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How Perceived Accuracy Drives Adoption of AI Personalized Recommendations: A Moderated Mediation Model

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Abstract

Artificial intelligence (AI)-powered personalized recommendation systems are reshaping how consumers search, evaluate, and purchase products, yet the psychological mechanisms through which perceived accuracy drives adoption remain underexplored. This study examines how perceived accuracy of AI recommendations influences consumer adoption willingness through perceived benefit and how this process is conditioned by product involvement. Drawing on the Technology Acceptance Model (TAM) and Product Involvement Theory, we develop an accuracy-centred moderated mediation model in which perceived accuracy (PA) leads to perceived benefit (PB), which in turn leads to consumer adoption willingness (AW) or (PA → PB → AW). The study uses survey data from 518 Chinese consumers with experience of using AI-personalized recommendations. The data are analyzed using Partial Least Squares Structural Equation Modelling (PLS-SEM) with multigroup analysis to examine age-based heterogeneity on consumer adoption willingness. The results show that perceived accuracy has a significant direct and indirect effect on adoption willingness, with perceived benefit acting as a partial mediator. Product involvement positively moderates the relationship between perceived accuracy and perceived benefit, and the proposed mechanisms are stable across age groups. The study opens the "black box" linking perceived accuracy to adoption, identifies key boundary conditions, and extends TAM by positioning perceived accuracy as an antecedent of perceived usefulness in AI recommendation contexts.

Keywords:

AI Personalized Recommendation;
Perceived Accuracy;
Consumer Adoption Willingness;
Perceived Benefit;
Product Involvement;
SEM.

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1- Introduction

Artificial intelligence (AI) has rapidly transformed digital ecosystems, influencing businesses across e-commerce, social media, and hospitality. Personalized recommendation systems, backed by machine learning and deep learning, have become an essential component of digital marketing for platforms such as Alibaba, TikTok, and Amazon. These systems analyze user data to predict preferences, deliver tailored content, and ultimately enhance user experience and business profitability [1, 2]. Personalization has become a need in today's information deluge, as users increasingly rely on algorithms to navigate fragmented digital spaces [3].

Within the landscape of AI-driven personalisation, "perceived accuracy"—user subjective judgement of how well recommendations align with their needs and preferences—emerges as a critical determinant of user behaviour. Unlike

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technical accuracy (measured by algorithmic metrics), perceived accuracy reflects psychological alignment, directly shaping user trust, decision efficiency, and willingness to engage with recommendations [4, 5]. For example, accurate recommendations can lower search costs and simplify decision-making processes, making users loyal to the AI platform—making accurate perception an essential element for understanding user adoption of AI platforms [6]. Experimental studies in domains such as banking, functional foods, and e-commerce have shown that the influence of perceived accuracy on adoption intention is positive and significant, and its impacts are moderated by users' demographic characteristics and product features [7-9].

By 'perceived accuracy' in this paper, we explicitly mean that after a certain period of time and situation, the subjective opinion of a user on the recommendation system is accurate, i.e., the sequence of suggested items always represents their comparatively consistent preference, needs and constraints over time and situations. This construct conceptually is associated with, but separate to, recommendation relevance and recommendation quality. We refer to recommendation relevance to the goal or task specialisation of a specific recommendation to a given user query or situational requirement (e.g., whether a given recommended product is relevant to the current search or browsing objective). Recommendation quality, by comparison, typically is a more global assessment of the set of system outputs in terms of its relevance, diversity, novelty, serendipity, timeliness and presentation into a single-dimension idea of how good the recommendation set ought to be. Perceived accuracy is narrower, concerned more with a perceived correctness of the coinciding logic supporting the recommendations: the users believe that the bulk of what they see is what they would have selected on their own, even though the set is not particularly representative. Therefore, a perceived recommendation list may be actually good and yet not highly diverse or serendipitous; high perceived recommendation quality usually assumes but not guarantees high perceived accuracy. The isolation of the special role of perceived accuracy as a driver of adoption compared to other quality-related variables can be achieved by establishing these conceptual boundaries.

TAM offers an initial theoretical framework to understand user adoption of new technologies by focusing on the critical roles of perceived usefulness and perceived ease of use [10]. Previous studies have extended TAM to AI contexts and confirmed the general validity [11, 12]. In addition, scholars have found that perceived benefit (which aggregates functional benefits such as time saving and emotional benefit) may play a potential mediator in adoption [13], and product involvement (the personal relevance and importance users attach to a product) may serve as an essential contextual factor affecting user reliance on external recommendations [14, 15]. Recently, scholars have started to incorporate perceived accuracy as an antecedent to perceived usefulness into extended TAM models for AI-mediated environments [16, 17].

Despite the relevance of the research papers as an initial point of departure, there are still a number of closely related gaps that undermine the ability to have a comprehensive perspective of how perceived accuracy can have its effect on adoption in AI-assisted recommendation systems. The effects of perceived accuracy have been confirmed to be positive, and new constructs, which include satisfaction, trust and usefulness, have been brought into the theorisation of the extension of TAM models [6-13, 16-20], yet the internal psychological mechanisms and situational conditions under which perceived accuracy acts are still under partial specification.

Firstly, perceived accuracy to adoption's psychological black box has not adequately been unpacked. Most empirical relationships define perceived accuracy as a direct antecedent to adoption, continuance intention or loyalty or at best have global factors like satisfaction or trust as coarse mediators [7-9, 11, 12, 18, 19]. This fact proves that accuracy is important; however, it fails to provide a clear explanation as to why more precise recommendations are embraced. Preliminary literature indicates that valid recommendations may help a person to achieve both functional and emotional benefits (e.g., a low cost of search, time-saving, and higher-quality decisions) [13], and these two avenues of benefits are, however, not researched in one framework. Consequently, the process of internal value formation between perceived accuracy and willingness to adopt has not been specified sufficiently. In response to this gap, the current research clearly specifies the conceptualisation of perceived benefit as a synthetic construct that incorporates both functional and emotional benefits and proves whether or not it mediates the relationship between perceived accuracy and adoption willingness.

Second, the limits regarding product engagement in AI-personalised recommendation contexts are still not fully explained. Involvement theory suggests that product involvement influences consumer information processing, risk assessment, and the use of diagnostic cues, thereby moderating the effects of advertising appeals, perceived risk, recommendation attributes, attitudes, and behavioural intentions [14]. Some studies on personalised recommendations also indicate that involvement can moderate user reliance on system-generated information [15, 19]. However, these studies rarely specify where this moderation occurs or at which stage of the decision-making process (e.g., benefit formation stage versus final adoption), nor do they clearly distinguish between different levels of involvement (e.g., younger vs. older consumers). As a result, it remains unclear under what conditions product involvement increases or decreases the effect of perceived accuracy. This study addresses this gap by proposing a model in which product involvement acts as a moderator in the relationship between perceived accuracy and perceived benefit, while also examining heterogeneity based on user age through a multigroup analysis.

Third, the concept of perceived accuracy has not been fully integrated into standard theories of technology acceptance like TAM. Most past implementations of TAM coupled with AI recommendation contexts consider perceived accuracy as a feature of a background system without explicitly and formally placing it as a primary antecedent of the AI-recommended core TAM construct, perceived usefulness [9, 10, 16, 17]. It results in inconsistent descriptions of the influence that quality characteristics of the recommendation will have on user acceptance, in particular to certain categories of users like middle-aged and older customers whose user adoption behaviour might vary when comparing them with that of young digital natives [5, 8, 12]. Recent reviews and empirical research have actually rendered a call to research that is more integrative of major attributes related to quality, such as perceived accuracy, into pre-existing theoretical frameworks to ascertain the heterogeneity in adoption between segments of users [21-23]. As one way to address it, the current study forms an accuracy-based extension of TAM whereby perceived accuracy is used as a primary input to perceived usefulness, operationalised as perceived benefit, and integrates it with a mediated connection (PA → PB → AW, with product involvement as a moderator) to present a more systematic picture of AI-powered recommendation adoption between different age groups.

With regard to this, the aim of the current study is to conduct a systematic review of the role that the perceived accuracy of AI-based personalised recommendations plays in consumer adoption willingness. We pursue four specific objectives: (1) to verify the direct positive impact of perceived accuracy on adoption willingness; (2) to reveal the mediating role of perceived benefit in this relationship; (3) to analyse how product involvement moderates the link between perceived accuracy and perceived benefit; and (4) to enhance the generalisability of conclusions by including a heterogeneous sample covering all age groups. In this study, an online survey with N = 518 people is used to collect the data and test the direct, mediated and moderating effect of variables using Partial Least Squares Structural Equation Modelling (PLS-SEM). In addition, a multi-group analysis is implemented to assess the phenomenon of age-based heterogeneity on consumer adoption willingness.

The paper contributes in three major ways to the literature. First, it cleans up the conceptual implementation of the adoption of AI recommendations by confirming that perceived benefit is an important partial mediator, which examines the perceived accuracy to perceived benefit to adoption willingness channel (PA → PB → AW) and enhances our knowledge of perceived value for the users. Second, it elucidates key borderlines by confirming the moderating effect of product involvement to be positive and gives hints of heterogeneity according to the age. Third, it broadens the use of the TAM by incorporating the perceived accuracy systematically as a critical antecedent of perceived usefulness into an accuracy-focused system and by using a sample that overtly consists of middle-aged and older users, which increases the explanatory strength of TAM to AI recommendation adoption for distinct age groups of users. Overall, the research has important missing links in the literature of AI-based personalised recommendations and specifically investigates how perceived accuracy relates to consumer adoption willingness and provides implications to practitioners to design more human-friendly AI-based recommendation systems.

The remainder of this paper is structured as follows. Section 2 presents the theoretical background and hypotheses development. Section 3 describes the research design, including sampling, measurement, and data analysis procedures. Section 4 reports the empirical results, followed by a discussion of the findings in Section 5. Section 6 concludes the study by summarising theoretical and practical implications, outlining limitations, and suggesting directions for future research.

2- Literature Review and Hypothesis Development

The technology acceptance model (TAM) is the theoretical foundation of this study and the evidence regarding the perceived accuracy and product involvement. TAM is a conceptual framework that can be used in the explanation of why users adopt new technologies with a primary focus being laid on the cognitive judgments or perceptions like perceived usefulness as a prerequisite to consumer adoption willingness [10-12]. Based on the recent extensions of TAM to an AI-mediated context, researchers state that judgments by users regarding how effectively AI systems absorb and comprehend their needs, reflected by perceived accuracy, are a key input in usefulness-related judgments [16, 17]. The conceptualization of perceived accuracy, in this research, is thus to be viewed as a major antecedent, which influences users in their benefit appraisal that takes place when they encounter personalized recommendations. Moreover, Product Involvement Theory states that the users vary in the level of personal relevance, perceived risk and cognitive effort to various product types, and this concept affects the manner in which the users process external information and trust technological cues [14, 15]. In this regard, we assume "accuracy → benefit → adoption" mechanism-based research perspective, which will be concerned with how perceived accuracy influences the willingness to adopt the product due to perceived benefit and how perceived benefit influences this mechanism under varying degrees of product involvement. The subsequent subsections discuss these theoretical premises further and formulate the hypotheses of the suggested moderated mediation model.

2-1- Technology Acceptance Model

2-1-1- Theoretical Origins and Development

The Technology Acceptance Model (TAM) originally proposed by Davis (1989) is arguably the most frequently cited model for studying user acceptance of technology. It assumes that Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) are two key determinants that influence users 'behavioral intention, which in turn predict users 'actual usage behavior [10, 24-26].

To enhance the explanatory power of TAM, Venkatesh and Davis later proposed TAM2 by adding subjective norm, image, job relevance, and output quality to explain social influence and cognitive instrumental processes on user behavioral intention under forced usage situations. Subsequently, TAM3 [25], focusing on determinants of PEOU such as computer self-efficacy, perceived enjoyment, and perceived usability, was developed to account for the influence of user training and support mechanisms on adoption behavior. Eventually, Venkatesh et al. (2003) published the Unified Theory of Acceptance and Use of Technology (UTAUT) by integrating TAM into TPB and TRA to make the model generalizable across organizational and cultural settings [24].

With considerable changes in technological environment (e.g., mobile internet, social media, artificial intelligence) and user behavior, Dwivedi et al. "upgraded" the classic UTAUT model by adding key variables such as trust, risk, habit, and cost value to make the model more suitable to explain and predict user technology adoption behavior in modern technological environment [27].

Based on TAM2, TAM3, and UTAUT, AI-oriented extensions further add information-quality constructs, such as perceived accuracy and personalization, to address the limitations of traditional models in evaluating algorithmic outputs and recommendation results [16, 17]. In the two recent AI personalisation and conversational service scenarios, evidence supports PA and PU linkage: in an airline customer-service chatbot scenario, a TAM-based extended-PLS-SEM study reports that perceived accuracy and completeness significantly enhance perceived usefulness and satisfaction, which in turn motivate usage intention [16]; in a fashion e-commerce recommendation scenario, an extended-TAM survey (n = 124) found that perceived accuracy exerts the strongest influence on trust and perceived usefulness, and both the measurement model and structural model fulfil reliability and validity requirements [17]. Therefore, in the application scenarios where users rely on recommended results, specifying PA → PU as a core path in extended TAM materially enhances explanatory power.

2-1-2- Application

TAM has been tested in various contexts, including education, health, and e-commerce. For example, in education, the impact of social influence, system quality, and students' attitudes on the adoption of learning technology such as LMS was examined using TAM [28, 29]. In health care, perceived privacy, data security, and regulations extended PU and PEOU as determinants of the acceptance of electronic health record (EHR) [30]. In e-commerce, perceived risk and trust were added as significant mediators influencing PU and PEOU on the adoption of mobile payment [31, 32].

2-1-3- TAM in AI Personalized Recommendation Systems

With the emergence of personalized recommendation systems in platforms such as TikTok, Shopee, Instagram, and many e-commerce websites, TAM has gradually extended to investigate users' acceptance of intelligent recommendation technology [4]. In such context, the perceived accuracy (PA) of recommendation provided by intelligent AI-powered recommendation system has been proposed as an important antecedent of perceived usefulness (PU) [33].

That is, users would consider a recommendation system more useful if they evaluate the recommendations as accurate and beneficial. Such accuracy would then lead to users perceived benefit (PB): the concrete benefit or usefulness that users could gain from accurate recommendations, such as time saving, discovering more relevant products they need, or getting better entertainment experience [4-6]. In this way, PB would then be regarded as the manifestation or mediating pathway through which PA affects PU. That is, when users evaluate the system to be accurate, they would then realise appropriate benefits, and further believe that the system relates as follows:

PA → PB → PU.

Furthermore, PEOU would still play a decisive role in adoption when systems are intuitive and transparent. An interactive interface design and explanation mechanism would then further reduce user cognitive cost and anxiety in interacting with AI systems and hence would then affect their perceived ease of use [34].

Although perceived precision would further affect PU and adoption intention, highly personalized recommendation may lead to privacy concerns, which would then have negative affect on users' perceived ease of use and technology acceptance through diminishing perceived ease of use [35]. Therefore, accuracy should be carefully controlled in recommendation systems to maintain technology acceptance. Recently, new findings have shown that perceived accuracy would further lead to perceived ease of use and then strengthen adoption willingness [17, 36, 37]; at the same time, putting up a caution that over-personalisation may reduce trust [36, 37].

When extending TAM to intelligent recommendation systems, we make a conscious theoretical choice: we focus on this chain: perceived accuracy → perceived benefit → adoption willingness chain. In this chain, perceived benefit is defined as the manifestation of perceived usefulness when users receive personalized recommendations. That is, when users evaluate recommendations as accurate, they would then further gain some concrete benefits, such as time-saving and informed decision-making, which further help them assess the system to be useful. Therefore, our model defines perceived accuracy as an important antecedent of the perceived usefulness construct from TAM. Meanwhile, we do not explicitly model perceived ease of use (PEOU). Usability and interface design in mainstream AI recommendation systems are already comparatively stable and standardised, and an extensive literature on TAM/UTAUT found that the positive contribution of PEOU to adoption of technology is already confirmed multiple times. Adding PEOU to our model would add a lot of complexity and multicollinearity that would not explicitly address our core research question, which is to decant the translation of output quality (perceived accuracy) into value perception and adoption. In this respect, we deem ease of usage to be a situational precondition and study an accuracy-based extension of TAM (PA → PB → AW), considering that the future research might involve PEOU and other variables that reflect on the quality of systems to gain a broader view of user acceptance.

2-2- Product Involvement Theory

The product involvement theory is related to the degree of psychological relatability or personal significance of a product category to a person. High product involvement demonstrates that the product is highly representative of the consumers' goals, values and self-identity, as opposed to low product involvement, demonstrating that the product is rather trivial, routine or habitual in the consumers' lives [14, 38]. A substantial body of literature demonstrates that engagement predetermines the amplitude of cognitive effort that consumers devote to the processing of product information and how product information centres attitude formation and decision-making.

Vaughn (1986) [38], based on this perception, distinguished two types of high-involvement products—financial services and durable goods and high-risk tourism products, and two types of low-involvement products—everyday fast-moving consumer goods and hedonic impulse purchases. In high involvement, consumers are more likely to process information in a systematic manner, seek and evaluate alternatives, and use diagnostic cues such as product attribute fit to the needs of consumers; in low involvement, consumers would more readily engage in heuristic processing, pay attention to lower-order peripheral cues (e.g., brand recognition, popularity) and put less effort into cognitive elaboration.

This theoretical prism is used to describe the reasons why the product involvement can influence the relationship between perceived accuracy (PA) and perceived benefit (PB). When the involvement is high, proper recommendations are an indication that the system has rightly interpreted the intricate needs of consumers and why these issues are important (or dangerous) to them. Moreover, the consumer might find it simpler to acknowledge both functional (e.g., saving time in a search, talking down information overload and enhancing the quality of decisions) and emotional advantages (e.g., feeling safer, in control and respected). Under those circumstances, an increase in perceived accuracy ought to lead to the enhancement of perceived benefit.

Conversely, low involvement means that less attention and cognitive effort are spent by consumers in assessing what the regulations are. Although recommendations may be viewed as true, the users may fail to expound on the functional and emotional implications, which compromises the perceived benefit attainment. They can still take the advice because it conveniently happens or because it is a habit, but this could be loosely located in a more consciously stated advantage appraisal.

The previous literature has, thus, revealed that the strength of some of the relationships could be changed due to product involvement, including the effectiveness of an advertising appeal on purchasing attitude, the role of perceived risk on purchase intention, and the impact of recommendation attributes on loyalty [39-42]. These two are aligned with the same literature in that we also think of involvement as a boundary condition, although this time we think more about its effect of activating the inner thinking process of an individual between perceived accuracy and perceived benefit and not just on its relation to adoption outcomes.

Therefore, in this paper we model product involvement as a threshold and amplification process which modulates the strength with which perceived accuracy can be converted into benefit appraisals, as opposed to being a second independent predictor of adoption willingness. The above modelling option will enable us to easily isolate the mediating role of perceived benefit in the TAM-based PA - PB - AW chain, following previous recommendation literature that mediators are viewed as constraints of internal value-formation trajectories [19, 43].

2-3- Perceived Recommendation and Consumer Adoption Willingness

Due to its outstanding content-matching ability and personalised experience, AI-personalised recommendation services are widely used in various fields [9, 44-46]. As a subjective perception index for the recommendation effect of a recommendation system, perceived accuracy reflects how well the recommended content meets consumer needs [5]. The higher the level of consumer-perceived accuracy of the recommendation system, the stronger their trust, satisfaction, and intention to continue using the system [11, 27].

Different scholars discussed how the consumers perceived accuracy of using different AI personalised recommendation systems affects consumer adoption willingness. High recommendation accuracy greatly improves consumer click-through and purchase intention. Yin et al. [9] empirically studied the influence of consumer-perceived accuracy of e-commerce environments on consumer adoption willingness in China. When consumers believe that the products or content recommended by AI strongly match their needs, consumer adoption willingness and trust will be improved. In addition, the trust of consumers will not only affect their short-term purchase intention but also promote their long-term willingness to be consumers.

Ding et al. [45] found that when the precision of personalised recommendations is high, users will have a good emotional experience in using Douyin (China's TikTok), and this good experience will promote continuous use of the recommendation service. In addition, their study also discussed the "information overload reduction" effect of perceived accuracy in personalised recommendation systems.

Highly accurate recommendations can effectively solve the problem of information overload for tourists and help them find suitable destinations, hotels and related services quickly, so as to improve the travel experience in the whole process [47]. In particular, in the personalised travel recommendation, the perceived accuracy of the recommendation system can not only improve tourists' trust in the recommendation system but also significantly improve their booking intention and brand loyalty [48]. Based on the above analysis, this paper proposes the following hypothesis.

H1: Perceived accuracy of AI personalized recommendations has a positive impact on consumer adoption willingness [7-9].

2-4- Perceived Accuracy and Perceived Benefit

Given the positive features of AI-personalised recommendations, the positive experiences that they bring about for consumers are positively noteworthy, namely, the problem of choice overload [49]. In this era of plenty, consumers even encounter a problem that they cannot choose, whereas personalised AI recommendations can filter out the content that meets consumers' own needs, interests, and expectations and bring them convenience so as to solve their problem of not being able to choose [50].

Perceived accuracy is an important parameter for assessing the efficiency of AI-powered personalised recommendation services, reflecting the degree of alignment between recommended content and user actual demand [51]. According to the limited attention model, precisely recommended content can help consumers quickly locate the information they require, reducing the time costs associated with searching and browsing and optimising the utilisation of their cognitive resources, allowing them to acquire and process information more efficiently [52]. High-precision recommendations can significantly lower consumer cognitive load, saving them considerable time and energy [53]. This way of obtaining information is an efficient method to satisfy a consumer need, which in turn increases their perceived value of AI-personalised recommendation services.

Existing studies have also found a positive relationship between personalised recommendation content and consumer-perceived benefit [54]. To obtain services that are better suited to their needs, consumers are willing to actively share their personal data and sensitive information, such as their current location, to gain from the potential benefits that accurate recommendations can provide [55]. Therefore, a higher degree of accuracy in personalised content can enhance consumers' perceived value and benefits to some extent and provide them with a higher quality consumer experience [56]. Based on the above analysis, this paper proposes the following hypothesis.

H2: Perceived accuracy of AI-personalised recommendations has a positive impact on perceived benefit [8, 36, 56].

2-5- Perceived Benefit and Consumer Adoption Willingness

Perceived benefit received extensive attention in the research on consumer adoption willingness. A large volume of empirical research has proven that, when consumers perceive that a product or service can offer considerable benefits, then consumer adoption willingness greatly enhances [57]. In the field of digital marketing and e-commerce research, when consumers perceive they can save time, have ease of usage, and even get a personalised experience, the consumer willingness to use that service greatly enhances [58]. Fong et al. [57] also found in their brand trust study that, when consumers are in low-involvement product situations, consumers adopt new brands and new technologies due to benefits they perceive, such as price discounts and emotional benefits. The positive relationship between perceived benefit and adoption willingness has also been proven in augmented reality marketing. Guo et al. [58] found in their quantitative research that, when consumers perceived benefit, not only the purchase willingness of brands enhanced, but also their propensity to share actively strengthened and brand loyalty improved.

In addition, in the green consumer behaviour field, Shao & Lin [59] found how perceived value influences consumer adoption willingness through the psychological cost mechanism. The SEM analysis results showed that when consumers believe that the environmental and social benefits brought by green products are greater than the purchasing costs, the consumer adoption willingness greatly increases. That is, the consumer willingness to pay and the intention to use green products for a long time significantly improves.

When AI-personalised recommendations are more accurate to consumers' interests, needs and even their personalised preferences, the consumers feel that they have attained some benefits. The high correlation between AI-personalised recommendations and consumer benefit stimulates consumer acceptance of recommendation information. In this case, the consumer adoption willingness will enhance greatly. The personalised recommendation mechanism of AI can significantly improve consumer willingness to adopt technology. The adoption willingness will be increased greatly due to the willingness to accept new technology [42]. As shown in the above analysis, the positive relationship between perceived benefit and consumer adoption willingness has got abundant empirical support in the fields of digital marketing, green consumption, and adoption of AI-personalised recommendation technology. Hence, this paper proposes the following hypothesis.

H3: Perceived benefits have a positive impact on consumer adoption willingness [18, 22, 57].

2-6- The Mediating Role of Perceived Benefit

In recent years, perceived benefit has drawn extensive attention as a mediating variable in technology acceptance, personalised marketing, and recommendation research. Research indicates that perceived benefit could be an effective variable to connect consumer-perceived features of recommendation systems (like accuracy, degree of personalisation, etc.) and adoption intentions [60]. When the recommended content is more accurate and nearer to consumers' interests, needs and preferences, consumers would find out the higher value of recommended information, and then the willingness to accept and adopt recommended information would be stimulated [61].

In the e-commerce field, researchers found that consumers would evaluate the quality of the recommendation system on the basis of the relevance and usefulness of the recommended content, and the perception of usefulness of recommended content would enhance the perceived benefit and further improve the purchase intention [9, 62]. Jing and Wang, in their study of consumer adaptation to digital marketing communication in the context of intelligent recommendation in tourism marketing, found that perceived benefit had a significant mediating effect in the relationship between perceived accuracy and user adoption intentions. This effect is particularly pronounced in scenarios involving data-driven personalised recommendations [43]. Mishra et al. [63] empirically supported this relationship in their study on AI-driven personalisation, revealing that relevant and useful recommendations significantly enhanced users' perceived benefits and their intention to purchase.

H4: Perceived benefit plays a mediating role between the perceived accuracy of AI-personalised recommendations and consumer adoption willingness [60-63].

2-7- The Moderating Effect of Product Involvement

The product involvement is a key moderating variable in the process by which people react to product information and marketing stimuli [64]. High involvement enhances the interest in seeking information, examining it cautiously, and applying diagnostic clues, but low involvement diverts attention to peripheral clues by reducing the extent of cognitive elaboration [14, 39-42, 65]. To this effect, product involvement can moderate not only downstream persuasion paths such as message → attitude or risk → purchase intention but also upstream cognitive relationships, such as the extent to which accurately perceived recommendations are converted into perceived benefit [15].

Regarding the personalised recommendations in the AI context, the content of the recommendation makes up one of the major informational inputs that need to be decoded by users prior to the formation of adoption intentions. In our model, thus, the moderating impact of product involvement is placed on the line between perceived accuracy and the perceived benefit and not on the ultimate line between the perceived benefit and the adoption willingness. This design is based on the fundamental assumption of the involvement theory to the effect that information processing and benefit appraisal are largely influenced by involvement; once the user has developed a global appraisal of benefits, the impact is likely to have a comparatively constant effect on intentions to adopt across the levels of involvement. Aljukhadar & Senecal [66] demonstrated that product involvement significantly moderates users' willingness to comply with recommendation systems, as highly involved users tend to engage in more deliberate evaluation of both functional and emotional benefits. Whatever the actual recommendations are, with high involvement, users are more likely to evoke conscious judgements of functional as well as emotional benefits, and under low involvement, the user is only likely to perceive them as handy without making significant alterations to their belief in benefits. It is possible to develop a hypothesis based on the analysis presented in the paper above:

H5: Product involvement degree moderates the impact of perceived accuracy of AI-personalised recommendations on perceived benefit [15, 19, 43].

The conceptual model is shown in Figure 1.

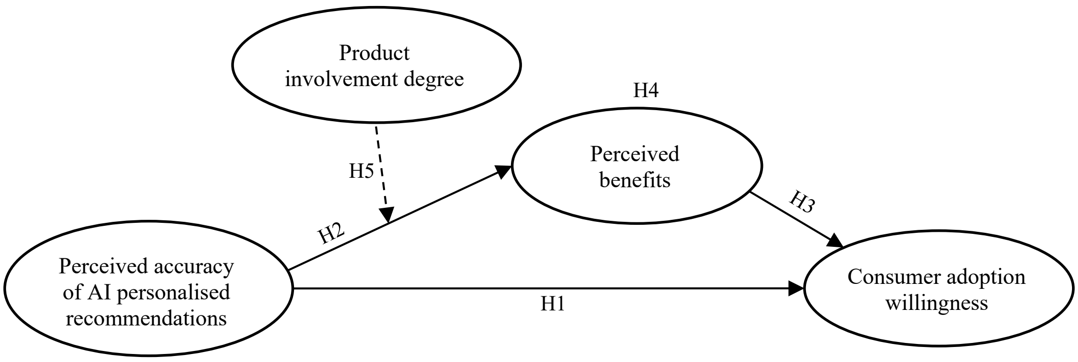

Figure 1. Research Model

3- Research Methodology

This study uses a quantitative research design based on the positivist paradigm that advocates for objective measurement and statistical validation of relationships between variables [67]. This approach is suitable for testing the causal relationships among perceived accuracy, perceived benefit, product involvement, and consumer adoption willingness because this approach can help in systematically testing the hypotheses mentioned above and generalizing the findings [67]. Figure 2 illustrates the overall research framework, outlining the progression from identifying research gaps and developing hypotheses to research design, data collection, analysis, and the final discussion and conclusions. This roadmap clarifies the logical structure of the study and guides readers through its methodological flow.

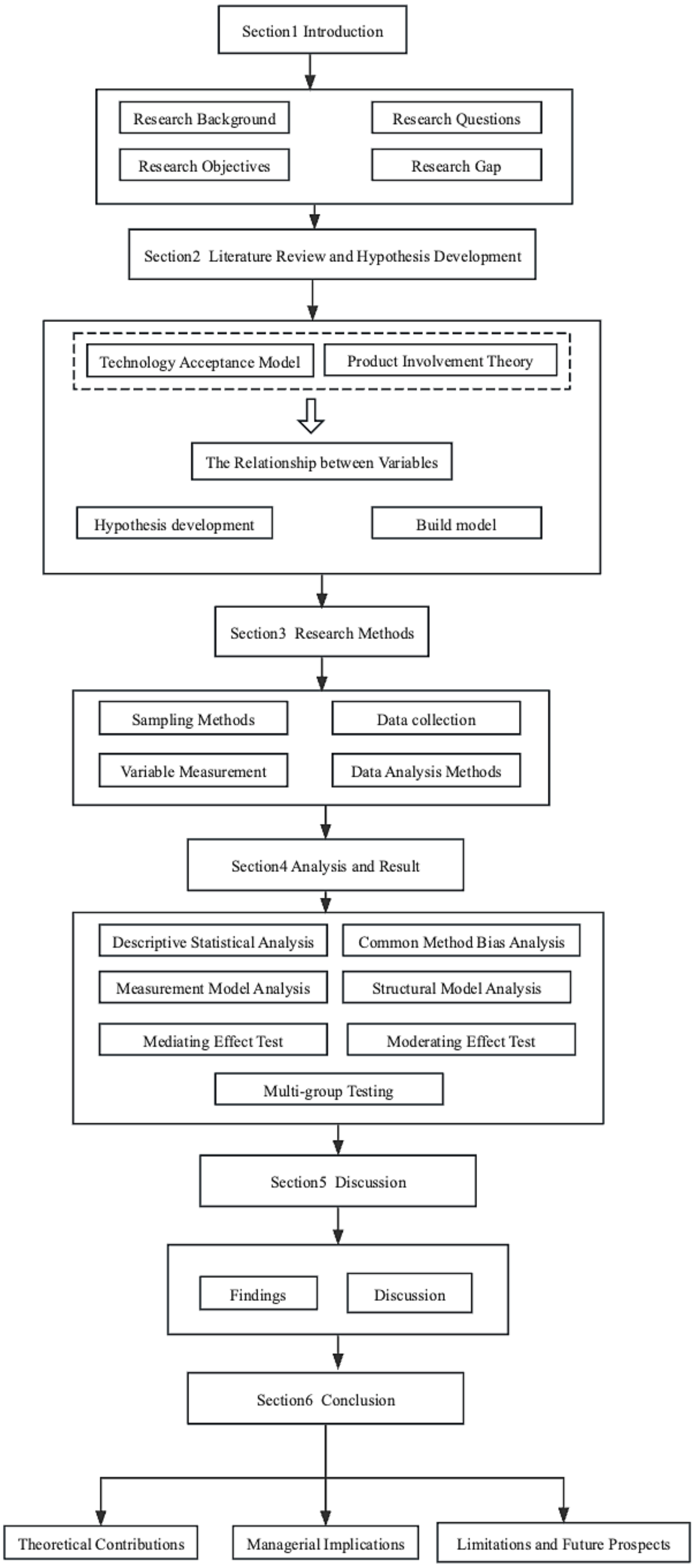

Figure 2. Research roadmap

3-1- Sampling Methods

The population of study are consumers who have used AI-personalised recommendation systems on various platforms, such as e-commerce (e.g., Amazon, Alibaba), social media (e.g., Instagram, TikTok), and hospitality services. This is to ensure that study participants have firsthand experiences with the phenomenon of interest, thereby enhancing response validity [68]. Given that the target population is broad, highly dispersed and lacks a complete sampling frame, a non-probability convenience sampling method was adopted and implemented via online survey platforms. To reduce sample bias from Wang [5], screening questions were designed to obtain participants' demographic information (age, gender, region, education level), ensuring appropriate representation from different age groups, especially middle-aged and older users (more than 50 years old). During data collection, the questionnaire was distributed across multiple online channels, and the evolving sample composition was monitored to avoid over-reliance on any single demographic group and to maintain sufficient representation of older users. In addition, strict data screening criteria (e.g., attention checks, response time and consistency checks) were applied to remove invalid/incomplete responses and improve the internal validity of the estimated relationships. This adjustment is necessary because, according to recent statistics from CNNIC [69], users aged more than 50 years account for 34.1% of China's internet users, so a heterogeneous convenience sample with adequate coverage of this group can still provide meaningful evidence on the structural relationships tested in this study, even though strict statistical generalisation to the entire population remains limited.

The minimum sample size was calculated using the inverse square root method, which is a standard sample size calculation method for PLS-SEM studies [70, 71]. The formula is as follows:

$$n_{min} > \left(\frac{Z}{P_{min}}\right)^2 \tag{1}$$

where Z represents the critical value for the significance level (5% significance level corresponds to a critical value of 2.486, which represents 80% statistical power), and P_{min} is the minimum path coefficient in the model. Shi & Mao [72] conducted a meta-analysis on the user adoption of personalised algorithm recommendations and found that the average path coefficient range of perceived accuracy-related variables affecting adoption willingness was 0.09–0.13, and the central value was approximately 0.11. This meta-analytic result provides justification for choosing P_{min} =0.11 because it represents the typical effect size of these variables. That is, the effect of these variables on adoption willingness was approximately 0.11. Substituting parameters into the formula above:

$$n_{min} > \left(\frac{2.486}{0.11}\right)^2 \approx 511 \tag{2}$$

According to the literature, the invalid response rate of online questionnaires is generally between 10% and 25% [73, 74]. Therefore, the sample size of this study should be greater than 511.

3-2- Data Collection

This study was conducted in accordance with the Declaration of Helsinki and approved by Walailak University's Human Research Ethics Committee (Approval No. WUEC-25-143-01). Prior to participation, all participants were given a full informed consent form that outlined the study's goal, methods, potential risks and benefits, and the ability to withdraw at any time. Only individuals who supplied explicit consent were allowed to complete the questionnaire. To protect participant confidentiality, all data were obtained anonymously during data processing, and any individually identifiable information was removed.

From May to June 2025, data were collected using an online questionnaire survey distributed on professional platforms (e.g., Questionnaire Star). The questionnaire has three parts: (1) screening questions to confirm respondents' experience with AI-personalised recommendations; (2) measurement items for core variables (perceived accuracy, perceived benefit, product involvement, and consumer adoption willingness); and (3) demographic data (age, gender, education level, etc.).

To improve response quality, the questionnaire was pre-tested with 50 respondents to refine ambiguous wording, ensuring clarity and readability. Procedural measures were implemented to reduce bias, such as emphasising anonymity and voluntary participation and randomising the order of items to avoid sequence effects [75]. In addition, potential method biases were considered following the guidelines of Kock [76]. A total of 518 responses were valid after excluding invalid responses (e.g., incomplete answers and consistent patterns of extreme ratings).

3-3- Measurement

The measurement instruments of these studies used the adapted versions of well-established scales. The constructs were measured as follows.

Perceived accuracy is measured by the degree of matching, continuity, and purchasing capability based on four items of scales used in recent recommendation studies on AI [77, 78].

Perceived benefit is measured by the three core utilitarian values, i.e., time-saving, convenience, and efficiency in making decisions, primarily adopted from studies on smart recommendations in social media and travel. The implementation of the use of AI-personalised recommendations as a measure of perceived benefit ranged over five questions that indicate both the functional and emotional benefits. The items require the respondents to assess the extent to which the recommendations can save them time and effort as well as improve quality decisions and feel more relaxed and confident with the choices they make. This is also consistent with evidence that misleading or incorrect AI suggestions can undermine users' trust and perceived decision assurance, highlighting the affective component of users' evaluations of recommendation systems [79]. In line with the previous studies, which describe perceived benefit or perceived usefulness as a total rating of the positive effects of using technology, we consider functional and emotional benefits as the components of one first-order variable in the empirical model. This unified operationalisation was supported by the fact that the exploratory factor analysis and confirmatory measurement tests showed that all the items of benefits were loaded on the same factor. The items have been adjusted according to the existing scales on smart recommendations in social media and travel [49, 80].

Product involvement adopted from Zaichkowsky's [14] classic scale, measured by the degree to which a product was personal relevant, important, and requiring deliberation.

Consumer adoption willingness is measured by the willingness to recommend, browse, and purchase, adopted from recent studies on recommendations by AI [9, 81]. All items were refined to fit the context of AI-powered personalised recommendations. The complete list of measurement items is demonstrated in Table 1.

Table 1. The measurement item of construct

Construct	Measurement Item	Item Content	Literature Source
Perceived Accuracy (PA)	PA1	The products or information recommended by AI personalized services match my personal preferences.	[77, 78]
	PA2	I believe AI personalized recommendation services can continuously recommend products or information that I need.	
	PA3	I believe the products or information recommended by AI personalized services meet my pricing needs.	
	PA4	Through AI personalized recommendation services, I can discover products or information that I had not noticed before but need or am interested in.	
Perceived Benefit (PB)	PB1	I believe that using AI personalized recommendation services can save me time.	[49, 80]
	PB2	I find AI personalized recommendation services very convenient for me.	
	PB3	I believe that using AI personalized recommendation services improves efficiency.	
	PB4	I believe that AI personalized recommendation services can broaden my horizons and help me make better decisions.	
	PB5	I believe that using AI personalized recommendation services can lead to customized discounts or benefits.	
Product Involvement (PI)	PI1	I actively seek relevant information about this product.	[17]
	PI2	This product is something I like and need.	
	PI3	I believe that the product I choose is closely related to my life.	
	PI4	I think choosing this product requires considerable thought.	
Consumer Adoption Willingness (AW)	AWI	I would recommend others to use AI personalized recommendation services.	[9, 81]
	AW2	I am willing to browse products or information recommended by AI personalized recommendation services.	
	AW3	I am willing to purchase items or accept information recommended by AI personalized recommendation services.	
	AW4	Overall, I am willing to browse with the assistance of AI personalized recommendation services.	

3-4- Data Analysis Methods

This study used Partial Least Squares Structural Equation Modelling (PLS-SEM) using SmartPLS 4.0 for data analysis since it is ideal for evaluating complicated models with latent variables and mediating/moderating effects [70]. The analysis was conducted in three stages:

First, data preparation was conducted, including handling missing values (mean imputation for cases with <10% missing data) and identifying outliers via z-score analysis ($|z| > 3.29$, $p < 0.001$), with valid outliers retained because of the robustness of PLS-SEM to extreme values [70].

Second, descriptive statistics (means, standard deviations, and frequency distributions) were produced for core variables and demographic factors to provide a picture of the sample and its distribution.

Third, the measurement model was tested for reliability (Cronbach's α and composite reliability > 0.7) and validity (convergent validity by AVE > 0.5 and factor loadings > 0.6; discriminant validity via HTMT < 0.85) [70].

Finally, the structural model was tested using bootstrapping (5,000 resamples) to examine path coefficients, mediating effects (via indirect effect tests with 95% confidence intervals), and moderating effects (via interaction terms for product involvement). Common method bias was assessed using Harman's single-factor test and VIF values (<3.3) to ensure the robustness of results [75, 76].

4- Analysis and Results

4-1- Descriptive Statistical Analysis

As shown in Table 2, descriptive statistical analysis of 518 valid responses regarding gender, age, region, monthly income, and educational background revealed the following: the gender distribution is balanced, with males accounting for 51.4% and females 48.6%. The age coverage is extensive, with the combined proportion of respondents aged 30-39 (29.5%), 40-49 (22.6%), and 50 and above (34.2%) reaching 86.3%, which echoes the design for sample diversity. In terms of region, 68.3% of respondents are from urban areas, and 31.7% are from rural areas. The monthly income is mainly concentrated in the ranges of 5,001-8,000 yuan (21.6%) and 8,001-12,000 yuan (20.8%), which is in line with the current income level of residents. The educational background is dominated by bachelor's degrees (39.6%), and the respondents as a whole have a good ability to understand the questionnaire. The reasonable sample structure provides a basis for the validity of the research conclusions.

Table 2. Descriptive Information of The Respondents (N=518)

Characteristic	Item	Frequency	Percentage
Gender	Male	266	51.4
	Female	252	48.6
Age	18 - 29 years	71	13.7
	30 - 39 years	153	29.5
	40 - 49 years	117	22.6
	50 - 59 years	116	22.4
	Above 60 years	61	11.8
Region	Urban	354	68.3
	Rural	164	31.7
Average monthly income level	Below 2000	56	10.8
	2001 - 5000 Yuan	98	18.9
	5001 - 8000 Yuan	112	21.6
	8001 - 12000 Yuan	108	20.8
	12001 - 20000 Yuan	96	18.5
	Above 20000 Yuan	48	9.3
Highest education level	High school or below	83	16
	Associate degree	101	19.5
	Bachelor's degree	205	39.6
	Master's degree	86	16.6
	Doctorate or above	43	8.3

The study describes the current usage status of AI-personalised recommendation platforms among respondents from the aspects of the characteristics of AI-personalised recommendation services, the duration of using such AI-personalised recommendations, the frequency of using such AI-personalised recommendation platforms, and the daily time spent on AI personalisation. The detailed results are shown in Table 3. The results show the following:

- First, AI-personalised recommendation services have distinct characteristics, which are reflected in two main: collecting more personal data (164 people, accounting for 31.7%) and providing more accurate suggestions (159 people, accounting for 30.7%).
- Second, regarding the duration of using such AI-personalised recommendations, 44.6% of the respondents indicated a usage period of 3-5 years, and 24.7% of the respondents indicated a usage period of 1-3 years.
- Furthermore, the results of the frequency of using such AI-personalised recommendation platforms show that the highest proportion, 37.3%, use them 2-3 times a week, indicating that the majority of respondents use AI-personalised platforms relatively frequently.
- Finally, in terms of the daily time spent on AI personalisation, the main durations are 30 minutes to 1 hour (193 people, accounting for 37.3%) and 1-2 hours (152 people, accounting for 29.3%).

Table 3. Current Usage Status of AI Personalized Recommendation Platforms (N = 518)

Characteristic	Item	Frequency	Percentage
Characteristics of AI Personalized Recommendation Services	Collect more personal data	164	31.7
	Capable of autonomous learning and self-correction	104	20.1
	Provide more accurate suggestions	159	30.7
	Use more complex algorithms	91	17.6
Duration of Use	Less than 1 year	55	10.6
	1 - 3 years	128	24.7
	3 - 5 years	231	44.6
	More than 5 years	104	20.1
Frequency of Use	Daily	93	18.0
	2 - 3 times a week	193	37.3
	Less than 5 times a month	132	25.5
	Uncertain, use when remembered	100	19.3
Daily Usage Duration	Less than 30 minutes	113	21.8
	30 minutes - 1 hour	193	37.3
	1 - 2 hours	152	29.3
	More than 2 hours	60	11.6

An analysis of platform usage frequency revealed that short-form video applications (e.g., Douyin, Kuaishou; mean score = 3.53) were the most common service context for receiving personalised AI recommendations among respondents. These were followed by social/content platforms (e.g., Xiaohongshu, Weibo; mean score = 2.98), shopping applications (e.g., Taobao, Pinduoduo; mean score = 2.88), and finally travel applications (e.g., Ctrip, Mafengwo; mean score = 2.33). This pattern outlines a clear adoption gradient for AI recommendation systems across different types of digital platforms.

4-2- Common Method Bias Analysis

Common Method Bias (CMB) is the variance that is carried by the measurement variables due to the use of the same method for measuring both the exogenous and endogenous constructs [82]. As all the exogenous as well as endogenous constructs of the study were measured through self-reported data from the same respondents, the CMB threat emerged [83]. Therefore, while analysing the data, the recommendations of Podsakoff et al. [84] were followed to interpret all the measurement items precisely through anonymous questionnaires. Additionally, a Harman's single-factor test was conducted via SPSS 26.0 following Liang et al. [85]. Exploratory factor analysis was performed on all items of the four constructs (perceived accuracy, perceived benefit, consumer adoption willingness, product involvement), with principal component extraction and maximum variance rotation applied to extract factors with eigenvalues > 1.

As shown in Table 4, Common method bias (CMB) was assessed using Harman's single-factor test. Exploratory factor analysis (EFA) with principal component analysis (PCA) was conducted on all 17 measurement items from the four constructs (perceived accuracy, perceived benefit, consumer adoption willingness, and product involvement). As presented in Table 4, the unrotated factor solution was examined. The core criterion of this test is to determine whether a single factor emerges or whether one factor accounts for the majority of the variance. The results extracted multiple components (factors) with eigenvalues greater than 1.0, which is the standard Kaiser criterion for factor retention [86]. In total, four components had eigenvalues above 1 (7.671 to 1.112) and explained 70.637% of the total variance. The first component could represent a common method factor explained 45.124% of the variance. Because less than half of the variance is explained (50%) [75], it can be concluded that no single factor dominates the covariance among the variables. As a consequence, common method bias is not a major issue for the current study.

We acknowledge, however, that the single-factor test by Harman is a relatively simplistic test that cannot rule out common method bias entirely. Thus, various procedural solutions in the design of the surveys helped reduce cases of common method variance; respondents were assured of anonymity and confidentiality, different measures of constructs were administered in different sections of the questionnaires with different wordings and anchors, and predictor and criterion variables were put in different parts of the questionnaire to limit cases of demand characteristics as well as consistency motives. Combined, these procedural controls and diagnostic findings lead to an opinion that common method bias can hardly invalidate the major conclusions of this study, though it cannot be completely ruled out.

Table 4. Results of Harman's single-factor test for common method bias

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	7.671	45.124	45.124	7.671	45.124	45.124
2	1.714	10.083	55.207	1.714	10.083	55.207
3	1.511	8.888	64.095	1.511	8.888	64.095
4	1.112	6.543	70.637	1.112	6.543	70.637
5	0.546	3.212	73.85	-	-	-
6	0.51	2.999	76.849	-	-	-
7	0.496	2.917	79.766	-	-	-
8	0.455	2.679	82.445	-	-	-
9	0.443	2.604	85.05	-	-	-
10	0.422	2.481	87.531	-	-	-
11	0.399	2.345	89.875	-	-	-
12	0.359	2.112	91.987	-	-	-
13	0.349	2.053	94.04	-	-	-
14	0.314	1.849	95.889	-	-	-
15	0.273	1.605	97.493	-	-	-
16	0.23	1.355	98.848	-	-	-
17	0.196	1.152	100	-	-	-

Extraction method: Principal Component Analysis (PCA)

Note: Components 1-4 have eigenvalues > 1 (Kaiser criterion) and are retained. Components 5-17 have eigenvalues < 1 and are not considered substantial factors.

Furthermore, to assess multicollinearity and potential CMB, Variance Inflation Factor (VIF) values were analysed using SmartPLS 4.0. The results revealed that all outer VIF values of measurement items ranged from 1.622 to 2.954, well below the critical threshold of 5 [76]. This suggests that there is no severe multicollinearity among variables, ensuring the reliability of data and the validity of structural relationships. The outer VIF values of all the measurement items are listed in Table 5 for verification. Collectively, these results demonstrate that common method bias does not significantly influence the data validity or research conclusions, providing a solid foundation for subsequent analyses.

Table 5. Collinearity statistics (VIF)

Construct	Measurement Item	VIF
Consumer Adoption Willingness (AW)	AW1	2.246
	AW2	2.457
	AW3	1.916
	AW4	2.954
Perceived Accuracy (PA)	PA1	1.981
	PA2	1.988
	PA3	1.841
	PA4	1.962
Perceived Benefit (PB)	PB1	2.673
	PB2	2.424
	PB3	2.367
	PB4	2.752
	PB5	2.475
Product Involvement (PI)	PI1	2.072
	PI2	1.854
	PI3	1.82
	PI4	1.622

Note: The VIF values are all below the conservative threshold of 3.3 [76], indicating that there are no concerns of multicollinearity.

4-3- Measurement Model Analysis

The reliability and validity of the measurement model were assessed via SmartPLS 4.0. The evaluation encompassed internal consistency reliability, convergent validity, and discriminant validity.

Table 6 shows the results for the internal consistency reliability and the convergent validity. All factor loadings were above 0.7. The composite reliability (CR) values of all the constructs were above the threshold of 0.7, and the average variance extracted (AVE) of each construct is larger than 0.5, which ensures an acceptable level of convergent validity [70].

Table 6. Structural Reliability and Validity Assessment

Construct	Measurement Item	Factor Loading	CR	AVE	Cronbach's Alpha
Perceived Accuracy	PA1	0.835	0.895	0.682	0.844
	PA2	0.831			
	PA3	0.808			
	PA4	0.828			
Perceived Benefit	PB1	0.866	0.931	0.729	0.907
	PB2	0.845			
	PB3	0.841			
	PB4	0.867			
	PB5	0.850			
Consumer Adoption Willingness	AW1	0.857	0.914	0.726	0.874
	AW2	0.844			
	AW3	0.820			
	AW4	0.886			
Product Involvement	PI1	0.849	0.891	0.671	0.836
	PI2	0.818			
	PI3	0.816			
	PI4	0.793			

Table 7 shows the results for the discriminant validity assessment via the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio. For the Fornell-Larcker criterion, the square root of each construct's AVE (diagonal values) is larger than the correlations between other constructs, which ensures the discriminant validity of the constructs. In addition, all HTMT values are below the conservative threshold of 0.85, which offers strong evidence for the discriminant validity of the constructs [70] (Cross-loadings matrix was checked and results can be confirmed that items show the largest loading on their targeted construct).

Table 7. Discriminant Validity Assessment: Fornell-Larcker Criterion (below diagonal) and HTMT Ratios (above diagonal)

Variable	AW	PA	PB	PI
AW	0.852	0.596	0.572	0.513
PA	0.513	0.826	0.569	0.651
PB	0.513	0.5	0.854	0.676
PI	0.441	0.547	0.59	0.819

Note: Diagonal elements (in bold) are the square roots of the AVE. Off-diagonal elements are the latent variable correlations (Fornell-Larcker) or HTMT values.

4-4- Structural Model Analysis

The structural model was evaluated by assessing collinearity, explanatory power, predictive relevance, and the significance of the hypothesised paths. First, variance inflation factor (VIF) values were examined to check for potential multicollinearity issues. As shown in Table 8, all inner VIF values were substantially below the conservative threshold of 3, indicating that multicollinearity does not pose a concern for parameter estimation in this model [70].

Table 8. VIF Values within the Structural Model

Variable	AW	PB
PA	1.536	1.444
PB	1.41	
PI		2.064
PI x PA		1.77

The explanatory power of the model was measured through the coefficient of determination (R^2). As shown in Table 9, the model explains 41.2% of the variance in Perceived Benefit (PB) and 44.7% of the variance in adoption willingness (AW), indicating moderate to substantial explanatory power of the model as recommended by [70]. The model fit is excellent since the Standardised Root Mean Square Residual ($SRMR = 0.042 < 0.08$) and the Normed Fit Index ($NFI = 0.880 > 0.80$) [71] are within acceptable limits.

Table 9. Structural Model Results (Path Coefficients, R^2, and Predictive Relevance)

Variable Path Relationship		β	Standard Deviation	T-value	P-value	95% Confidence Interval		Result
Hypothesis	Path					Lower Limit	Upper Limit	
H1	PA → AW	0.203	0.049	4.126	0.000	0.109	0.303	Supported
H2	PA → PB	0.272	0.062	4.391	0.000	0.146	0.386	Supported
H3	PB → AW	0.261	0.043	6.037	0.000	0.178	0.345	Supported

Note: R^2 (PB) = 0.412, Adjusted R^2 (PB) = 0.409; R^2 (AW) = 0.447, Adjusted R^2 (AW) = 0.443; Q^2 (PB) = 0.395; Q^2 (AW) = 0.383; Model Fit: SRMR = 0.042, NFI = 0.880.

The predictive relevance of the model was tested by employing the Stone-Geisser (Q^2) test using a blindfolding procedure [72]. Since the Q^2 of PB is 0.395 and the Q^2 of AW is 0.383, both well above zero, we can conclude that the model has a predictive relevance for the endogenous constructs [70].

Hypothesis testing results, which are based on the bootstrapping with 5,000 samples, are presented in Table 9 and Figure 3. All hypothesised paths were significant ($p < 0.001$), which gives strong support for the hypothesised relationships. Perceived accuracy (PA) had a significant direct effect on adoption willingness (AW) (β = 0.203, supporting H1) and Perceived Benefit (PB) (β = 0.272, supporting H2). In addition, Perceived Benefit (PB) had a significant direct effect on adoption willingness (AW) (β = 0.261, supporting H3). The positive and significant coefficients for both the direct path from PA to AW and the mediating path from PA to PB to AW show that PB plays a part in mediating the relationship between PA and AW.

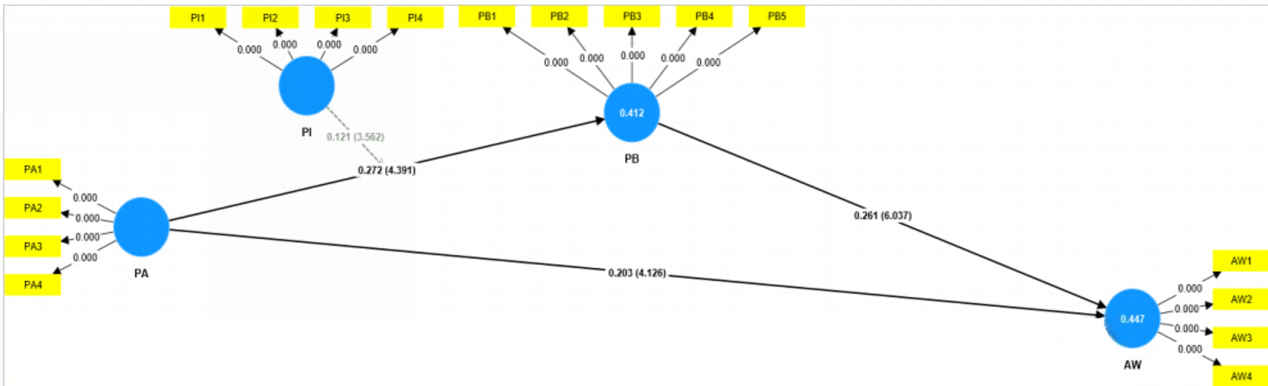

Figure 3. Structural Equation Modeling (SEM) Diagram

4-5- Mediating Effect Test

This study adopted the widely used Baron and Kenny method in academia to verify whether perceived benefit plays a mediating role between perceived accuracy and adoption willingness. The significance of the influence was tested by bootstrapping, combined with the examination and analysis of total indirect effects, specific indirect effects, and total effects for mediating effects.

The mediating effect test results are shown in Table 10:

Mediating path: Perceived Accuracy → Perceived Benefit → Consumer Adoption Willingness

The indirect effect was significant at $p < 0.05$ ($\beta = 0.071$, *t*-value = 3.631, p-value = 0.000, CI = 0.035–0.111), indicating that perceived benefit mediates the relationship between perceived accuracy and consumer adoption willingness. The direct effect was also significant at $p < 0.05$ ($\beta = 0.203$, *t*-value = 4.126, p-value = 0.000, CI = 0.109–0.303). Thus, perceived benefit exhibits a partial mediating effect between perceived accuracy and consumer adoption willingness.

Table 10. Testing the Mediating Effect

Effect	Variable Path Relationship		β	Standard Deviation	T-value	P-value	95% Confidence Interval		Result
	Hypothesis	Path					Lower Limit	Upper Limit	
Indirect Effect	H4	PA→PB→AW	0.071	0.020	3.631	0.000	0.035	0.111	Supported
Direct Effect	H4	PA→AW	0.203	0.049	4.126	0.000	0.109	0.303	Supported
Total Effect	H4	PA→PB→AW	0.274	0.048	5.665	0.000	0.182	0.373	Supported

4-6- Moderating Effect Test

This study treats the moderating variable as a continuous variable, following the common practice in management research, since its data were obtained via questionnaires. Testing the moderating effects requires considering the data type of the moderating variable. When both the moderating variable and the independent variable are continuous, the approach is to centre the independent variable and the moderating variable at their means, construct their product term, and include it in the regression model. The significance of the product term's coefficient is then tested to determine the presence of a moderating effect. The implementation steps of the regression analysis for moderating effect testing are as follows:

Centring Processing**:** Due to potential multicollinearity among variables, both the independent variable and moderating variable are centred. This involves calculating the mean of each variable and subtracting the mean from the original variable to obtain the centred variable.

Constructing the Product Term**:** The centred independent variable is multiplied by the centred moderating variable to form the product term.

Effect Testing**:** Examine the influence of the independent variable and moderating variable on the dependent variable. If the coefficient of the product term is significant, a moderating effect is confirmed.

This study uses Smart-PLS 4.0 data analysis software and employs the bootstrap method to test the moderating model. First, the results of the tests of the moderating effect of product involvement on the relationship between perceived accuracy and perceived benefit are shown in Table 11. Product involvement has a significant direct positive impact on Perceived Benefit ($\beta = 0.563$, *t*-value = 9.963, p-value = 0.000, CI = 0.456–0.676). After the moderating effect of product involvement is incorporated, the interaction term between perceived benefit accuracy and product involvement still has a significant positive effect on perceived benefit ($\beta = 0.121$, *t*-value = 3.562, p-value = 0.000, CI = 0.059–0.193). Therefore, product involvement plays a moderating role in the relationship between perceived accuracy and perceived benefit.

Combined with the significant direct positive impact of perceived accuracy on perceived benefit ($\beta = 0.272$, *t*-Value = 4.391, p-value = 0.000, CI = 0.146–0.386), where both $\beta = 0.272 > 0$ and $\beta = 0.121 > 0$, it can be concluded that product involvement strengthens the positive relationship between perceived accuracy and perceived benefit.

Table 11. Results of the Test on the Moderating Effect of Product Involvement between Perceived Accuracy and Perceived Benefit

Variable Path Relationship		β	Standard Deviation	T-value	P-value	95% Confidence Interval		Result
Hypothesis	Path					Lower Limit	Upper Limit	
	PA → PB	0.272	0.062	4.391	0.000	0.146	0.386	
H5	PI → PB	0.563	0.057	9.963	0.000	0.456	0.676	Supported
	PA*PI → PB	0.121	0.034	3.562	0.000	0.059	0.193	

4-7- Multigroup Testing

In terms of age, this paper classifies the respondents into different groups. Specifically, those aged 18-49 years are categorised into the youth group, whereas those aged 50 years and above are classified into the middle-aged and elderly groups. The study examines the performance differences between these two groups across various paths, and the results are presented in Table 12. Finally, the hypothesis path coefficient test results for the two age groups are obtained. The results show the following:

Table 12. Path Coefficient Estimates from Multigroup Analysis of Respondents' Age Groups

	Path	Youth Group			Middle-aged & elderly groups			Path Difference	Significance
		Standardized Coefficient	T	P	Standardized Coefficient	T	P		
H1	PA → AW	0.240	4.028	0.000	0.129	1.567	0.117	0.111	0.278
H2	PA → PB	0.308	4.300	0.000	0.136	1.224	0.221	0.172	0.196
H3	PB → AW	0.277	5.382	0.000	0.240	3.341	0.001	0.037	0.676
H4	PA→PB→AW	0.085	3.374	0.001	0.033	1.128	0.259	0.052	0.170
H5	PA*PI → PB	0.124	2.695	0.007	0.084	1.554	0.120	0.040	0.566

Perceived Accuracy → Adoption Willingness (PA → AW): Under the moderating effect of age, there is no significant difference in the positive impact of perceived accuracy on adoption willingness ($P = 0.278 > 0.05$). Combining the path coefficients, it can be seen that the youth group perceives a slightly greater positive impact ($\beta = 0.240$, $p = 0.000$) than the middle-aged and elderly groups do ($\beta = 0.129$, $p = 0.117$).

Perceived Accuracy → Perceived Benefit (PA → PB): There is no significant age-related difference in the positive effect of perceived accuracy on perceived benefit ($P = 0.196 > 0.05$). The youth group reported a greater positive effect ($\beta = 0.308$, $p = 0.000$) than did the middle-aged and elderly groups ($\beta = 0.136$, $p = 0.221$).

Perceived Benefit → Adoption Willingness (PB → AW): No significant age difference is found in the positive impact of perceived benefit on adoption willingness ($P = 0.676 > 0.05$). The youth group exhibited a slightly greater positive effect ($\beta = 0.277$, $p = 0.000$) than the middle-aged and elderly groups ($\beta = 0.240$, $p = 0.001$).

Mediation Effect: PA → PB → AW: The mediating role of perceived benefit between perceived accuracy and adoption willingness does not differ significantly by age ($P = 0.170 > 0.05$). The youth group had a slightly stronger mediating effect ($\beta = 0.085$, $p = 0.001$) than did the middle-aged and elderly groups ($\beta = 0.033$, $p = 0.259$).

Moderation Effect: PA*PI → PB: The moderating role of product involvement between perceived accuracy and perceived benefit does not differ significantly by age ($P = 0.566 > 0.05$). The youth group reports a slightly stronger moderating effect ($\beta = 0.124$, $p = 0.007$) than the middle-aged and elderly groups ($\beta = 0.084$, $p = 0.120$).

The detailed path structures for the youth groups and the middle-aged and elderly groups are illustrated in Figures 4 and 5, respectively.

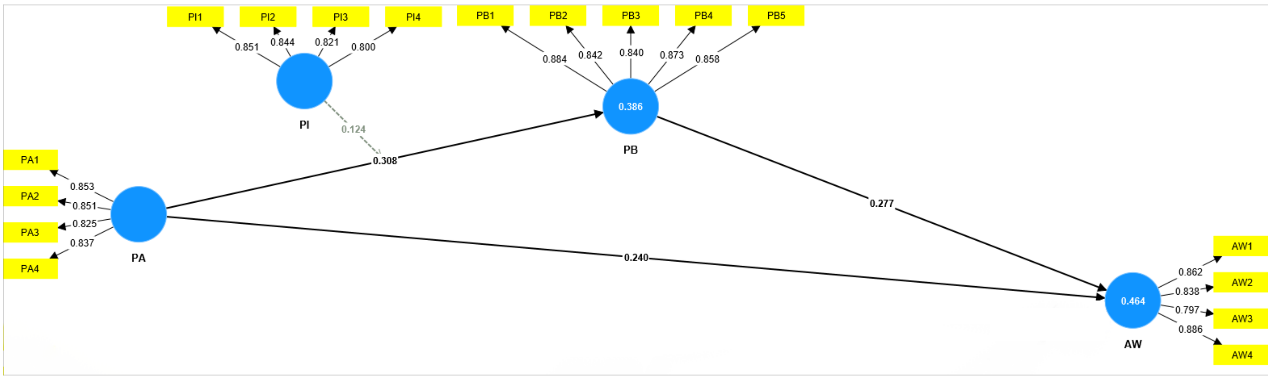

Figure 4. Path Test Results of the Youth Group

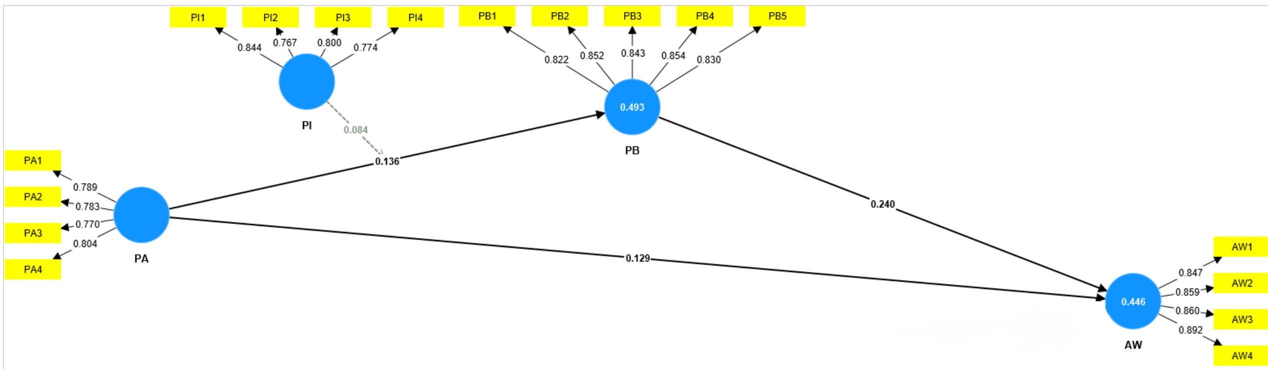

Figure 5. Path Test Results of the Middle-aged and Elderly Groups

5- Discussion

5-1- Findings

Based on the technology acceptance model (TAM) and product involvement theory, this paper takes a PLS-SEM analysis of 518 valid survey respondents and draws the following conclusions.

Perceived accuracy has a positive impact on consumer adoption willingness. When users believe that the recommended content matches their needs, users recognise the functional value of personalised matching recommendations, as they help in making efficient decisions by saving time, which leads to cognitive pleasure. The data analysis results show that the increase of 1 unit in the perceived accuracy will lead to the increase of 20.3 percentage points in adoption willingness, which proves that the "perceived usefulness" plays a central role in TAM.

Perceived benefit plays a key mediating role in the above relationship and establishes a transmission path of "accurate recommendations → enhanced perceived benefit → increased adoption willingness". Specifically, accurate recommended content can reduce information search cost (37.3% of users report daily use of 30–60 minutes, suggesting that accurate recommendations may substantially reduce perceived search effort), optimise decision quality (31.8% of users think the efficiency has been improved), and generate a sense of personalised satisfaction. The net benefit perception finally transforms into usage intention.

Product involvement has a positive moderating effect on the relationship between perceived accuracy and perceived benefit. For high-involvement products such as luxury goods and electronic products, users will digest recommendation information more deeply and treat accuracy as a decision-aiding tool. According to the findings, the influence of perceived accuracy on perceived benefit will be enhanced by 12.1%. This is because when buying high-involvement products, consumers make high-risk purchases and value more the certainty brought by a recommendation system. Therefore, they will spend more cognitive resources on recommendation information.

Furthermore, multigroup analysis results show that there is a trend that young users (18-49) may have stronger path coefficients compared to old users (more than 50 years old) in the model and the relationship between perceived accuracy and perceived benefit ($\beta\_young=0.308$ vs $\beta\_old=0.136$), and the moderating effect of product involvement ($\beta\_young=0.124$ vs $\beta\_old=0.084$). However, multigroup analysis did not show significant differences (all $p>0.05$). The fact that young users have consistently shown stronger path coefficients is suggestive and needs further research.

5-2- Discussion

5-2-1- The Relationship Between Perceived Accuracy, Perceived Benefit, and Adoption Willingness

This study shows that perceived accuracy (PA) has a significant and positive direct and indirect effect on adoption willingness (AW). The direct effect shows the rationale that in addition to content agreement, PA also indicates user trust in the system and a decreased perception of uncertainty, particularly in a digital context where recommendation overload is prevalent. As found by Kim et al. [11] and Yin et al. [9], accuracy is a heuristic signal that increases trust and enables users to make intuitive choices, which explains why PA positively influences AW independently from value evaluation. Along similar lines, Lim et al. [7] found that PA has a significant positive effect on adoption willingness in AI banking services, which further confirmed that PA was an important cross-domain determinant of trust and adoption.

The indirect effect through perceived benefit (PB) follows the logic of expected value maximisation that helps users internalise the value of accurate recommendations in terms of saved time, reduced search cost, and increased satisfaction [87, 88]. This not only validates and extends TAM [10] but also further deepens it because PA is an important antecedent of perceived usefulness, represented by PB. While traditional TAM focuses on perceived usefulness and ease of use in general system contexts, our study identifies accuracy as a contextual predictor of usefulness in the specific system context of a personalised recommendation system based on AI. This differs from previous studies, such as Ding et al. [45], which found that emotional benefits are the most important pathway. Our results instead show that functional benefits prevail in a commerce platform, which is functionally driven by the business context of the system. In line with this, Wang et al. [8] reported that efficiency benefits such as time savings and convenience were decisive in driving adoption of AI in purchasing functional food, further supporting our results.

Moreover, the results show that PB is not unidimensional. Although the measurement scale in this study only focused on functional value (decision efficiency, reduction of search cost), based on user feedback and previous literature [18], emotional benefits (satisfaction, personalisation, being understood) cannot be ignored, as they take a large proportion of perceived value. This partially agrees with Fong et al. [57], who found that in a low-involvement context, emotional value is more important. However, the findings show that in a high-stakes context within an e-commerce setting, functional benefits prevail, which differs from previous work. Recently, work by Yin et al. [9] also supports the findings of this study, which showed that consumers' perceived heterogeneity in their preferences and seek different types of hedonic and functional benefits in their responses to AI recommendations.

Our results extend Zhang & Xiong [89] by positioning value not only as an outcome but also as a mediating process between PA and AW. Similarly, Park & Son [36] found that consumption goals moderate the effect of how accuracy leads to adoption; that is, the formation of value is context-specific. Our study connects these two lines of works by showing the structured unpacked TAM pathway PA → PB → AW.

5-2-2- The Moderating Mechanism of Product Involvement

The moderating role of product involvement (PI) is reinstated, i.e., the positive influence of perceived accuracy (PA) on perceived benefit (PB) is significantly higher when it applies to high-involvement products compared to low-involvement products. This implies that when consumers encounter products which they consider significant or risky, then relevant AI suggestions are further enhanced at producing convenience, value and reassurance sentiments, whereas in the instance of low-involvement items, even relevant suggestions have a sluggish effect on boosting perceived benefit. Our theoretical choice to position PI on the PA → PB link instead of the PB → AW link is supported by the empirical observation: involvement primarily moderates the perception of the informational value of accurate recommendations, but the effects of perceived benefit on adoption willingness through the levels of involvement are very strong. This finding is consistent with Jing & Wang [43], who demonstrated that the technical accuracy of AI recommendations was vital for loyalty in high-risk tourism purchases.

In addition, the multigroup analysis reveals a trend suggesting that younger users may be more responsive to recommendation accuracy for high-involvement products. Although this difference did not reach statistical significance, it may be associated with their greater digital literacy and preference for autonomous decision-making, echoing insights from Zhao & Wagner [88] on generational patterns in technology adoption. As digital literacy is known to influence how users process recommendation information, younger users' higher cognitive flexibility and familiarity with digital interfaces make them more responsive to nuanced variations in recommendation precision. This only partially contrasts with prior evidence from low-involvement contexts, where perceived value or benefit has been found to play a more dominant role in driving adoption decisions than detailed diagnostic cues [19]. Our results suggest instead that high-involvement conditions heighten the salience of PA, especially among younger digital natives. Ding et al. [45] further support this by showing that younger users on Douyin place heavier weight on PA than older cohorts, who rely more on brand heuristics.

Furthermore, older users are more likely to depend on heuristic cues or prior experience because of their lower digital literacy, which in turn decreases their sensitivity to recommendation accuracy. In this respect, the results of Zhang et al. [89], who demonstrated that the digital literacy difference among older and younger consumers affects their sensitivity to personalised recommendations, are aligned with our findings. Furthermore, these results are also in line with the results presented by Suryadi et al. [90], who demonstrated that knowledge and innovativeness moderate trust and attitudes in AI adoption. Extending this line of reasoning to our context, digital literacy and decision styles appear as two boundary conditions explaining the heterogeneous impact of PI across users. Future research should explicitly test these two constructs to shed light on the heterogeneous impact of PI across user segments.

To conclude the discussion section, the findings of this study are broadly consistent with prior research while also extending it to several important respects. Consistent with earlier studies on AI-powered recommendations [7-9, 16], perceived accuracy shows a robust direct and indirect impact on adoption willingness. However, our results advance this literature by unpacking the internal mechanism: rather than treating accuracy as a simple predictor, we demonstrate that its influence operates primarily through perceived benefit, thereby clarifying the "accuracy → value → adoption" chain that earlier studies implicitly assumed but did not empirically specify. Furthermore, while previous research typically positioned product involvement as a moderator of the usefulness–intention link [39-42], our findings reveal that involvement already shapes the earlier cognitive stage in which users interpret accuracy cues and form benefit appraisals. This upstream boundary condition offers a more refined understanding of how product characteristics interact with AI recommendation accuracy. Finally, although some studies have identified age-based differences in technology adoption [22, 23], our multigroup analysis suggests that the core accuracy-to-benefit mechanism is stable across age segments, indicating that older users evaluate recommendation accuracy in ways similar to younger users once they engage with the system.

6- Conclusions

6-1- Theoretical Contributions

The first contribution relates to extending TAM in AI personalisation scenarios. This research extends the application of the Technology Acceptance Model by specifying perceived accuracy as a particular antecedent of perceived usefulness in personalised recommendation scenarios. By showing the path PA → PB → AW, we address the historical neglect of accuracy in personalised systems and provide a more precise filter for user acceptance in the delivery of algorithms.

The second contribution relates to illuminating the mediating process of perceived benefit. By empirically testing the mediating process of PB, we illuminate how the recommendation quality (PA) leads to the user-perceived benefit (PB) and eventually to behaviour (AW). The study bridges the system attributes (from a more macro perspective) and user outcomes (from a more micro perspective) to extend both the TAM and AI personalisation literatures.

The third contribution relates to clarifying boundary conditions of PI. The moderating effect of PI not only can support the classic involvement theory but also can have the risk-based interpretation, i.e., the PA change to PB has a larger slope when the perceived risk is high. This contribution explains when and why the recommendation accuracy matters more.

This study offers an extension of TAM in a contextualised manner; namely, we find perceived accuracy is a fundamental antecedent of perceived usefulness in AI recommendation scenarios. We show the path of PA → PB → AW and provide a more precise mechanism that explains how users form their usefulness perceptions in algorithmic environments. Compared with directly applying TAM to the AI context, we specify what the usefulness perceptions come from rather than simply exploring the correlation between usefulness perceptions and adoption outcomes.

6-2- Managerial Implications

The first contribution relates to improving recommendation algorithm accuracy. As shown in the study, users expect the recommended products to be accurate. In addition to improving the accuracy of recommendation algorithms, the platform should further improve the degree of match between the recommended products and user needs by continuously improving algorithm models based on multi-dimensional user profiles (including interests, usage scenarios, and historical behaviours) to increase the user sense of "recommendation relevance" and enhance their adoption willingness.

The second contribution relates to improving communication of perceived benefit. The benefits brought by accurate recommendations should be concretely reflected in the user interface. For example, in addition to technical descriptions, messages such as "Through this recommendation, you save about 18 minutes of search time" or "Based on your preferences, we have found 6 most relevant options" should be included to translate technical benefits into user-perceivable benefits.

The third contribution relates to using involvement-differentiated strategies. For high-involvement products (such as electronics, luxury goods, automotive, and travel services), the platform should provide comprehensive recommendation rationales, including detailed comparisons of product parameters, summaries of user reviews, and clear explanations of "why this product matches your needs". Increasing information depth enables users to understand the accuracy of recommended products and makes them better equipped to make purchasing decisions in high-risk purchase contexts.

For low-involvement products (such as fast-moving consumer goods and daily necessities), the platform should focus on improving efficiency and convenience in making recommendations. Recommendation logic should be simplified as much as possible, and the cognitive load of users should be reduced as much as possible. Emphasis should be placed on the time-saving benefits, and the focus should be on making purchasing easier rather than providing extensive product information.

The fourth contribution relates to using age-based considerations for personalised experiences. Although there was no significant statistical correlation between age and product accuracy perception, the trend showed that young users are more likely to be satisfied with product accuracy. Therefore, for user groups with different age structures, more detailed technical comparisons can be presented for young users, and more information on trustworthiness and reliability can be provided for older users.

6-3- Research Limitations and Future Prospects

There are also several limitations in this study that provide rich extension points for future research.

Firstly, the research model in this study only considers the influence of perceived accuracy on users, and other important recommendation qualities, such as serendipity and diversity, were not involved. Future studies can extend the research model to include these dimensions for a better understanding of how multi-faceted recommendation quality affects user adoption.

Secondly, the finding was based on a non-probability convenience sample, as it was distributed online, making any rigid statistical generalisability of the findings impossible. Although the weakness of the identified relationships is supported by the heterogeneous composition of the sample and the theory-driven approach of the structural model, future research might use the probability-based or panel design of a sample or replicate the model across countries and platform settings. This will support the robustness of identified relationships and the number of dimensions. The identified relationships are not specified in this study. Future studies could also employ stratified sampling by age to ensure more balanced representation across younger and older cohorts.

Thirdly, the measurement of perceived benefit only considered consumers' overall benefit evaluation and did not separately include subconstructs for functional and emotional benefits. Even though our unitary measure is consistent with previous studies, where one thought of perceived benefit or perceived usefulness provides a unitary measurement and reduces to the empirical measure of the single-factor structure of the benefit items, further studies can develop independent but parallel scales on functional and emotional benefit to understand whether the former and the latter have different mediation roles in the process of adoption.

Fourthly, although three multigroup analyses by age showed some suggestive results (i.e., users of different ages may be more sensitive to recommendation accuracy, especially for high-involvement products), statistically significant differences were not found. Future studies can either use a much larger balanced sample of age groups or employ experimental/longitudinal designs to further explore whether there are significant differences in the moderating effect of age. It would also be interesting to explore what factors may cause such differences, e.g., digital literacy, formation of trust, differences in needs and decision-making processes/preferences across generations.

Fifthly, product involvement was confirmed as a significant moderator, but the study did not differentiate the types of high-involvement products (e.g., luxury goods, electronics, etc.). These products may have different risk perceptions and decision processes. Future studies can further explore whether the moderating effect varies for different types of products with different attributes.

Sixthly, in line with our accuracy-centred extension of TAM, this study did not explicitly model Perceived Ease of Use (PEOU); future research could integrate PEOU and additional system-quality constructs into the PA–PB–AW chain to further enrich the comprehensiveness of the extended TAM framework in AI recommendation scenarios.

Finally, this study primarily used Harman's single-factor test and procedural remedies to address the issue of common method bias. While these approaches are widely used, they are less powerful than more advanced techniques such as marker-variable methods or latent-variable factor modelling. Future research could incorporate theoretically unrelated marker variables or apply confirmatory factor analysis with an explicit method factor to provide a more rigorous assessment of common method variance in AI recommendation contexts.

In summary, this study proves that the perceived accuracy of AI-personalised recommendations has a positive impact on consumer adoption willingness through perceived benefit, and the process is moderated by product involvement. This conclusion provides a theoretical basis for platforms to balance technical accuracy and user value perception in providing personalised recommendations to help build a personalised recommendation system for users.

7- Declarations

7-1- Author Contributions

Conceptualization, X.Z., S.P., and P.P.; methodology, X.Z., S.P., and P.P.; software, X.Z.; validation, X.Z.; formal analysis, X.Z. and S.P.; investigation, S.P. and P.P.; resources, S.P.; data curation, S.P., P.P., and A.K.; writing—original draft preparation, X.Z., S.P., P.P., and A.K.; writing—review and editing, X.Z., S.P., P.P., and A.K.; visualization, X.Z.; supervision, S.P. and P.P.; project administration, X.Z. and S.P. All authors have read and agreed to the published version of the manuscript.

7-2- Data Availability Statement

Data available on request due to restrictions (e.g., privacy or ethical issues): The data presented in this study are available on request from the corresponding author. The reason why the data are not publicly available is that the data of this study contain the personal sensitive information of human subjects (such as consumers' privacy perception feedback on AI personalized recommendations, personal usage habits, and other private data related to the research topic).

7-3- Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

7-4- Institutional Review Board Statement

This study was conducted in accordance with the Declaration of Helsinki and was approved by the Human Research Ethics Committee of Walailak University (Approval Number: WUEC-25-143-01; Date of Approval: 30 April 2025). The study protocol for the project titled "The Double-Edged Sword Effect of AI Personalized Recommendations: A Study on The Dual Effects of Accuracy and Privacy Invasion on Consumers' Adoption Willingness" (Project No. WU-EC-GS-0-115-68) was reviewed and approved prior to data collection.

7-5- Informed Consent Statement

Informed consent was obtained from all subjects involved in the study.

7-6- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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