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Article

The impact of AR-enabled try-on experiences on consumer purchase decisions: the moderating role of AI-powered recommendation agents

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ABSTRACT

This study investigates how AR try-on functionalities affect consumer purchase behaviors in terms of psychological empowerment processes and uses AI recommendation attributes as boundary conditions. Drawing on skill acquisition theory and dual-process theory, this study hypothesizes a dual-pathway model in which AR interactivity influences perceived control, AR immersion influences perceived value, and both perceptual phenomena influence purchase intention positively. Using the techniques of structural equation modeling and multi-group analysis, data were collected from 500 Chinese consumers through three major e-commerce platforms (Tmall, JD.com, Dewu). The results show that perceived control is a mediator between AR interactivity and purchase intention (indirect effect = 0.406, 95% CI [0.324, 0.495]), and perceived value is a mediator of the relationship between AR immersion and purchase intention (indirect effect = 0.474, 95% CI [0.389, 0.566]). AI-AR integration level significantly enhances the interactivity-control pathway ($\Delta\chi 2 = 12.87$, $p < .001$), while AI feedback timeliness amplifies the immersion-value pathway ($\Delta\chi 2 = 10.34$, $p < .001$). These findings imply that the combinations of AR and AI technologies have impacts on consumer decision-making and that the characteristics of AI technology act as boundary conditions. This research has theoretical implications for technology-based consumer empowerment and provides some usable advice on how to better integrate AR-AI technology in online shopping.

1. Introduction

The digital transformation in the retail industry has profoundly affected how consumers make purchases. A challenge in online shopping is that consumers cannot feel the items they intend to purchase before initiating the transaction. Augmented Reality has demonstrated considerable capacity to address the trade-off between the convenience of online shopping and the tangible nature of items available through offline channels. AR technology has enabled consumers to visualize items in their real-life context before making a purchase through try-out options available on leading e-commerce sites [1]. The Chinese e-market has enabled leading e-platforms such as Tmall, JD, and Dewu to indulge in the AR functionality domain, thus allowing consumers to experience an untouched domain that replicates the procurement process undertaken at offline shopping malls [2]. Of course, this has been a challenge that has existed ever since the advent of e-commerce domains. At the same time, there have been improvements in augmented reality, and the use of artificial intelligence in recommendation systems has increased significantly, enhancing the ability to understand consumer behavior and predict their preferences [3]. The system uses sophisticated algorithms, which interpret large bodies of data, including browsing, purchase, and demographic-related tasks, to create personalized recommendations for products. The combination of the graphical capabilities of augmented reality and the recommendations generated through it indicates a revolution in the formulation of digital marketing strategies. Retailers that have implemented this technology have reported a marked increase in consumer metrics related to augmented reality applications [4]. However, the combination of these technologies is currently at a very nascent stage, indicating a substantial gap in acceptance across platforms. In AR-enabled environments, a notable departure from customer behavior in other online shopping interfaces is that interactivity enabled in AR has been shown to enhance perceived control during the product evaluation process [5]. The immersive quality of AR stimuli tends to elicit cognitive and affective responses associated with decision-making tasks [6]. Research studies dealing with three-dimensional product presentations have revealed that high-quality visual presentations lead to a favorable influence on brand attitudes and obtaining product-related information [7]. The customer experience in the context of AR mediation involves touch points that differ significantly from traditional online buying behaviors [8]. This poses fundamental issues for retailers seeking to optimize returns for technology investment

Despite growing research on the applications of AR in retail environments, several gaps still in the existing body of knowledge. The majority of the knowledge that has been produced so far on the applications of AR and AI has treated each of these as a distinct phenomenon [9]. Previous studies have focused primarily on the adoption of technology and subsequent behaviors, with relatively less focus on the underlying psychology that links the attributes of AR to behaviors. Cross-cultural studies are relatively rare, and the Chinese market in particular presents unique patterns of adoption when compared to the Western market [10]. There is a lack of empirical studies on the moderating role of characteristics of AI recommendations in mediated experiences of AR. Current research on the combination of AI and augmented reality in e-commerce has started to address this issue, yet there is a lack of adequate exploration of psychological empowerment processes.

This study focuses on the gaps by analyzing how the AR try-on feature affects consumer purchasing behaviors through psychological empowerment, and at the same time, considering the role of characteristics of AI recommendations. Drawing upon skill acquisition theory [11] and dual-process models of cognition [12,13], the current research proposes a model detailing two channels—interactivity-control and immersion-value—along which the impacts of AR features on purchase intentions proceed. The proposed model has been verified using a survey of 500 Chinese consumers on the three most popular e-commerce sites. Contributions of this study include advancing knowledge in human-technology interactions in retail environments by applying theories of skill acquisition together with dual process cognition to investigate AR-facilitated processes of consumer empowerment. This research reveals specific boundary conditions, such as the level of AI-AR integration and the timeliness of AI feedback, under which AR features lead to even stronger effects on psychological outcomes, adding to the literature of AI-AR synergy [14,15]. This research offers practical recommendations for improving e-commerce platforms in developing countries and applies in a unique Chinese internet context. The integration of a psychological empowerment approach and a focus on a unique Chinese context are distinctive features that distinguish this work from other research that examined AR and AI in isolation.

2. Theoretical framework and hypotheses

2.1 Theoretical foundations

This research integrates two theories to understand the psychological processes by which augmented reality try-on experiences shape consumers' purchase decisions. Skill acquisition theory explains how skills developed from technology use enhance control, whereas dual-process theory explains how the nature of augmented reality stimulates the simultaneous use of analytical and intuitive problem-solving processes for value determination.

Skill acquisition theory was first postulated by Fitts and Posner [11] and describes the process of learning through three different levels: cognitive, associative, and autonomous. At the cognitive level, people study the mechanics and rules of interaction within the system. With the advancement of the user into the associative stage, the user refines their engagement techniques. When the user reaches the autonomous stage, engagement occurs systematically and habitually. In regard to shopping facilitated by the technology of AR, the first engagement relates to the virtual try-on capabilities that are made possible through deliberate processing. These processes entail actions like rotation and manipulation of parameters. As engagement continues to take place, the first stage of engagement will develop into mastery of the interface of the AR system. The development of mastery of the interface will directly affect engagement and control since users will develop mastery and competence in their capability to evaluate the product themselves [16]. The theory of skill acquisition underscores that interactivity of the user in the AR will enhance user control of shopping because of the manipulation of the product while acquiring skills.

The dual-process theory provides further explanation of the cognitive processes at play while engaging in AR. The dual-process theory defines two channels of information processing, namely System 1, which is driven by fast, intuitional, and automated responses to sensory inputs, and System 2, which is driven by slow, analytical, and deliberate processing of information [12,13]. What makes AR technology special is its simultaneous use of these two channels. The visual realities captured in AR, as well as the spatial anchors embedded in AR immersion, trigger a rapid affective processing of products in a very intuitive manner via System 1 as consumers subconsciously judge product-environment fit. Simultaneously, AR's interacting manipulation capabilities also require analysis through System 2 processing; hence, it becomes easy for a consumer to assess product characteristics such as size, color, or fit. This combination of processing is very different from the current conventional online shopping site that exclusively deals with static image processing. Immersive AR interaction facilitated by system 1 thinking supports indirect development of experiential knowledge. According to dual-process theory, immersion in AR creates a sense of product reality; hence, perceived value increases.

The integration of the proposed theories would provide a thorough rationale for the dual-pathway model. The skill-acquisition theory would explain the immersion-value pathway. When acquiring skill proficiency in AR, the development of self-reliance in autonomous decision-making takes place, which would come into play as perceived control. On the other hand, dual-process theory would explain the immersion-value pathway. AR contributes to immersive experiences that drive the consumer to make intuition-driven judgments, leading to an increased perceived product value. All these theoretical explanations jointly clarify that psychological empowerment, as a mediator that captures perceived control and perceived value, represents an essential linking mechanism from AR features to purchase intentions.

2.2 AR technology features and psychological empowerment

Building on the theoretical foundations outlined above, hypotheses will be formulated below linking aspects of AR technology to the psychological empowerment process as the dependent variable. Two key AR attributes —interactivity and immersion— are hypothesized to positively contribute to purchase intentions through different, but complementary, empowerment processes: perceived control and perceived value, respectively.

AR interactivity is the level at which the consumer is able to manipulate the virtual representation of the product within the AR interface. This manipulation includes actions such as the ability to turn the product around and change the colors and size [17]. Unlike passive evaluation of static images, interactivity in AR allows self-testing, which enables consumers to control both information access and evaluation processes. This active manipulation of information changes the focus of evaluation from pre-arranged displays in a store to evaluation in accordance with personal criteria [18].

Perceived control refers to consumers' belief in their own capability and freedom to exclusively seek information and make confident purchasing decisions. Research on interactive web platforms has noted that user-controlled interfaces can increase perceived control as they allow consumers to gain adequate information to make confident decisions [5]. In the context of shopping via AR, mastery of interaction functions will strengthen consumers' confidence in product evaluation and reduce the uncertainties that often prevent them from making online purchases. With the consumers being able to navigate the interface to get the information they want, their control perceptions will improve. This attitudinal level of control subsequently increases the motivation for making a purchase because the consumer exercises personal judgments about the suitability of the product. The following hypotheses are offered:

H1a: AR interactivity positively influences perceived control.

H1b: Perceived control positively influences purchase intention.

H1 (Mediation): Perceived control mediates the positive relationship between AR interactivity and purchase intention. This mediation hypothesis is supported when both H1a and H1b are significant.

AR immersion refers to how well virtual goods are incorporated into customers' surroundings so that a sensation of presence is created [17]. Through the application of AR technology, the consumer has a unique opportunity to visualize the furniture piece or the cosmetic on their face, enabling the translation of the product specifications into experiential knowledge. This assists in narrowing the experience divide that occurs in the case of e-commerce. It is perceived value that is referred to as the consumers' general product benefit assessment, accomplished through the process of benefit accrual compared to costs, including reduced uncertainty about the product's appropriateness [19]. Consumer confidence in the product's future performance is increased by the vivid and lifelike presentation facilitated through AR immersion. The lowering of uncertainties associated with product appearance and performance within real-world settings created by immersion can help to decrease risks involved with online buying. In addition, the richness of immersive AR experience triggers a positive affective reaction going beyond functional assessment [6]. Highly immersive consumers perceive high value, as they expect increased benefits from improved product and fit attributes and lower costs because of reduced returns. High perceived value is positively related to purchase intentions. The following hypotheses are therefore posited:

H2a: AR immersion positively influences perceived value.

H2b: Perceived value positively influences purchase intention.

H2 (Mediation): Perceived value mediates the positive relationship between AR immersion and purchase intention. This mediation hypothesis is supported when both H2a and H2b are significant.

2.3 The moderating role of AI recommendation characteristics

Having established the direct correlations between AR features and psychological empowerment, the next section will examine the role that recommendation systems combined with artificial intelligence might have on the potential amplification of these variables by optimizing the responsiveness of the purchasing process. Two variables related to artificial intelligence will function as boundary variables that will increase the correlations between AR and psychological empowerment variables.

The degree of integration for AI-AR indicates how well AI recommendation systems incorporate data generated from real-time AR interactions exhibited by the consumers [20]. A high degree of integration indicates that the AI engines can easily discover consumers' behavior with regard to product exploration and test times and attributes manipulated during the AR interaction. Low integration happens where the AI suggestions are not specific to the AR interactions.

Justification for using integration level as the moderation variable can be found in existing research studies that prove perceived system responsiveness augments user control [15]. If AI recommendation outputs correlate highly with consumer behaviors in AR manipulation, this means that instead of an outside restriction, consumers experience AR interactivity as an extension of their exploratory process. This further enhances the autonomy that interactivity in AR enables. As far as customers are concerned, they feel they play an active role in influencing the recommendations they make, thus supporting the association between manipulation efforts and information outcomes. Poorly integrated systems with generic recommendations unrelated to AR interactions may impair control benefits by undermining interactivity in AR.

Alternative attributes for AI impact processes through different means. Accuracy affects trust in results instead of managing processing control. In addition, explainability is linked to transparency instead of agency [15,21]. However, the level of integration is directly related to the sensitivity of the whole system to the various user behaviors. This research presents the following hypothesis:

H3: AI-AR integration level positively moderates the relationship between AR interactivity and perceived control, such that the positive effect of AR interactivity on perceived control is stronger when the AI-AR integration level is high.

The timeliness of AI feedback refers to the speed at which the recommendation systems, aided by artificial intelligence, react to the activities of consumers in the AR environment [15]. The speed is high if instantaneous changes in recommendations as consumers interact with AR functionality, creating a fluid interactive process, and low timeliness if there are delays before a response is observed, disrupting the interactive process.

The use of feedback timeliness as a moderator is supported by the study on cognitive flow and immersion [22]. Feedback from artificial intelligence keeps the continuity of immersion going by providing intelligent suggestions at the point of time when the consumer needs assistance and is not distracted from the evaluation process. Since immediate feedback is provided in the AI output, system enhancement is seamlessly integrated into the AR environment experience, rather than being presented as an interrupt. This impacts positively on immersion, which is a motivator of value perception, while it also highlights the responsiveness of the immediate needs of consumers. Since feedback is delayed, immersion is interrupted, thus making a less noticeable correlation between the vividness of AR images and value.

With respect to AI features, timeliness plays a special role in mediating immersion effects, as immersion arises from continuous sensory engagement [6]. This work proposes that timeliness directly affects whether the recommendation process maintains or disrupts immersive flow, whereas accuracy and explainability have greater effects on recommendation quality and understanding, respectively. A hypothesis based on this is as follows:

H4: The timeliness of AI feedback has a positive moderation effect on the relationship between AR immersion and perceived value, since the positive association between AR immersion and perceived value is enhanced when the timeliness of AI feedback is high.

2.4 Research model

Figure 1 illustrates the conceptual research framework that combines the underlying theoretical foundations and proposed relationships outlined in the previous sections. The research framework comprises two pathways through which the presence of features in AR technology affects consumer purchasing intentions via mechanisms of psychological empowerment. The interactivity-control pathway posits that AR interactivity will heighten perceived control (H1a), thereby strengthening purchase intention (H1b), with perceived control as the mediating variable (H1). The immersion-value pathway posits that AR immersion will heighten perceived value (H2a) and strengthen purchase intention (H2b), with perceived value as a mediating variable (H2).

The proposed framework also incorporates AI-recommendation features as boundary conditions. The degree of AI-AR integration is hypothesized to moderate the interactivity-control pathway, such that the effect of AR interactivity on control is strengthened by high AI-AR integration (H3). The timeliness of AI system feedback is proposed to moderate the immersion-value pathway, such that the effect of AR immersion on value is strengthened by the timeliness of AI feedback (H4). This unifying theoretical framework describes how the capabilities of AR visualization and the personalization functionality of AI combine to shape the modern digital shopping experience. The mechanism underlying the proposed model is based on the specification of the boundary conditions that concern the capabilities of AI and the importance of the timing factor.

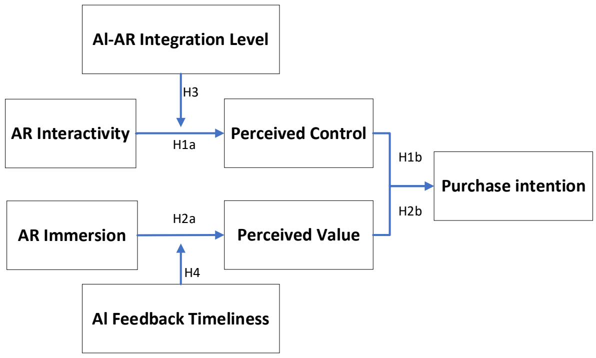

Figure 1. Conceptual research model

3. Methodology

3.1 Research design

This study employs a quantitative cross-sectional research design to examine the psychological processes by which the presence of AR technology features influences consumer buying behavior in China [25]. The research was conducted on three popular e-commerce sites, namely Tmall, JD.com, and Dewu, which are famous for incorporating virtual try-on functionality enabled by AR technology for the beauty and apparel sectors. In this experiment, ecological validity was enhanced by actively recruiting consumers with a real-world AR try-on experience rather than assigning them to an experimental condition only. The categories of products-beauty (lipstick and foundation) and clothing (footwear and apparel)-studied here were among the ones showing the highest level of AR development in the Chinese market.

The design of the research focuses on the features of the technology itself in terms of interactivity and immersion within the context of AR technology. These features are considered the central determinants of consumer psychological empowerment, while AI recommendation features, including the integration level and timeliness of feedback, serve as conditions that moderate consumer outcomes with respect to the features of AR technology. A conceptual framework was proposed and investigated using structural equation modeling that clearly outlines mediation and moderation relationships [24,25].

3.2 Data collection procedure

The method used in this research was purposive sampling, and the targeted subjects were Chinese consumers who had experience with AR. The sampling was done on the online questionnaire hosted on the Wenjuanxing website, and promotion was done on the platforms of Xiaohongshu and Douyin. The selection criteria for the research involved the consideration that the respondents had to be between 18 and 45 years old, and they had to have experience with the virtual try-on service provided by AR on the platforms of Tmall, JD.com, and Dewu at least once within the last six months.

A period of four weeks was allowed for data collection. Initially, the survey started with screening questions related to the experience with the AR feature. This emphasized the importance of data verification by recalling the last AR try-on experience accomplished by the respondents in order to increase the accuracy of the survey responses [26]. Quality controls included two attention-check items ("Please respond

'Strongly Agree' to this question" and "I have never used any electronic device throughout my life," where agreeing to either statement suggested careless answering) and a requirement to take a minimum of three minutes to complete the survey, established by pilot testing where the average time took approximately 8 minutes; those taking the survey in under one-third of this time were deemed to have taken the survey carelessly. Of the 100 excluded responses, 38 did not pass attention checks, 29 took the survey in under three minutes, 21 had partially completed surveys, and 12 had been systematically answering questions (such as answering every question with the same response)

A total of 600 questionnaires were administered, and there were 500 valid answers (effective response rate: 83.3%). The remaining 100 cases were eliminated due to incompleteness of information, failure of attention checks, insufficiency of completion time, and repetition of answers. The rate of missing information per item for the valid answers was low, and full information maximum likelihood (FIML) estimation was used for subsequent analysis [23].

3.3 Measurement of variables

All constructs were measured using seven-point Likert scales (1 = strongly disagree, 7 = strongly agree). For established constructs, scales were adapted from existing literature, and scales for original constructs were designed specifically for this research and AI-related constructs in particular. The two aspects of augmented reality—AR interactivity and AR immersion—were measured using four items adapted respectively from Yim et al. [17]. The interactivity scale measured how much consumers could control virtual product display, and immersion measured how much virtual products were realistically embedded into physical space. Perceived control was measured using three items adapted from Skinner [16], which measured how much control consumers felt during the shopping process. Perceived value was measured using four items adapted from an existing scale by Zeithaml [19].

The level of AI-AR system integration was measured using four items adapted from Yoon and Lee [20] and intended to assess how well AI recommendations responded to interaction behaviors in an AR environment. The timeliness of AI feedback was measured using three items adapted from Shin [15] and intended to tap AI speed. These two AI-related scales were examined through a pilot test conducted using 30 consumer participants, and results were acceptable in terms of reliability ($\alpha = 0.87$ and 0.84, respectively) and item clarity. The results of the confirmatory factor analysis are summarized in Section 4.2. The purchase intention was measured through four items adapted from Yi et al. [27] and intended to tap purchase and word-of-mouth referrals of an AR shopping experience. The control variables include demographics (age, gender, education, and income), online shopping frequency, familiarity with an AR system, and type of platform.

3.4 Data analysis methods

Preliminary analyses, which included descriptive statistics, tests for normality, and correlation analysis, were conducted to fully describe data properties. Skewness and kurtosis statistics were also checked to ensure appropriateness for maximum likelihood estimation techniques [25]. Confirmatory factor analysis (CFA) was conducted using the AMOS 24.0 program for analyzing the measurement model. Reliability and validity were further assessed through Cronbach's alpha and composite reliability (CR), as well as average variance extracted (AVE), Fornell-Larcker criterion, and HTMT ratio, respectively [28]. Model data fit was assessed through χ^2, df, χ^2/df, CFI, TLI, RMSEA with 90% confidence interval, and SRMR. Common method bias (CMB) in this research was treated by using multiple techniques: procedural corrections that included ensuring anonymity and employing multiple item types, Harman's single-factor test, and the common latent factor (CLF) method [23].

Structural equation modeling (SEM) was used to test these proposed relations, with an alternative model being analyzed to test robustness. Testing of mediation hypotheses (H1, H2) was done using bootstrapping, with 5,000 resamples, using bias-corrected 95% confidence intervals. Testing of moderation hypotheses (H3, H4) was done using multi-group SEM analysis, using median-split techniques to create groups in the moderator variables, with path coefficients being contrasted between groups using chi-square difference tests ($\Delta\chi^2$) [24]. A priori power analysis suggested a minimum requirement of a sample size of 400 to obtain adequate power to detect a medium effect size (β = 0.20–0.30). A sample size of 500 meets this requirement.

3.5 Ethical considerations

This study was approved by the Institutional Review Board of the University (Approval No.: IRB-2024-BM-087; approval date: October 15, 2024). Data collection commenced in late October 2024 and was completed within four weeks, ensuring full compliance with ethical approval requirements. A full description of the aims and procedures of the research, as well as the rights of the participants, has been provided in the beginning of the questionnaire. Informed consent was obtained through the electronic method, in the sense that the participants had to click the 'I agree' option in order to proceed. The participation was voluntary, and the participant was free to withdraw at any time. The research was done anonymously, ensuring the privacy of those being studied was not compromised. Additionally, the research did not request any personal details, such as name, telephone number, or identification numbers, from those participating in the research work. The research abided by the Personal Information Protection Law of China, especially concerning consent and data minimization for such research works.

4. Results

4.1 Sample characteristics

In Table 1, the demographic characteristics of the 500 subjects are described. In the sample group, the subjects were dominantly female (56.4%) instead of male (43.6%), and most of them fall within the age group 26-35 years old (48.6%), while their educational attainment is slightly higher with 73.6% having a bachelor's degree and 17.4% holding a graduate degree, as per the demographic composition linked to early adopters of online shopping technology. The demographic composition linked to the dispersion of income represents the Chinese middle class, where 51.2% received between 3,000 and 8,000 per month in RMB.

The engagement rate of E-commerce, about 60% of the respondents, revealed their habits of online shopping over once a week, combined with familiarity with Augmented Reality, of which about 28.4% of the respondents were less knowledgeable about Augmented Reality with less than three months of familiarity, followed by mid-group persons of 3-6 months, contributing about 37.4%, and experienced persons of about 34.2%, over six months of familiarity. The usage of Augmented Reality platforms included Tmall, about 42.6%, JD.com of about 35.2%, and Dewu of about 22.2%, combined with categories of products like Beauty of about 53.4% and Fashion of about 46.6%. The current sampling represents the target population, which includes Augmented Reality users actively operating in the e-commerce sector of China.

Table 1. Sample characteristics (N = 500)

Characteristic	Category	Frequency (%)
Gender	Male	218 (43.6)
	Female	282 (56.4)
Age	18-25 years	195 (39.0)
	26-35 years	243 (48.6)
	36-45 years	62 (12.4)
Education	High school or below	45 (9.0)
	Bachelor's degree	368 (73.6)
	Master's degree or above	87 (17.4)
Monthly Income	Below 3,000 RMB	87 (17.4)
	3,000-8,000 RMB	256 (51.2)
	Above 8,000 RMB	157 (31.4)
Online Shopping Frequency	More than once a week	298 (59.6)
	1-3 times per month	167 (33.4)
	Less than once a month	35 (7.0)
AR Familiarity	Newcomer (< 3 months)	142 (28.4)
	Intermediate (3-6 months)	187 (37.4)
	Experienced (> 6 months)	171 (34.2)
Platform Used	Tmall	213 (42.6)
	JD.com	176 (35.2)
	Dewu	111 (22.2)

4.2 Reliability and Validity Tests

Table 2 highlights the reliability and convergent validity statistics for the measurement scales. The values of Cronbach's alpha and composite reliability range from 0.856-0.918 and 0.862-0.920, respectively, surpassing 0.70 and establishing a reliable standard. The average variance extracted also ranges from 0.672-0.743, surpassing 0.50 and establishing a standard for acceptable convergent validity. A twofold method was utilized to examine the discriminant validity. The Fornell and Larcker method is established since the square root of AVE values (0.820-0.862) are greater than the corresponding correlation values shown in Table 3. Beyond this, all heterotrait-monotrait HTMT ratios are between 0.62 and 0.81, which are below 0.85; hence, they satisfy the criteria for another method utilized to examine the discriminant validity.

The evaluation of common method bias (CMB) also took place using a series of techniques. The single-factor test conducted by Harman showed that the first unrotated factor explained 38.2% of the total variation, which is below the 50% criterion. Moreover, the CLF technique was employed, where the CLF explained 18.6% of the total variation, and all theoretical loadings were still significant after incorporating the method factor. This indicates that CMB is not a serious matter that could affect validity.

4.3 Descriptive Statistics and Correlation Analysis

Table 3 summarizes the means and standard deviations of each of the study variables, along with correlations. On seven-point scales, the means were 4.76-5.31, indicating positive attitudes toward AR features, psychological empowerment aspects, AI recommendation dimensions, and purchase intention. Standard deviations were 1.09-1.29. These relatively high means might be attributable to the possibility of social desirability biases that always accompany self-administered studies. To counter this problem to some extent, procedural safeguards such as anonymity and varied formats were considered.

Analysis of correlations showed that there were positive and significant relationships between the variables ($p < 0.01$), and the correlation coefficients ranged between 0.52 and 0.78. As was expected in theory, the highest correlation coefficient was found between AR interactivity and perceived control ($r = 0.71$), and between AR immersion and perceived value ($r = 0.74$). Purchase intention was found to have strong correlation coefficients for perceived control ($r = 0.75$) and perceived value($r = 0.78$), respectively, which offer preliminary support for the suggested mediation effects. Looking at the correlation findings in relation to the evidence of discriminant validity in Section 4.2 of this research, there is justification for proceeding to investigate structural models.

Table 2. Reliability and validity tests

Variable	Items	Cronbach's α	CR	AVE
AR Interactivity	4	0.887	0.891	0.672
AR Immersion	4	0.902	0.905	0.705
Perceived Control	3	0.856	0.862	0.676
Perceived Value	4	0.893	0.897	0.686
AI-AR Integration Level	4	0.910	0.913	0.725
AI Feedback Timeliness	3	0.879	0.883	0.716
Purchase Intention	4	0.918	0.920	0.743

Table 3. Descriptive statistics and correlation matrix

Variable	M	SD	1	2	3	4	5	6	7
1. AR Interactivity	5.23	1.12	1						
2. AR Immersion	4.98	1.24	.67**	1					
3. Perceived Control	5.05	1.18	.71**	.58**	1				
4. Perceived Value	5.31	1.09	.63**	.74**	.66**	1			
5. AI-AR Integration	4.87	1.21	.54**	.61**	.59**	.62**	1		
6. AI Feedback Time.	4.76	1.29	.52**	.58**	.55**	.64**	.73**	1	
7. Purchase Intention	5.18	1.15	.68**	.72**	.75**	.78**	.63**	.65**	1

Note: M = Mean; SD = Standard Deviation; **p < 0.01 (two-tailed). N = 500

4.4 Hypothesis Testing

In this section, the results of hypothesis testing through SEM and multi-group analysis are discussed. The approach of analysis involved three stages. In the first stage, mediation roles of control and value perceptions were tested (H1-H2). In the subsequent stage, the moderating roles of AI recommendation attributes were examined (H3-H4). In the final stage, robustness tests were conducted across product types and platforms.

The measurement model was first tested for validity using confirmatory factor analysis. The seven-factor model had a good fit: $\chi^2/df = 2.31$, CFI = 0.965, TLI = 0.958, RMSEA = 0.049 (90% CI: 0.042–0.056), SRMR = 0.038. All standardized loadings exceeded 0.70 and were highly significant ($p < 0.001$), indicating that the measurement model is adequate. The structural model results were analyzed to determine the proposed paths and relationships. The results presented good fit statistics: $\chi^2/df = 2.37$, CFI = 0.962, TLI = 0.955, RMSEA = 0.052 (90% CI: 0.045-0.059), SRMR = 0.041. Another model with reversed paths from purchase intention to perceived control and perceived value presented a significantly poorer fit ($\Delta\chi^2 = 47.82$, $\Delta df = 2$, $p < 0.001$), supporting the hypothesized causal direction.

Table 4 displays the results of the standardized path coefficients. AR interactivity had a significantly positive effect on the perceived control variable ($\beta = 0.698$, $p < 0.001$), supporting H1a. Perceived control had a significantly positive effect on the purchase intention variable ($\beta = 0.582$, $p < 0.001$), supporting H1b. A Bootstrap test with 5,000 resamples provided a significantly positive indirect effect for AR interactivity on the purchase intention variable via the perceived control variable (indirect effect = 0.406, 95% CI [0.324, 0.495]), supporting H1.

As expected in research reporting, AR immersion showed a strong positive effect on perceived value ($\beta = 0.726$, $p < .001$), thereby supporting H2a. Perceived value, in turn, had a significant effect on purchase intention ($\beta = 0.653$, $p < .001$), supporting H2b. The indirect effect of AR immersion on purchase intention through perceived value was also significant (indirect effect = 0.474, 95% CI [0.389, 0.566]), supporting H2. The immersion-value chain showed a slightly larger total effect compared to the interactivity-control chain, suggesting the use of vividness as an effective stimulus for purchase intention. Figure 2 shows the structural model with standardized path coefficients.

A multi-group analysis was carried out in order to test how the characteristics of AI recommendations could moderate the proposed relationships. For every moderator, the respondents were divided into high and low groups, and this created two subsamples of 250 respondents each. While the use of median splits could reduce statistical power, the current method improves interpretability and is commonly used in research on moderation.

The results of the multi-group model are presented in Table 5. Concerning H3, the difference between the high and low AI-AR integration group regarding the path weight from AR interactivity to perceived control is significant and greater in the high AI-AR integration group ($\beta = 0.781$; $p<0.001$) than in the low AI-AR integration group ($\beta = 0.542$; $p<0.001$). The chi-square difference test reveals that this difference is significant ($\Delta\chi^2=12.87$, $p<0.001$), supporting H3 and indicating that the more integrated with AI recommendations the AR interactivity is, the stronger the enhancement of perceived control by AR interactivity will be.

For H4, there was a strong difference in the AR immersion-perceived value relationship under high AI feedback timeliness ($\beta = 0.798$, $p < 0.001$) compared to the low timeliness condition ($\beta = 0.589$, $p < 0.001$). The difference between these two conditions was significant ($\Delta\chi^2 = 10.34$, $p < 0.001$), confirming H4.

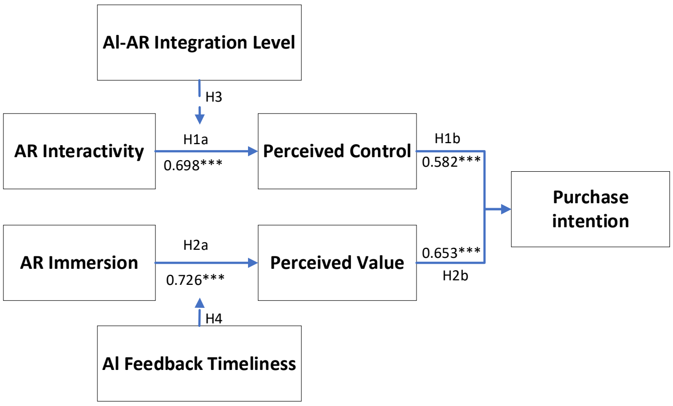

Figure 2. Structural equation model with path coefficients

Table 4. Structural equation modeling results

Path	Std. β	S.E.	t-value	p-value	Hypothesis
AR Interactivity → Perceived Control	0.698	0.041	17.02	<.001	H1a
AR Immersion → Perceived Value	0.726	0.0387	18.76	<.001	H2a
Perceived Control → Purchase Intention	0.582	0.0463	12.57	<.001	H1b
Perceived Value → Purchase Intention	0.653	0.0441	14.81	<.001	H2b
Mediation Path	Indirect Effect	95% CI Lower	95% CI Upper		Hypothesis
AR Interactivity → Perceived Control → Purchase Intention	0.406	0.324	0.495		H1 (via H1a×H1b)
AR Immersion → Perceived Value → Purchase Intention	0.474	0.389	0.566		H2 (via H2a×H2b)

Note: Std. β = Standardized coefficient; S.E. = Standard error; CI = Confidence interval. Measurement model fit: $\chi^2/df = 2.31$, CFI = 0.965, TLI = 0.958, RMSEA = 0.049 (90% CI: 0.042–0.056), SRMR = 0.038. Structural model fit: $\chi^2/df = 2.37$, CFI = 0.962, TLI = 0.955, RMSEA = 0.052 (90% CI: 0.045–0.059), SRMR = 0.041. Indirect effects tested via bootstrap analysis with 5,000 resamples; mediation is significant if 95% CI excludes zero.

Table 5. Multi-group analysis results for moderation effects

Moderator	Path	Low Group Std. β (S.E.)	High Group Std. β (S.E.)	$\Delta\chi^2$	p-value	Hypothesis
AI-AR Integration Level	AR Interactivity → Perceived Control	0.542 (0.061)	0.781 (0.048)	12.87	<.001	H3 Supported
AI Feedback Timeliness	AR Immersion → Perceived Value	0.589 (0.058)	0.798 (0.045)	10.34	<.001	H4 Supported

Note: N = 250 per group (median split). Std. β = Standardized path coefficient; S.E. = Standard error; $\Delta\chi^2$ = Chi-square difference test between groups. Multi-group analysis conducted using AMOS 24.0. Significant $\Delta\chi^2$ indicates moderation effect ($p < .001$).

This result shows how timely AI feedback maintains cognitive flow in immersive AR applications in a manner that increases the value-creation capabilities of AR immersion. The magnitude of both moderation effects was comparable (H3: $\Delta\beta = 0.239$; H4: $\Delta\beta = 0.209$), showing that the two factors collaboratively increase the paths of empowerment. Figure 3 illustrates the interaction effects. The generalizability of results was checked through several robustness tests. Multi-group invariance tests were employed to check if there were differences in structural paths based on product type (beauty vs. fashion) and platforms (Tmall, JD.com, Dewu). Chi-square difference test results showed no differences based on product type ($\Delta\chi^2 = 3.21$, df = 4, p = 0.52) or platforms ($\Delta\chi^2 = 5.87$, df = 8, p = 0.21). This shows that the dual-pathway model holds similarly for different types of products and different platforms of e-commerce.

The results were also checked for robustness against alternative models. A direct effects model, in which direct paths were specified between AR features and purchase intention, did not achieve meaningful incremental fit improvement (ΔCFI < 0.005, ΔRMSEA < 0.003), thus supporting the proposed mediation-only model. A simpler alternative model, specifying a single mediator combining perceived control and perceived value, showed substantially poorer fit (ΔCFI = 0.042, ΔRMSEA = 0.031), thus supporting the theoretical differentiation between control and value paths. These robustness checks thus serve to validate and generalize the results.

5. Discussion

This study theoretically contributes to the literature on the role of AR technology in digital commerce by identifying the two unique psychological processes associated with the functionality of AR and the influence these processes exert on the purchasing decision. This study found that the interactivity and immersion associated with AR influence the two unique and distinct processes, namely the influence of perceived control and perceived value, which are then enhanced by the unique aspects associated with the recommendations provided by AI. This study builds on recent literature on the nature of immersion engagement with the consumer [28], and the nature of the behaviors associated with the shopping activities of consumers that entail virtual technology [29].

Drawing on the dual-pathways approach, it is possible to identify some major differences in the cognitive processes of interactive and immersive AR experiences. Interactive AR functions enhance control beliefs by allowing active manipulation of virtual product representations, thereby being consistent with autonomy-supportive views on technology, which assume that autonomy-supportive technologies increase decision confidence [30]. Immersive AR, in turn, augments perceived value by experiencing vividness, which reduces product fitness concerns in a multi-sensory-congruent virtual space [31]. More recent eye-tracking research on attention processes in AR product presentation [32] also confirms the crucial role of immersion in comprehensive product assessment. A similar magnitude of the indirect effect values (indirect effects: 0.406 vs. 0.474) also suggests a multi-dimensional strategy in managing an augmented reality experience.

The findings from the moderation analysis offer key implications of the synergistic AI-AR interaction that have not been extensively examined from a quantitative perspective in prior research. The extent of AI-AR integration as well as the timeliness of AI feedback suggest the presence of strong enhancement effects of a comparable order of magnitude ($\Delta\beta = 0.239$ and 0.209), which indicate the operation of AI through holistic rather than fragmented processes. That is, responsive and well-integrated AI enables consumer agency in AR interaction contexts while sustaining immersive flow [21,22] and therefore amplifies the psychological consequences of AR use. These findings disagree with views of AI-AR as two radically different phenomena [33] and demonstrate that the combination of the two yields emergent rather than simply additive effects. Chi-square differences indicate that poor integration of AI-AR inhibits AR's empowering ability for consumers. The findings are illustrative of the importance of technology sophistication as an enabler of key consumer decision-making processes in online platforms. In concert with the skill acquisition theory, the findings clarify that responsiveness to AI enables consumers in their transition from novice AR browsing into confident evaluation of merchandise [34]. Modern consumers are understood to seek a seamless technology interface to ensure that their evaluative freedom is retained with the provision of intelligent support only when this might be needed.

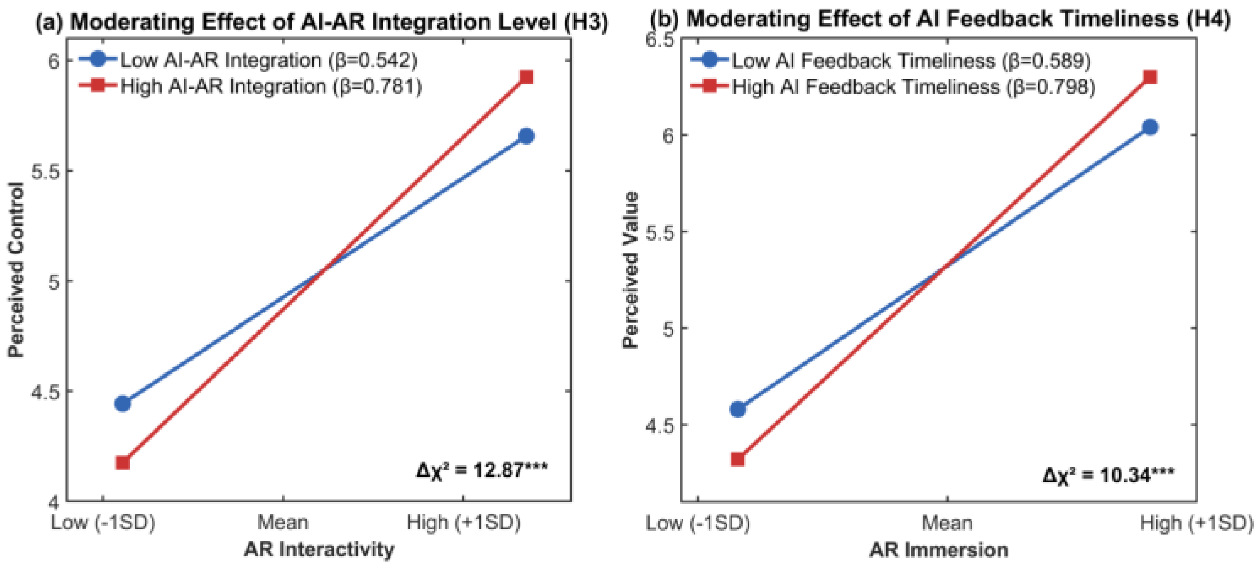

Figure 3. Moderation effects of ai recommendation characteristics

Identifying some moderation effects clarifies that the very same consumers make implicit judgments whether or not AI-related enhancements serve their interests rather than commercial interests as a whole [35]. This means that technological responsiveness and transparency are basic prerequisites for acceptance in settings where consumers remain wary of manipulative intent.

These studies, in sum, represent both theoretical and practical aspects with regard to demonstrating how the concepts of psychological empowerment could be used to develop superior shopping interfaces. The findings highlight key issues regarding the importance of consumer empowerment in a technologically mediated shopping environment. On a theoretical level, by identifying the exact mechanisms through which augmented reality and AI interact with choice processes, this research provides practical and theoretical insights into human-technology interaction dynamics to a far greater degree of specificity and fidelity than if the psychological concepts under investigation were presented as general principles with broad application potential outside of the Chinese online shopping environment.

6. Conclusion

This study demonstrates how two key psychological processes underlying empowerment, namely perceived control and perceived value, serve as mediators of the AR effects on consumer purchase intentions, with attributes of AI recommendations playing a key role in setting boundary conditions. Results indicated that interactivity of augmented reality positively affects decision confidence based on autonomy-supportive processes, while immersion in augmented reality positively affects perceived value grounded in experiential realism. Integration of AI and augmented reality, along with timely feedback of AI recommendations, both positively influence the two psychological processes, suggesting that visualization in augmented reality is super-additively effective when combined with personalization in artificial intelligence recommendations. This research offers several contributions to consumer psychology on the topic of retail technology. From the theoretical aspect, combining skill acquisition theory and dual-process theory clarifies the consumer psychological processes governing engagement in immersive technology. By establishing the definition of AI attributes as boundary conditions, the theory on human-AI interactions is clarified. From the practical perspective, while the findings suggest that consumer engagement through AR in e-commerce platforms depends on more than advanced AI technology, and instead on the proper integration of AI personalization that does not undermine AR-facilitated consumer exploration, but instead upgrades it. There are several limitations that need to be mentioned. The cross-sectional design does not permit inference of causality, and longitudinal studies might explore the progression of psychological empowerment processes while consumers gain more experience with AR technology. Self-report methods might pose the risk of social-desirability biases despite procedural efforts to control for this problem. However, the method of median splitting might reduce statistical power compared to continuous approaches. The transfer of dual-process theory into AR research might overlook the complex mutual relationship between intuitive and analytical processes. This is because recent studies have questioned the absolute distinction between Systems 1 and 2. Instead, they proposed that Systems 1 and 2 might interplay in a more complex manner than theoretically suggested. Future studies could explore if individual differences in cognitive styles moderate these processes. Cross-cultural studies could be carried out to validate findings with a broader group of consumers, possibly those in other nations, since Chinese consumers may have a unique set of adoption behaviors in new technologies. Experimental methods may be used in which participants are subjected to manipulations of both AI integration quality and response rate to increase construct validity. Further study of other product categories, like houseware products and vehicles, may aid in determining boundary conditions. The incorporation of neuroscientific methods, like eye tracking techniques, could provide a clearer and richer understanding of AR-AI synergy.

Ethical issue

The authors are aware of and comply with best practices in publication ethics, specifically regarding authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with research ethics policies. The authors adhere to publication requirements that the submitted work is original and has not been published elsewhere.

Data availability statement

The manuscript contains all the data. However, more data will be available upon request from the authors.

Conflict of interest

The authors declare no potential conflict of interest.

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