment with XAI’s transparency and explainability.

Differentiated Effects of AI Self-Efficacy. While AI self-efficacy positively influenced perceived value, it did not significantly affect perceived needs. This indicates that confidence in one’s ability to use AI enhances appreciation for its value but does not directly increase the recognition of XAI's necessity.

Contrasting Effects of AI Anxiety. AI anxiety positively influenced perceived need but had no significant effect on perceived value. Individuals experiencing anxiety about AI recognize a need for XAI to mitigate their concerns but may struggle to appreciate its broader value due to apprehension about AI technology.

In summary, perceived value and perceived need are pivotal in driving users' intention to adopt XAI. Individual factors such as locus of control, AI self-efficacy, and AI anxiety play significant roles in shaping these perceptions, providing valuable insights for XAI development and promotion.

7.2. Implications

The findings of this study have important implications for both academics and practitioners in the XAI field. Here are some key implications based on the provided information.

Academic Implications. This study reinforces the causal chain proposed by the Technology Acceptance Model (TAM), which posits that external factors influence beliefs, which subsequently shape the intention to use a technology. By validating this framework, the study provides robust support for the relevance and applicability of TAM in understanding user acceptance of XAI. Future research can build on this foundation to examine the acceptance of other innovative technologies and further explore the adaptability of TAM across different contexts.

Moreover, the study highlights the importance of individual differences, such as personality traits and human-technology-related characteristics, in shaping users’ perceptions of technology. It underscores that beliefs such as perceived needs and perceived value are critical determinants of users’ intentions to adopt XAI. These findings suggest that future research should place greater emphasis on individual differences when examining the adoption of innovative technologies, as these factors play a pivotal role in influencing users’ decision-making processes.

Practical Implications. The findings of this study offer valuable insights for practitioners aiming to address the primary concerns of potential XAI users and enhance their acceptance intentions. By understanding the critical roles of perceived need and perceived value, practitioners can formulate strategies to strengthen user acceptance. These strategies may include designing user-friendly interfaces, providing clear and transparent explanations of AI reasoning, and emphasizing the tangible benefits and value that XAI delivers.

Additionally, the study highlights the importance of internal locus of control. Individuals with a strong internal locus of control—those who believe they can influence events affecting them—exhibit higher perceived need and perceived value for XAI. These individuals are more likely to recognize the benefits of XAI and demonstrate a greater willingness to use it. Practitioners can leverage this insight by involving such individuals in the design, evaluation, and promotion of XAI. Their feedback can help ensure that XAI systems align with user preferences for control and transparency.

In summary, this study provides actionable insights for both practitioners and academics in the development and promotion of XAI. It emphasizes the significance of internal locus of control in shaping users' acceptance intentions and confirms the applicability of TAM’s causal chain in understanding technology adoption. Furthermore, it underscores the influence of individual differences on user perceptions, highlighting the need for continued research in this area to refine strategies and improve user-centered designs.

7.3. Limitations

The study acknowledges several limitations that should be taken into consideration:

Limited sample size and generalizability. The research was conducted with a relatively small sample of potential AI users in Taiwan. This limits the generalizability of the results to other populations and contexts. To validate and expand upon these findings, future studies should include larger, more diverse samples from various countries and cultural backgrounds.

Early stage of XAI development. Explainable AI (XAI) applications are still in the early stages of their development and adoption. The general population’s limited familiarity and understanding of XAI may have influenced participants’ intentions to adopt it. As XAI technology matures and gains broader recognition, future research should investigate adoption dynamics at different stages of XAI development to account for these evolving perspectives.

Lack of differentiation among XAI applications. This study examined XAI adoption as a general concept, without differentiating between specific types of XAI applications. However, user concerns and acceptance factors may vary significantly depending on the application’s context and purpose. Future research should explore adoption intentions across various XAI applications, identifying similarities and differences to provide more tailored insights.

These limitations underscore the need for further research to enhance the understanding of XAI adoption. By incorporating larger, more diverse samples, considering the evolving nature of XAI, and examining application-specific factors, future studies can strengthen the validity and applicability of findings, enabling more informed decision-making and practical implementations.

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