



Article

Seeing Is Believing: The Impact of AI Magic Mirror on Consumer Purchase Intentions in Medical Aesthetic Services

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Abstract

The integration of AI into online platforms is reshaping consumer experience and behavior. While existing research has largely focused on the role of AI in search services and experience services, few studies have examined the role of AI in the context of credence services. This study fills this gap by investigating an AI-powered preview tool in the context of online medical aesthetic platforms. Specifically, this study investigates how the AI Magic Mirror influences consumer purchase intentions in medical aesthetic services. Using secondary data analysis and two experimental studies, we examine the main effects, as well as mediation and moderation effects. The findings consistently demonstrate that the AI Magic Mirror significantly increases consumer purchase intentions. This relationship is positively mediated by perceived value and negatively mediated by perceived risk. In addition, the main effect is stronger for procedures with higher fit uncertainty and is more pronounced for those with lower popularity. These results provide theoretical insights into AI application in credence service contexts and offer practical implications for the design of AI-enhanced online service platforms.

Keywords: AI magic mirror; purchase intentions; medical aesthetic services; perceived value; perceived risk; fit uncertainty; procedure popularity



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1. Introduction

Advancements in artificial intelligence (AI) have served as a transformative catalyst, endowing e-commerce platforms with the capability to deliver enhanced value to consumers [1]. Specifically, AI not only autonomously develops complex technological networks based on predefined goals, thereby enhancing consumers' perceived value of AI-enabled services [2], but also leverages data-driven learning to generate consumer benefits [3], thereby promoting the robust growth of e-commerce. The AI e-commerce market grew from USD 8.06 billion in 2024 to USD 9.19 billion in 2025 at a compound annual growth rate (CAGR) of 14.0%. This upward trend is projected to continue, reaching USD 16.42 billion by 2029 at a CAGR of 15.6% [4]. This rapid development has attracted considerable scholarly attention. However, existing research has predominantly focused on the role of AI in search and experience services, while its application in credence service contexts remains insufficiently explored. Compared to search and experience services, credence services involve higher uncertainty and information asymmetry [5]. These characteristics not only make the role of AI potentially distinct in such contexts but also highlight the need for AI to enhance platform effectiveness. Understanding how AI functions in the context

of credence services thus presents a critical research issue. In this study, we focus on the role of AI in credence services by examining an AI-powered virtual preview tool, AI Magic Mirror, on online medical aesthetic platforms, contributing to a deeper understanding of AI in e-commerce.

Medical aesthetic services, as credence services, are characterized by information asymmetry, professional specialization, and associated risks and uncertainties [6]. Consumers find it challenging to foresee outcomes before making a purchase and to assess service quality after completion [7], resulting in a lack of consumer trust and purchase delays or even abandonment [5,8]. Traditional strategies such as reviews, free sampling, return policies, or insurance are insufficient to address these challenges, as medical aesthetic services are highly individualized and often involve irreversible outcomes [9–11]. AI Magic Mirror, leveraging extensive facial data and cosmetic procedure information through data mining, deep learning, and image processing, provides vivid previews of potential treatment outcomes and personalized cosmetic solutions, thereby better supporting consumers' understanding, evaluation, and purchase of services by simulating firsthand experience prior to purchase [12].

However, the highly realistic facial analysis and predictions provided by the AI Magic Mirror may exacerbate consumers' appearance-related anxiety and trigger psychological resistance. In particular, when judgments regarding their appearance or recommended procedures deviate from their expectations, such experiences may foster unfavorable attitudes and reduce purchase intentions. Moreover, AI is not always perceived as trustworthy [13]. Consequently, how the AI Magic Mirror influences consumer purchase decisions in medical aesthetic services remains unclear. To address this gap and advance understanding of AI in e-commerce, we propose the first research question: *How does the AI Magic Mirror influence consumer purchase intentions in medical aesthetic services?* Moreover, the AI Magic Mirror has the potential to alleviate consumer concerns about medical aesthetic services by enhancing perceived value and reducing perceived risk, which are two key factors in building consumer trust and facilitating purchase decisions. Accordingly, this study draws on the theoretical frameworks of perceived value and perceived risk to examine the underlying mechanisms in the relationship between the AI Magic Mirror and consumer purchase intentions in medical aesthetic services. This leads to our second research question: *What mediating mechanisms underlie the impact of the AI Magic Mirror on consumer purchase intentions in this context?* Furthermore, to gain a deeper understanding of how the AI Magic Mirror influences consumer purchase intentions in medical aesthetic services, this study investigates how its effects vary from the procedure perspectives, specifically in relation to fit uncertainty and procedure popularity. To this end, we propose the third research question: *How does the impact of AI Magic Mirror on consumer purchase intentions in medical aesthetic services vary based on fit uncertainty and procedure popularity?*

To investigate the above questions, we employ a dual approach that combines secondary data analysis and experimental design. First, we conduct an initial analysis using real transaction data from a leading medical aesthetic platform (Study 1) to investigate the relationship between AI Magic Mirror and service sales, along with the moderating effects of fit uncertainty and procedure popularity. Subsequently, we design and conduct two experiments (Study 2 and Study 3) to validate the main and moderating effects observed in Study 1 and to examine the mediating mechanism through perceived value and perceived risk in the relationship between AI Magic Mirror and consumer purchase intentions. We obtain consistent results across all three studies. The AI Magic Mirror enhances both service sales and consumer purchase intentions. This effect is stronger for services with high fit uncertainty, but is weakened when procedure popularity is high. Specifically, the

impact of the AI Magic Mirror on purchase intention is mediated by perceived value and perceived risk.

This study advances the understanding of AI applications on e-commerce platforms by examining the impact of AI Magic Mirror on consumer purchase decisions for medical aesthetic services. It holds important implications for research on AI applications, consumer behavior, and e-commerce. By investigating the mediating roles of perceived value and perceived risk, the study strengthens the theoretical foundation and provides empirical evidence for how AI Magic Mirror influences consumer decisions. Furthermore, by testing the moderating effects of fit uncertainty and procedure popularity, the study offers a more nuanced understanding of how AI applications affect consumer decision-making. These findings provide strategic insights for online medical aesthetic platforms seeking to leverage AI applications to facilitate consumer decision-making and boost service sales, and may also inform broader industries such as fitness and wellness by enhancing their development and competitiveness.

2. Literature Review

2.1. AI in E-Commerce

AI pertains to the capacity of a system to accurately capture and analyze external data, to learn from such data, and utilize this acquired learning to attain particular objectives, complete particular tasks, and resolve broad issues via adaptable adjustments [14]. In recent times, notable progress in computational power and the emergence of novel machine learning techniques, coupled with the exponential growth of volume, increase in the richness of variety, and improvement of veracity of data, have collectively enhanced platform AI capability [1]. Platform AI capability is defined as the platform's ability to continuously learn from data and enhance products and services for each consumer [1]. This capability is evident across various dimensions of e-commerce platforms and is currently applied primarily in search services and experience services.

First, the primary means by which platform AI capability could augment value as perceived by consumers is predictive capabilities [15]. Recommender systems provide consumers with personalized suggestions by utilizing available data to predict individual needs and facilitate decision-making [16]. However, Recommender systems may also trigger algorithm aversion among consumers [17,18]. Second, AI chatbots could influence consumer trust and purchase intentions. Although the warmth and competency perceived from chatbots may arouse skepticism, it in turn affects consumer trust in the service provider, consequently influencing consumer decision-making [19]. Third, AI assistants could influence consumers' utilitarian and hedonic values [20,21]. AI assistants elevate consumer convenience to an unprecedented level, enabling repetitive shopping tasks to be accomplished solely through voice commands [22–25]. Fourth, AI applications can impact consumers' perceived risk of services on online platforms [21]. For example, AI word-of-mouth systems influence consumers' word-of-mouth and purchasing behavior by affecting perceived risks [26].

Despite existing research exploring the application of AI on platforms from various perspectives, the majority of studies center around search and experience services. There is a paucity of research examining how AI can be employed in credence services on e-commerce platforms. Credence services are characterized by high uncertainty and irreversible consequences, which amplify consumers' perceived risk [7]. Previous research indicates that consumers exhibit different attitudes and behaviors toward services depending on their type and associated level of risk [27,28]. Therefore, existing research findings may not fully apply to the context of credence services. This study addresses this gap by examining how

the AI Magic Mirror influences consumer purchase intentions for medical aesthetic services, thereby contributing to research on AI applications in e-commerce platforms.

2.2. AI in Medical Aesthetics

In the field of medical aesthetics, AI technology has long been applied to medical aesthetic and plastic surgery, particularly with the advent of facial recognition algorithms and deep learning, which have fundamentally transformed the capabilities of physicians to optimize cosmetic procedures and enhance aesthetic outcomes [29]. Currently, AI technology is utilized to assist physicians in diagnosis, making decisions, and preoperative planning, as well as outcome prediction and evaluation in the realm of cosmetic procedures and medical aesthetics [30]. Given the significant visual components in medical aesthetics, the extraction and processing of essential features from images, along with the generation of realistic images related to cosmetic procedures, are focal points of AI technology in this field [31]. These technologies are commonly employed in the diagnostic process with medical images and facial images [32,33]. Nowadays, these technologies are embedded in online platforms to assist consumers in evaluating and selecting service procedures: this is the AI Magic Mirror.

The AI Magic Mirror uses data and algorithms to simulate service outcomes, allowing consumers to visually preview the outcomes in advance. This simulation helps reduce fit uncertainty and the perceived risk of irreversible outcomes. However, the effectiveness of the AI Magic Mirror in the context of medical aesthetic services remains unclear [18]. First, trust in AI remains a subject of debate. While Gerlich et al. (2024) argue that AI earns trust through its fairness and accuracy [34], Ryan (2020) contends that AI cannot build trust due to its inability to assume responsibility [13]. Second, the visualization of the AI Magic Mirror is also uncertain. Although its simulated results may support consumer judgment and decision-making, they may also increase appearance-related anxiety and perceived risk. Therefore, in the context of medical aesthetics, both consumer trust in AI and the effect of the AI Magic Mirror's visualization warrant closer examination.

2.3. Perceived Value and Perceived Risk

Perceived value is first introduced by Zeithaml, who defines it as the consumer's overall evaluation of the utility of a product or service, based on a subjective trade-off between the benefits received and the costs incurred during the decision-making process [35]. Sweeney and Soutar (2001) conceptualize perceived value as typically consisting of four dimensions: functional value (e.g., quality, performance), emotional value (e.g., pleasure, enjoyment), social value (e.g., social approval, status), and monetary value (e.g., price) [36]. Perceived risk, first introduced by Bauer (1969), refers to the level of uncertainty consumers associate with decision-making during the purchasing process [37]. Perceived risk is typically categorized into five dimensions, including financial, functional, physical, psychological, and social risks [38]. In the field of e-commerce, perceived value and perceived risk play a critical role in shaping consumer behavior [39]. Accordingly, how AI applications embedded in platforms influence consumer behavior through perceived value and perceived risk has attracted increasing scholarly attention.

AI technologies often enhance perceived value to promote favorable consumer behavior. For example, AI applications such as voice assistants and virtual streamers increase consumer engagement, purchase intentions, and electronic word-of-mouth by enhancing their perceived value [40,41]. Perceived value also mediates the relationship between AI experiences and sustainable behaviors, highlighting its central role in consumer and AI interaction [42]. At the same time, AI can also facilitate consumer decision-making by reducing perceived risk, especially in situations where uncertainty or ambiguity is high. AI

word-of-mouth systems mitigate concerns about product quality, which fosters consumer trust and increases purchase behavior [26]. Together, perceived value and perceived risk serve as core mechanisms through which AI influences consumer responses to purchase recommendations from AI-powered voice assistants [43].

Existing studies repeatedly demonstrate that perceived value and perceived risk serve as mediators in the relationship between AI applications and consumer behavior. In the context of medical aesthetic services, we think these two constructs similarly mediate the effect of the AI Magic Mirror on consumer purchase intentions. Medical aesthetic services involve multiple dimensions of perceived value, including functional value (such as quality and performance), emotional value (such as pleasure and enjoyment), social value (such as social approval and status), and monetary value (such as price). At the same time, consumers also perceive various types of risk, including financial risk (such as money), functional risk (such as unsatisfactory outcomes), psychological risk (such as disappointment or regret), and social risk (such as negative social evaluation). Therefore, perceived value and perceived risk are essential intermediary factors in understanding how the AI Magic Mirror influences consumer purchase intentions for medical aesthetic services.

2.4. Fit Uncertainty

Uncertainty refers to a situation in which consumers are unable to accurately assess the value of a product or service due to incomplete information [12]. Prior research discusses two types of uncertainty: quality uncertainty, which relates to a consumer's inability to evaluate the performance and quality of a product or service [44], and fit uncertainty, which refers to a consumer's difficulty in determining whether a product or service meets their individual needs [45]. Fit uncertainty is particularly salient in credence services, as the utility of such services often depends on the degree of personalized fit with the consumer [45]. Therefore, this study focuses on the fit uncertainty associated with medical aesthetic services.

Fit uncertainty is a critical factor influencing consumer purchase intentions and satisfaction [44]. Prior studies find that fit uncertainty negatively affects purchase intentions, and reducing such uncertainty can increase purchase volume and enhance consumer loyalty [46]. As a result, mitigating fit uncertainty has been a persistent concern in research. For search services, where attribute information is clear and easily shared, providing additional information, such as reviews, textual descriptions, visual depictions, instant messaging tools, or Q&A content, is often effective in reducing fit uncertainty [47]. However, for experiential services, where service characteristics are difficult to articulate and consumer preferences vary substantially, informational approaches may be insufficient [46]. In such cases, methods like imitation, augmented reality (AR), and live streaming have been shown to reduce fit uncertainty [48,49]. Compared to search and experience services, credence services present even greater challenges in terms of fit uncertainty, as service outcomes are often more difficult to assess, even post-consumption [44,50]. In this study, the AI Magic Mirror is proposed as a tool to reduce consumers' fit uncertainty regarding medical aesthetic services, thereby increasing their purchase intentions.

In the context of medical aesthetics, fit uncertainty refers to consumers' difficulty in evaluating whether a service aligns with their personal preferences and whether the expected results are compatible with their individual characteristics. Previous research shows that fit uncertainty moderates the relationship between imitation and purchase intentions, suggesting that the effect of imitation varies across services with different levels of fit uncertainty [51]. Similarly, the higher the fit uncertainty of a medical aesthetic service, the more likely consumers are to rely on the AI Magic Mirror to make informed purchase

decisions. Therefore, the effect of AI Magic Mirror may vary across medical aesthetic services with different levels of fit uncertainty.

3. Hypotheses Development

3.1. AI Magic Mirror and Purchase Intention

Research indicates that consumer trust is a critical factor in facilitating purchase decisions, particularly in the context of credence services [10]. Medical aesthetic services, as a type of credence service, combined with consumers' limited familiarity with the procedures and uncertainty about the outcomes, make it difficult for consumers to develop trust, thereby hindering their purchase decisions [10]. Many existing consumer trust enhancement strategies rely on others' experiences (such as reviews and recommendations) [52,53], which may not be entirely effective for medical aesthetic services that are personalized and involve more risks. Notably, there is no strategy more critical to consumers' understanding, evaluation, and purchase of a service than their own service experience prior to making a purchase [12]. However, the outcomes of medical aesthetic services are inherently irreversible. The integration of an AI-based virtual preview application, the AI Magic Mirror, into medical aesthetic platforms enables consumers to virtually preview the outcomes of service procedures [30]. This not only helps consumers gain a clearer understanding of their individual service requirements but also enables them to visualize potential outcomes with greater realism and personalization, thereby boosting their trust and facilitating purchase decisions [12]. Accordingly, we hypothesize the following:

H1: *AI Magic Mirror increases consumer purchase intentions for medical aesthetic services compared to the non-use of the AI Magic Mirror.*

3.2. Mediation by Perceived Value

Perceived value refers to a consumer's overall evaluation of the utility of a product or service based on a trade-off between the benefits and the costs [35]. In existing studies, perceived value is widely recognized as a key driver of consumer purchase intentions [41]. Therefore, enhancing perceived value of consumers is crucial in the context of e-commerce platforms. Recent advancements in AI technologies provide new avenues for platforms to generate consumer value. AI could enhance consumers' perceived value of AI-enabled services through goal-oriented applications and data-driven learning [1]. On medical aesthetic platforms, the AI Magic Mirror, an AI-based virtual preview application, enhances how consumers perceive the usefulness and value of medical aesthetic services [54]. Specifically, AI Magic Mirror allows individuals to preview the outcomes of service procedures, such as a more prominent nose, larger eyes, or fuller lips, and enables consumers to visualize the beauty value of these services in a vivid and realistic manner. Observing a more attractive appearance of themselves often elicits positive emotions and a desire for such improvements to become reality [55]. Therefore, the AI Magic Mirror significantly enhances the perceived value of medical aesthetic services for consumers, thereby increasing their purchase intentions. Accordingly, we hypothesize the following:

H2: *The impact of AI Magic Mirror on consumer purchase intentions is mediated by perceived value.*

3.3. Mediation by Perceived Risk

Perceived risk refers to consumers' concerns about the possibility and severity of negative outcomes associated with a purchase decision [37]. According to Baker (1990), purchase-related perceived risk arises from both the potential consequences of making the wrong choice and uncertainty about the likelihood of adverse outcomes occurring [56]. In the context of medical aesthetics, perceived risk significantly reduces consumer purchase

intentions, given the high uncertainty and irreversible outcomes of credence services [57]. The AI Magic Mirror helps mitigate this risk by leveraging visual simulation technology, which addresses core sources of perceived risk. First, by allowing consumers to preview post-treatment appearances, it reduces ambiguity about the service outcome and enhances consumers' understanding of what to expect. Second, by enabling comparisons across different service options in a personalized and visual manner [58], the AI Magic Mirror decreases uncertainty, thereby alleviating anxiety about making the wrong choice [59]. In doing so, it reduces both outcome-related and choice-related risk perceptions, thereby increasing consumer purchase intentions. Accordingly, we hypothesize the following:

H3: *The impact of AI Magic Mirror on consumer purchase intentions is mediated by perceived risk.*

3.4. Moderation by Fit Uncertainty

Fit uncertainty refers to the uncertainty consumers face when evaluating whether the characteristics of a service align with their preferences and if the service outcomes are appropriate for their individual features [45]. As the adage goes, there are a “thousand people among a thousand faces,” reflecting the inherent variation in aesthetic preferences and needs. In the context of medical aesthetic services, fit uncertainty is an important consumer concern. Therefore, consumers need to mitigate the risk caused by fit uncertainty. However, the degree of fit uncertainty varies across different types of service procedures. The extent to which consumers seek to mitigate fit uncertainty depends on the level of fit uncertainty inherent in the service [60,61]. When facing services with high fit uncertainty, consumers exhibit a stronger need to evaluate the appropriateness of the service procedure [62]. In such cases, consumers are more likely to rely on the AI Magic Mirror, which helps visualize personalized treatment outcomes and alleviates fit-related concerns, thereby exerting a greater influence on their purchase intentions [45]. Conversely, for services characterized by lower fit uncertainty, the role of the AI Magic Mirror becomes less critical, and its influence on purchase intention is correspondingly reduced. Therefore, we propose the following:

H4: *Fit uncertainty strengthens the impact of AI Magic Mirror on consumer purchase intentions for medical aesthetic services.*

3.5. Moderation by Procedure Popularity

Procedure popularity refers to the level of recognition, prevalence, or widespread acceptance of a service in the market, typically reflected by indicators such as sales volume, number of reviews, or social reputation [12]. In the context of medical aesthetic services, procedures with high popularity are typically extensively purchased, thoroughly documented, and widely recognized by consumers, thereby providing them with abundant reference cases, publicly available information, and reduced concerns [63]. Therefore, consumers can more easily make purchase decisions for highly popular procedures, reducing their reliance on additional decision-support tools such as the AI Magic Mirror. In contrast, procedures with low popularity often diverge from general consumer preferences, and are characterized by limited reference information and heightened uncertainty, which collectively increase the difficulty of consumer decision-making [12]. In such cases, consumers are more likely to rely on the AI Magic Mirror to better understand the procedure and make purchase decisions [64]. Prior research indicates that products or services with lower popularity tend to derive greater benefit from enhanced information availability [65]. In line with this, the AI Magic Mirror is more effective in promoting consumer purchase intentions for low-popularity medical aesthetic procedures. Based on this reasoning, we propose the following:

H5: Procedure popularity weakens the impact of AI Magic Mirror on consumer purchase intentions toward medical aesthetic services.

The theoretical model is shown in Figure 1 below.

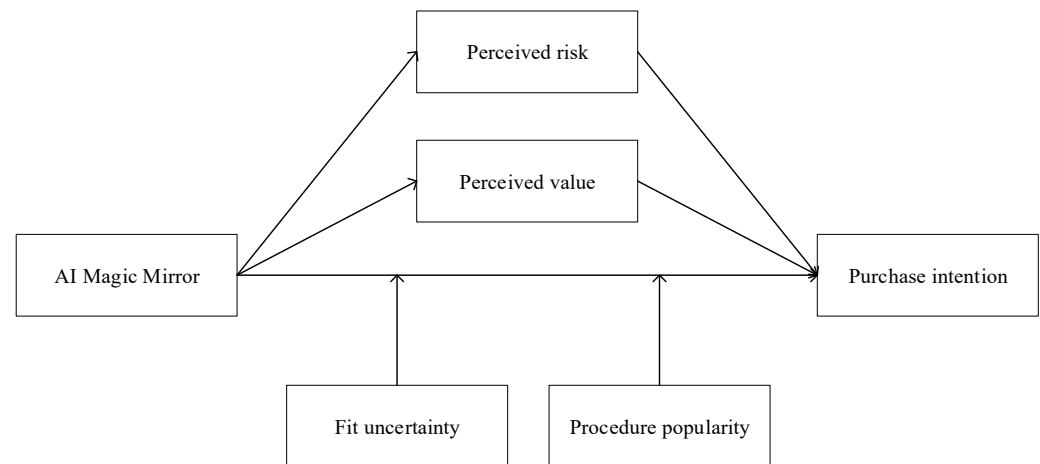


Figure 1. Theoretical model.

4. Materials and Methods

4.1. Study 1: Secondary Data Analysis

4.1.1. Data Collection Variable Measurement

To examine the role of the AI Magic Mirror on online medical aesthetic platforms, we used data crawled in July 2022 from the leading medical aesthetics platform in China. The dataset comprises four interrelated components: reviews, procedures, doctors, and hospitals. The four datasets are merged using reviewID, procedureID, doctorID, and hospitalID as key identifiers. Following the removal of missing values and outliers, the final dataset consists of 31,386 observations.

We use the number of sales of a service procedure as the dependent variable. We design the independent variable as a binary dummy variable. A value of 1 denotes a service procedure that can be simulated with the AI Magic Mirror, while a value of 0 signifies a service procedure that cannot be simulated with the AI Magic Mirror. We considered fit uncertainty and procedure popularity of service procedure as moderating variables. We classify service procedures into high- and low-fit uncertainty groups based on the extent to which their outcomes vary across individuals. Procedures whose effects differ significantly from person to person are categorized as high-fit uncertainty, whereas those with relatively consistent outcomes across users are considered low-fit uncertainty. Additionally, we categorize service procedures into high- and low-popularity groups using data from medical aesthetic industry reports. Specifically, procedures ranked among the top ten in terms of gross merchandise volume (GMV) are classified as high-popularity, while all others are considered low-popularity. Moreover, we introduce controls for hospital, physician, and product attributes that could potentially exert an influence on the dependent variable. Table 1 provides a description and summary of the variables.

Table 1. Description and summary of the variables.

Variable	Description	N	Mean	Min	Max	SD
LogSales	Log of procedure sales	31,386	3.299	0.693	9.935	1.581
AI	Equals 1 if the procedure can be simulated using the AI Magic Mirror and 0 otherwise	31,386	0.648	0	1	0.478
PAveScore	Average rating of procedure	31,386	4.767	0	5	0.845
ProPrice	Price of the procedure	31,386	4022	1	228,900	8432
ReRatio	Platform return rate for unused procedure	31,386	0.304	0	1	0.439
DRating	Rating of the doctor	31,386	3.017	0	4.550	1.691
DServNum	Procedure sales of the doctor	31,386	1240	0	16,259	2423
DTitle	Equals 1 if the doctor is a doctor, 2 if attending doctor, 3 if associate chief doctor, 4 if chief doctor	31,386	1.711	1	4	0.837
DoctorNum	The number of doctors in a hospital	31,386	7.511	0	30	6.642
ReputNum	The number of reputations in a hospital	31,386	1.921	1	2	0.269
HosFollow	The number of followers in a hospital	31,386	4659	0	30,000	6540
PRevNum	The number of procedure reviews	31,386	16.54	0	106	24.81
FRevTime	Duration until the first review	31,386	22,244	21,258	22,807	437.9
FitUncer	Dummy variable: 1 for high-uncertainty procedure, and 0 for low-uncertainty procedure	31,386	0.253	0	1	0.435
ProPop	Dummy variable: 1 for high-popularity procedure, and 0 for low-popularity procedure	31,386	0.157	0	1	0.364

4.1.2. Empirical Models and Results

We employ ordinary least squares (OLS) regression models to examine the impact of AI Magic Mirror on sales of service procedure and to explore how this effect varies across the fit uncertainty and procedure popularity [66]. The models are specified as follows:

$$Y_i = \beta_0 + \beta_1 AI_i + \beta_2 Controls_i + \varepsilon_{it} \quad (1)$$

$$Y_i = \beta_0 + \beta_1 AI_i \times Mo_i + \beta_4 Controls_i + \varepsilon_{it} \quad (2)$$

In the above models, Y_i represents the sales of service procedure i . The term AI_i is a dummy variable that equals 1 if the service procedure i can be simulated using the AI Magic Mirror and 0 otherwise. $Controls_i$ include hospital, physician, and procedure attributes of service procedure i . Mo_i refers to fit uncertainty and procedure popularity, which are all the dummy variables of service procedure i . Fit uncertainty equals 1 for a high-uncertainty procedure and 0 for a low-uncertainty procedure; procedure popularity equals 1 for a procedure with high popularity and 0 otherwise.

We obtain the initial results from the regression analysis, which reveal a 36% increase in sales of service procedures when the AI Magic Mirror is used compared to when it is not. This finding offers initial support for the positive impact of AI Magic Mirror on service procedure sales ($\beta_1 = 0.308, p < 0.001$). We also perform a series of robustness tests. First, to address concerns regarding potential violations of standard regression assumptions, we further estimate the model using robust standard errors. Second, considering that product sales are nonnegative count variables, we also conduct robustness checks using a negative binomial regression model. Then, we use mean-centered variables to reduce potential multicollinearity. Last, in order to make the group of procedures using AI Magic Mirror more comparable to the group of procedures not using AI Magic Mirror, we apply PSM to generate a more balanced sample of data [67]. Specially, we use hospital, physician, and product attributes as covariates and apply caliper nearest-neighbor matching, excluding 76 samples outside the common support region. After matching, all covariate differences are nonsignificant (as shown in Figure A1). All findings align with the main effect, further

confirming that the AI Magic Mirror positively influences the sales of service procedures. The overall results are presented in Table 2.

Table 2. Main effects.

Variable	(1) OLS	(2) OLS robust	(3) Negative binomial	(4) Centered	(5) PSM
AI	0.308 *** (22.57)	0.308 *** (21.84)	0.098 *** (21.06)	0.308 *** (21.84)	0.306 *** (21.67)
PAveScore	0.023 ** (2.97)	0.023 ** (2.84)	0.010 *** (3.45)	0.023 ** (2.84)	0.023 ** (2.85)
ProPrice	−0.000 *** (−37.76)	−0.000 *** (−21.99)	−0.000 *** (−22.85)	−0.000 *** (−21.99)	−0.000 *** (−21.87)
ReRatio	0.169 *** (11.11)	0.169 *** (10.72)	0.055 *** (11.58)	0.169 *** (10.72)	0.168 *** (10.64)
DRating	0.005 (1.31)	0.005 (1.34)	0.002 (1.21)	0.005 (1.34)	0.005 (1.35)
DServNum	0.000 *** (7.69)	0.000 *** (6.67)	0.000 *** (6.81)	0.000 *** (6.67)	0.000 *** (6.59)
DTitle	0.045 *** (5.70)	0.045 *** (5.69)	0.016 *** (6.31)	0.045 *** (5.69)	0.045 *** (5.69)
DoctorNum	0.015 *** (12.73)	0.015 *** (11.94)	0.004 *** (11.87)	0.015 *** (11.94)	0.016 *** (12.01)
ReputNum	0.447 *** (18.10)	0.447 *** (20.27)	0.182 *** (19.88)	0.447 *** (20.27)	0.439 *** (19.82)
HosFollow	0.000 *** (6.03)	0.000 *** (6.18)	0.000 *** (6.64)	0.000 *** (6.18)	0.000 *** (6.09)
PRevNum	0.032 *** (110.31)	0.032 *** (87.16)	0.007 *** (90.64)	0.032 *** (87.16)	0.032 *** (86.40)
FRevTime	−0.001 *** (−51.79)	−0.001 *** (−49.49)	−0.000 *** (−52.45)	−0.001 *** (−49.49)	−0.001 *** (−49.29)
_cons	20.142 *** (54.21)	20.142 *** (51.72)	6.319 *** (54.93)	16.843 *** (43.25)	20.103 *** (51.56)
N	31386	31386	31386	31386	31310
R ²	0.483	0.483		0.483	0.482

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Model (2) examines the moderating effects of fit uncertainty and procedure popularity on the relationship between AI Magic Mirror and sales of service procedures. As shown in Table 3, we find that the AI Magic Mirror has a stronger effect on purchase intentions for services with high fit uncertainty than on those with low fit uncertainty ($\beta_1 = 0.562$, $p < 0.001$). In contrast, its effect on purchase intentions is weaker for highly popular procedures than for those with low popularity ($\beta_1 = -0.592$, $p < 0.001$).

Table 3. Moderated effects.

Variable	(1) LogSales	(2) LogSales
AI	0.106 *** (6.83)	0.433 *** (29.03)
AI × FitUncer	0.562 *** (34.93)	
AI × ProPop		−0.592 *** (−33.60)
PAveScore	0.024 ** (3.10)	0.020 * (2.56)

Table 3. *Cont.*

Variable	(1) LogSales	(2) LogSales
ProPrice	−0.000 *** (−22.43)	−0.000 *** (−22.33)
ReRatio	0.159 *** (10.22)	0.169 *** (10.87)
DRating	0.004 (0.95)	0.006 (1.48)
DServNum	0.000 *** (6.76)	0.000 *** (6.14)
DTitle	0.041 *** (5.28)	0.039 *** (4.99)
DoctorNum	0.013 *** (10.25)	0.015 *** (11.49)
ReputNum	0.421 *** (19.39)	0.399 *** (17.96)
HosFollow	0.000 *** (5.53)	0.000 *** (6.00)
PRevNum	0.030 *** (83.54)	0.031 *** (84.86)
FRevTime	−0.001 *** (−44.38)	−0.001 *** (−46.64)
_cons	18.427 *** (47.13)	19.132 *** (49.40)
N	31386	31386
R ²	0.500	0.496

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Although the initial results obtained from the secondary data analysis are consistent with our hypotheses, the inherent limitations of such data prevent us from establishing a robust causal relationship between the use of the AI Magic Mirror and consumer purchase intentions. Therefore, to further validate the causal effect of the AI Magic Mirror on purchase intentions, we conducted two experimental designs. These experiments not only confirmed the impact of the AI Magic Mirror on consumer purchase intentions, but also demonstrated the moderating roles of fit uncertainty and procedure popularity. Additionally, they allowed us to further explore the underlying mechanisms by examining the mediating roles of perceived value and perceived risk.

4.2. Study 2: Experimental Study

Study 2 employs an experimental design to empirically test the impact of the AI Magic Mirror on purchase intention (H1) and the moderating effect of fit uncertainty (H4) by manipulating experimental variables. Additionally, the study examines the mediating roles of perceived value (H2) and perceived risk (H3).

4.2.1. Study 2 Design

This study adopts a 2 (AI Magic Mirror: usage vs. non-usage) $\times$ 2 (fit uncertainty: high vs. low) between-subjects experimental design. Two representative cosmetic procedures are selected: double eyelid surgery and photon skin rejuvenation. Double eyelid surgery is characterized by high fit uncertainty, as its effectiveness largely depends on individual facial features. In contrast, photon skin rejuvenation, a relatively standardized skin care procedure, represents low fit uncertainty. To ensure internal validity, all variables are held constant across conditions except for the procedure name. In the treated condition,

participants use the AI Magic Mirror feature from the medical aesthetic platform to perform facial scanning and visualize simulated outcomes. In the control condition, participants use a mobile phone camera to observe their appearance and imagine the potential results, thereby simulating a decision-making process without the support of AI Magic Mirror.

(1) Sample

A total of 500 participants are randomly assigned to one of the four experimental conditions (125 participants per group). Responses that fail the attention check or are incomplete are excluded from the analysis. The final sample consists of 384 valid responses. Demographic analysis shows that the majority of participants are female (72.9%), and most fall within the age range of 21 to 40 years (87.0%). The educational background is generally high, with 88.3% holding at least a bachelor's degree. Participants represent a wide range of occupations, and 58.9% report previous experience with cosmetic treatments. These sample characteristics are consistent with the primary consumer profile in the current Chinese cosmetic market, supporting the external validity of study. The sample information is presented in Table 4.

Table 4. Sample information of Study 2.

Variable	Category	Freq	Perce (%)	Variable	Category	Freq	Perce (%)
Age	≤20	13	3.39	Gender	Male	104	27.08
	21–30	192	50.00		Female	280	72.92
	31–40	142	36.98		Student	60	15.62
	41–50	27	7.03	Occupation	State-owned enterprise employee	41	10.68
	51–60	9	2.34		Public institution employee	28	7.29
	>60	1	0.26		Civil servant	19	4.95
Education Level	High school/Vocational school	9	2.34		Private enterprise employee	206	53.65
	Associate degree	36	9.38		Foreign-invested enterprise employee	22	5.73
	Bachelor's degree	268	69.79		Freelancer/Self-employed	7	1.82
	Master's degree	64	16.67	Prior Experience	Other	1	0.26
	Doctoral degree	7	1.82		No	158	41.15
					Yes	226	58.85

(2) Procedure

The experiment proceeds as follows. Participants are randomly assigned to one of four conditions and receive standardized instructions. Those in the AI Magic Mirror group use the designated AI Magic Mirror function on the medical aesthetic platform to scan their faces and experience a virtual simulation of the assigned procedure. In contrast, participants in the control group use their front camera to observe their faces and imagine the post-procedure effects. After the experience, all participants complete a questionnaire assessing key variables, including purchase intention, perceived value, and perceived risk, along with manipulation checks related to AI Magic Mirror and fit uncertainty, as well as demographic information. All measures are adapted from established scales in the existing literature and are assessed using a seven-point Likert scale, which is modified and adjusted to suit the context of this study (as shown in Table 5).

Table 5. Measurement scales and reliability analysis.

Scale	Items	Factor Loading	Cronbach's α
Perceived Value [68]	(1) The overall quality of this medical aesthetic service is acceptable.	0.925	0.908
	(2) This medical aesthetic service is worth the money.	0.924	
	(3) This medical aesthetic service makes me feel good.	0.915	
	(4) Undergoing this medical aesthetic service makes a good impression on other people.	0.873	
Perceived Risk [69]	(1) I would worry that this medical aesthetic service did not provide value for my money.	0.825	0.873
	(2) I would worry about service quality or equipment problems if I underwent this medical aesthetic service.	0.869	
	(3) I would worry about physical danger or injury if I underwent this medical aesthetic service.	0.848	
	(4) I would worry about disappointment with the outcome of this medical aesthetic service.	0.879	
	(5) There is a risk of disapproval from friends, family, or associates regarding my decision to undergo this medical aesthetic service.	0.897	
Purchase Intention [70]	(1) It is very likely that I would purchase this medical aesthetic service.	0.902	0.916
	(2) The probability that I would consider buying this medical aesthetic service is very high.	0.889	
	(3) If I were going to purchase a medical aesthetic service, I would very probably choose this one.	0.758	

4.2.2. Study 2 Results

(1) Manipulation check results

To assess the effectiveness of the experimental manipulations, we conduct two checks. First, we validate the AI Magic Mirror manipulation by asking participants whether they used an AI virtual preview application to view the post-procedure effect. Participants who failed to comply with the manipulation are excluded from the analysis. Second, we test the manipulation of fit uncertainty using independent samples *t*-tests, which reveal that participants in the double eyelid surgery condition report significantly higher fit uncertainty than those in the photon skin rejuvenation condition ($M_D = 5.46$ vs. $M_P = 5.25$, $t(382) = 2.136$, $p < 0.05$). These results confirm the success of both manipulations and support the validity of the subsequent moderation analyses.

(2) Reliability and Validity Results

Before testing the hypotheses, we assess the reliability and validity of the measurement scales. All constructs demonstrate strong internal consistency, with Cronbach's α values exceeding 0.87. Exploratory factor analysis (EFA) shows that all items load highly on their respective factors (generally > 0.80), and the extracted single factors explained a high proportion of the total variance (all $> 72\%$). These results support the reliability and construct validity of the measurement instruments utilized in the study (as shown in Table 5).

(3) Main Results

To test Hypothesis 1, this study conducts a one-way ANOVA to examine the main effect of AI Magic Mirror on consumer purchase intentions for medical aesthetic services. After controlling for procedure type, gender, age, education level, occupation, and consumer

experience, the analysis reveals a significant positive effect of AI Magic Mirror on consumer purchase intentions ($F(1, 363) = 74.682, p < 0.001$), as shown in Table 6. The corresponding effect size is 0.17, indicating that the use of the AI Magic Mirror leads to an approximate 17% increase in consumer purchase intentions [71]. In practical terms, this improvement could translate into a substantial boost in the sales of medical aesthetic services. Specifically, the mean purchase intention in the AI Magic Mirror condition is 4.614 ($SE = 0.273$), which is significantly higher than that in the non-AI Magic Mirror condition, with a mean of 3.604 ($SE = 0.283$). The mean difference between the two groups is 1.011 (95% CI [0.781, 1.241], $p < 0.001$). These results suggest that the AI Magic Mirror significantly enhances consumer purchase intentions for medical aesthetic services, thus supporting Hypothesis 1.

Table 6. Main effect in Study 2.

Variable	Square Sum	Freedom	F Value	<i>p</i>
AI Magic Mirror	89.087	1	74.682 ***	0.000
Procedure Type	3.534	1	2.962	0.086
Gender	0.017	1	0.014	0.906
Age	17.291	5	2.899 *	0.014
Education	1.108	4	0.232	0.920
Occupation	33.782	7	4.046 ***	0.000
Consumer experience	12.382	1	10.380 **	0.001
Adj R ²			0.273	
N			384	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Next, we employ the PROCESS macro (Model 4) to test the mediating roles of perceived value (H2) and perceived risk (H3) in the relationship between AI Magic Mirror and purchase intention, controlling for consumer experience, procedure type, and demographic covariates. Regarding the mediating roles of perceived value, the results show that AI Magic Mirror positively impacts perceived value ($\beta = 0.703, p < 0.001$), which in turn positively impacts purchase intention ($\beta = 0.825, p < 0.001$). Bootstrap analysis with 5000 resamples confirms a significant indirect effect of perceived value (indirect effect = 0.580, 95% CI = [0.411, 0.760]), supporting H2. This suggests that the AI Magic Mirror boosts consumer purchase intentions by increasing their perceived value of the service. Regarding the mediating roles of perceived risk, the results show that AI Magic Mirror negatively influences perceived risk ($\beta = -0.881, p < 0.001$), which in turn negatively affects purchase intention ($\beta = -0.193, p < 0.001$). The mediating effect of perceived risk is also significant (indirect effect = 0.170, 95% CI = [0.093, 0.264]), providing support for H3. This suggests that the AI Magic Mirror boosts consumer purchase intentions by reducing their perceived risk of the service. After controlling for both mediators, the direct effect of AI Magic Mirror on purchase intention remains significant ($\beta = 0.252, p < 0.001$), indicating that perceived value and perceived risk partially mediate the relationship.

Finally, we examine the moderating effect of fit uncertainty on the relationship between AI Magic Mirror and purchase intention. Using the PROCESS macro (Model 1), we identify a significant positive interaction between AI Magic Mirror and fit uncertainty ($\beta = 0.6227, p < 0.001, \Delta R^2 = 0.014$), as shown in Table 7. Specifically, when the service procedure has high fit uncertainty, the positive effect of AI Magic Mirror on purchase intention is stronger (effect size = 1.220, $p < 0.001$), whereas the effect is weaker when the service procedure has low fit uncertainty (effect size = 0.598, $p < 0.001$). These findings support H4. This suggests that the AI Magic Mirror is more effective (effect size = 0.6227, $p < 0.001$) in enhancing purchase intentions for medical aesthetic services with greater individual

outcome uncertainty. The same moderating effect is observed when fit uncertainty is treated as a continuous variable, as shown in Figure 2.

Table 7. Moderating effect of fit uncertainty.

Variable	Coefficient	Std. Error	t-Value	p-Value	95% Confidence Interval
Constant	5.1657 ***	0.5419	9.5330	0.0000	[4.1002, 6.2312]
AI Magic Mirror	−0.0248	0.3395	−0.0731	0.9418	[−0.6923, 0.6427]
Fit Uncertainty	−0.5408 ***	0.1544	−3.5024	0.0005	[−0.8444, −0.2372]
AI × Fit Uncertainty	0.6227 **	0.2183	2.8528	0.0046	[0.1935, 1.0518]
ΔR^2	0.0144 **			0.0046	
Low Fit Uncertainty	0.5979 ***	0.1510	3.9602	0.0001	[0.3010, 0.8947]
High Fit Uncertainty	1.2205 ***	0.1601	7.6239	0.0000	[0.9057, 1.5353]

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

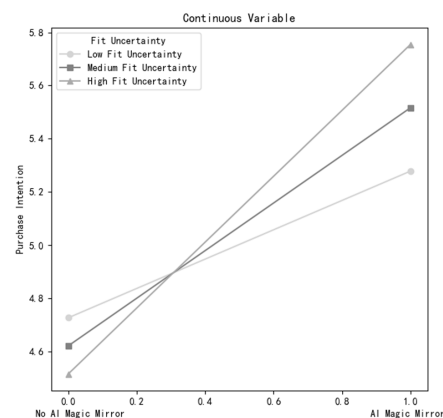


Figure 2. Moderating effects of fit uncertainty.

Study 2 validates the findings of Study 1. The results demonstrate that the AI Magic Mirror significantly enhances consumer purchase intentions (H1) and confirm the moderating role of fit uncertainty (H4). Importantly, the experiment identifies two underlying mechanisms through which the AI Magic Mirror affects purchase intentions: by increasing perceived value (H2) and by reducing perceived risk (H3). These findings provide causal evidence for the influence of the AI Magic Mirror on consumer purchase behavior. However, Study 2 manipulates fit uncertainty by employing different service categories. Although this approach reflects real-world conditions, it may introduce unobserved confounding variables related to differences across service categories. To test the robustness of these findings and further explore the boundary condition of procedure popularity, we designed Study 3.

4.3. Study 3: Experimental Study

Study 3 aims to further validate the core findings and examine the boundary conditions of procedure popularity. To ensure the robustness of the results, this study adopts a consistent service category framework to re-examine the effect of the AI Magic Mirror on purchase intention (H1) and the mediating roles of perceived value and perceived risk (H2 and H3). Moreover, Study 3 investigates the moderating effect of procedure popularity (H5), thereby deepening our understanding of the role of AI Magic Mirror in shaping consumer purchase intentions.

4.3.1. Study 3 Design

This study adopts a 2 (AI Magic Mirror: usage vs. non-usage) × 2 (procedure popularity: high vs. low) between-subjects experimental design. The implementation of the AI

Magic Mirror replicates the approach used in Study 2. Importantly, the stimuli in Study 3 are designed to manipulate perceived procedure popularity. To manipulate perceived procedure popularity, two service procedures with distinct levels of consumer recognition are selected: double eyelid surgery for the high-popularity condition and lower eyelid elongation for the low-popularity condition. All other webpage elements, including the basic description, reference price, and visual presentation, remain identical across conditions to ensure consistency apart from procedure popularity.

Sample. Study 3 recruited 500 participants. After excluding invalid responses, the final sample consists of 395 participants. As shown in Table A1, the demographic profile closely mirrors that of Study 2: 73.7% are female, 88.4% are aged between 21 and 40, and 87.9% hold at least a bachelor's degree. Additionally, 59.5% report prior experience with service procedures. The consistency in sample characteristics supports cross-study comparisons and enhances the generalizability of the findings.

Procedure. The experimental procedure largely follows that of Study 2. Participants are randomly assigned to one of four experimental conditions and, after reading the instructions, proceed to the experience phase. In the AI Magic Mirror condition, participants use the AI Magic Mirror to simulate the assigned procedure. In the non-AI Magic Mirror condition, participants use their phone cameras to observe their faces and imagine the potential outcome. After the experience, all participants complete a questionnaire measuring purchase intention, perceived value, and perceived risk using a seven-point Likert scale. They also respond to manipulation checks related to AI Magic Mirror usage, perceived procedure popularity, prior experience, and demographic information.

4.3.2. Study 3 Results

(1) Manipulation Check Results

Manipulation check results confirm the effectiveness of the experimental design. The manipulation of AI Magic Mirror is validated through direct questioning and participant screening. The manipulation of procedure popularity proves successful, as participants in the high-popularity condition report significantly greater perceived popularity than those in the low-popularity condition ($M_H = 5.89$ vs. $M_L = 5.63$, $t(361.846) = 2.829$, $p = 0.005$).

(2) Reliability and Validity Test Results

The reliability and validity tests for the main variables, including purchase intention, perceived value, and perceived risk, show results consistent with those of Study 2. Cronbach's α coefficients remain high (generally > 0.80), and exploratory factor analysis (EFA) confirms the structural validity of the scale all $> 72\%$, as shown in Table A2. These results indicate that the measurement instruments used in this study are both reliable and valid.

(3) Main Results

We examine the impact of AI Magic Mirror on purchase intention. After controlling for gender, age, education level, occupation, and consumer experience, a one-way ANOVA analysis shows that AI Magic Mirror significantly increases consumer purchase intentions ($F(1,374) = 35.381$, $p < 0.001$), as shown in Table A3. The corresponding effect size is 0.086 in this sample [71]. Specifically, the mean purchase intention in the AI Magic Mirror condition is 4.667 ($SE = 0.275$), significantly higher than 3.954 ($SE = 0.277$) in the control group, with a mean difference of 0.713 (95% CI [0.477, 0.948], $p < 0.001$). These findings are highly consistent with those of Study 1 and Study 2, confirming the positive effect of AI Magic Mirror on purchase intentions.

We then test the mediating effects of perceived value and perceived risk. Using the PROCESS macro (Model 4) and controlling for relevant covariates, the results for the perceived value pathway show that AI Magic Mirror significantly enhances perceived value ($\beta = 0.52$, $p < 0.001$), and perceived value significantly increases purchase intention ($\beta = 0.79$,

$p < 0.001$). The indirect effect through perceived value is significant (Indirect effect = 0.41, 95% CI [0.24, 0.57]), supporting H2. For the perceived risk pathway, AI Magic Mirror significantly reduces perceived risk ($\beta = -0.35, p = 0.012$), and perceived risk significantly decreases purchase intention ($\beta = -0.15, p < 0.001$). The indirect effect through perceived risk is also significant (Indirect effect = 0.05, 95% CI [0.01, 0.11]), supporting H3. The direct effect of AI Magic Mirror on purchase intention remains significant after including both mediators, indicating partial mediation.

Finally, we test the moderating effect of procedure popularity (H5). Using the PROCESS macro, we find a significant negative interaction between AI Magic Mirror and procedure popularity on purchase intention ($\beta = -1.075, p < 0.001, \Delta R^2 = 0.041$), as shown in Table A4. Conditional effects analysis shows that under low procedure popularity, the positive effect of AI Magic Mirror on purchase intention is strong and significant (effect size = 1.302, $p < 0.001$). However, under high procedure popularity, the effect is no longer significant (effect size = 0.227, $p = 0.157$). This result supports H5. This result suggests that, compared to low-popularity procedures, the AI Magic Mirror is significantly less effective in enhancing purchase intentions for high-popularity medical aesthetic services (effect size = $-1.075, p < 0.001$). The same moderating pattern is observed when procedure popularity is treated as a continuous variable, as shown in Figure A2.

Study 3 validates the moderating effect of product popularity (H5) in the relationship between the AI Magic Mirror and purchase intention, which is consistent with the findings of Study 1. The results indicate that the impact of the AI Magic Mirror on consumer purchase intention is stronger for low-popularity procedures than for high-popularity ones. In addition, this study reconfirms the positive main effect of the AI Magic Mirror on purchase intention and the mediating roles of perceived value and perceived risk (H1–H3), further strengthening the robustness of these core findings.

5. General Discussion

5.1. Findings

This study investigates the impact of the AI Magic Mirror on consumer purchase intentions in medical aesthetic services, as well as its underlying mechanisms and boundary conditions. First, using online platform data (Study 1), we conduct an initial examination of how the AI Magic Mirror influences consumer purchase intentions and explore the moderating roles of fit uncertainty and procedure popularity. Subsequently, we conduct two experimental studies (Study 2 and Study 3) to further validate the impact of the AI Magic Mirror on purchase intentions and to examine the moderating effects of fit uncertainty and service popularity, respectively. In addition, we explore the mediating roles of perceived value and perceived risk in the relationship between the AI Magic Mirror and purchase intentions.

We identified several important findings. First, the AI Magic Mirror significantly increases consumer purchase intentions in medical aesthetic services. This suggests that by allowing consumers to preview potential post-treatment outcomes, the AI Magic Mirror enhances their understanding of procedures and reduces uncertainty, leading to increased purchase intention. Although it may also induce appearance-related anxiety and algorithmic bias that reduces purchase intentions, the positive effect of AI Magic Mirror appears to outweigh the negative impact. Second, perceived value and perceived risk mediate the relationship between the AI Magic Mirror and purchase intentions. This suggests that the AI Magic Mirror shapes consumer purchase intention by altering how they evaluate the service. AI applications thus do not merely offer convenience but actively reframe consumers' assessment of personalized and potentially irreversible services, carrying important implications for marketing design and trust-building strategies for credence services. Third,

fit uncertainty positively moderates the relationship between the AI Magic Mirror and purchase intentions, implying that services with higher fit uncertainty pose greater risks and thus require more support from the AI Magic Mirror during decision-making. Finally, procedure popularity negatively moderates this relationship, suggesting that consumers are less familiar with less popular service procedures and therefore rely more heavily on the AI Magic Mirror when making purchase decisions.

5.2. Theoretical Contributions

The study holds substantial theoretical significance. First, this study investigates the impact of AI Magic Mirror on consumer purchase intentions in the context of online medical aesthetic platforms, extending the exploration of AI applications in credence services on online platforms. An increasing number of platforms have enhanced their AI capabilities, such as personalizing recommendations [62], enhancing trust through AI chatbots [19], improving convenience and perceived value via AI assistants [20], and reducing perceived risk through AI systems [28]. However, existing research has primarily focused on the role of AI applications in search and experience services [18]. By extending AI-based virtual preview applications to credence services, this study broadens the understanding of platform AI capabilities in e-commerce.

Second, this study extends the theory of perceived value and perceived risk. Given the importance of perceived value and perceived risk in consumer purchase decision-making in e-commerce, existing studies have explored how various AI applications promote consumer behavior by enhancing perceived value or reducing perceived risk. However, few studies investigate how these two constructs function as mediators in the relationship between AI-based virtual preview applications and credence services. By examining perceived value and perceived risk as mediating mechanisms between the AI Magic Mirror and consumer purchase intentions in medical aesthetic services, this study extends the theoretical boundaries of perceived value and perceived risk.

Third, by examining the moderating roles of fit uncertainty and product popularity, this study advances the theoretical understanding of the role of AI Magic Mirror on medical aesthetic services. In the context of medical aesthetic services, fit uncertainty and product popularity, as two key characteristics of service procedures, shape the relationship between the AI Magic Mirror and consumer purchase intentions. The findings reveal that the AI Magic Mirror has a stronger impact on purchase intentions for procedures with high fit uncertainty than on those with low fit uncertainty. Conversely, the effect is more pronounced for less popular procedures than for highly popular ones. These insights deepen our understanding of how AI-based virtual preview applications influence consumer decision-making on medical aesthetic platforms.

5.3. Managerial Implications

This study offers several practical implications. First, the consistent finding that AI Magic Mirror enhances consumer purchase intentions is notable. To maximize its effectiveness, platforms should integrate AI Magic Mirror functionalities directly into service-specific pages, providing consumers with immersive visual previews that facilitate decision-making. Moreover, the application of such AI applications can extend beyond medical aesthetics platforms to other platforms, such as fitness or wellness platforms, where simulated outcomes (e.g., body shaping or weight loss) could guide consumer choices.

Second, since the AI Magic Mirror enhances purchase intentions by increasing perceived value and reducing perceived risk, platforms should tailor its functionality to specific medical aesthetic services, offering more immersive and procedure-specific simulations to elevate perceived value. Additionally, enhancing data training and image processing

capabilities could improve simulation realism, thereby increasing consumer trust and lowering perceived risk. However, these implementations must comply with regulatory standards and data privacy, and must also ensure that informed user consent is properly obtained [72,73]. Furthermore, ethical considerations such as preventing user manipulation and avoiding the reinforcement of appearance-based anxiety should be integrated into the system design to support responsible AI deployment [54,74].

Third, the results indicate that the impact of AI Magic Mirror on purchase intention is stronger for procedures with higher fit uncertainty and lower popularity. Therefore, platforms should prioritize promoting the AI Magic Mirror for such services. For procedures characterized by high fit uncertainty or low popularity, platforms may enhance conversion by integrating trial programs, personalized recommendations, or targeted social media campaigns to increase user engagement with the AI Magic Mirror in these contexts.

5.4. Limitations and Future Research

This study has several limitations. First, the secondary data used in Study 1 were incomplete and served only as preliminary evidence; while the experimental designs simulated AI Magic Mirror scenarios, they may not fully reflect real-world service contexts. Future research could collaborate with platforms to conduct natural experiments and obtain more robust data. Second, this study uses a China-based online sample, which may limit the generalizability of the findings. Cultural differences may influence consumer responses to AI. Future research can explore other cultural to enhance the robustness of the results [75,76]. Third, the study primarily focused on perceived value and perceived risk, overlooking deeper psychological and social factors that may influence medical aesthetic decisions, such as appearance anxiety, self-identity, and social comparison pressure [77,78]. Future work could incorporate psychological risks and identity distortions to explore more effects. Last, the study examined only procedure-related characteristics, fit uncertainty and popularity, as boundary conditions. Future research may consider incorporating attributes related to hospitals and physicians to gain a more comprehensive understanding of how AI Magic Mirror affects consumer purchase intentions [79,80].

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Abbreviations

The following abbreviations are used in this manuscript:

AI Artificial intelligence

Appendix A

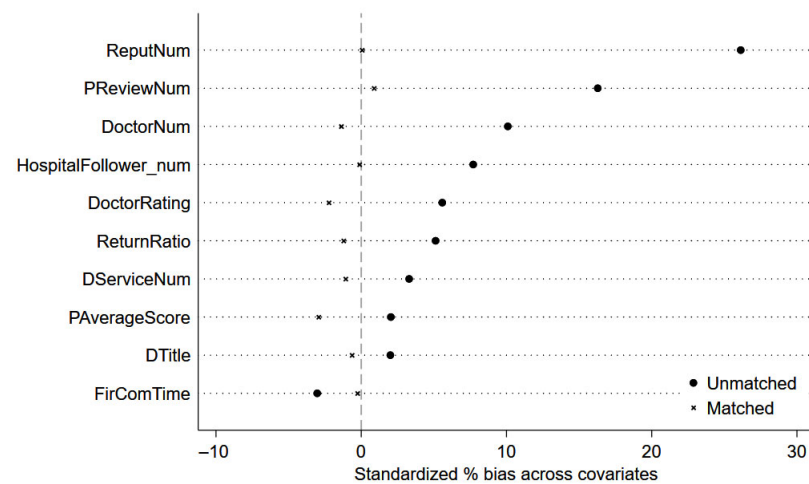


Figure A1. PSM results.

Table A1. Demographic characteristics of the sample in Study 3.

Variable	Category	Frequency	Percentage (%)
Gender	Male	104	26.33
	Female	291	73.67
Age Group (years)	≤20	19	4.81
	21–30	203	51.39
	31–40	146	36.96
	41–50	19	4.81
	51–60	7	1.77
	>60	1	0.25
Education Level	High school/Vocational school	9	2.28
	Associate degree	39	9.87
	Bachelor's degree	275	69.62
	Master's degree	68	17.22
	Doctoral degree	4	1.01
	Student	68	17.22
Occupation	State-owned enterprise employee	43	10.89
	Public institution employee	30	7.59
	Civil servant	17	4.3
	Private enterprise employee	212	53.67
	Foreign-invested enterprise employee	15	3.8
	Freelancer/Self-employed	6	1.52
	Other	4	1.01
Consumer Experience	No	160	40.51
	Yes	235	59.49

Table A2. Reliability and validity results of Study 3.

Variable	Item	Factor Loading	Cronbach's α
Purchase Intention	PurchaseIntent1	0.927	0.896
	PurchaseIntent2	0.917	
	PurchaseIntent3	0.890	

Table A2. *Cont.*

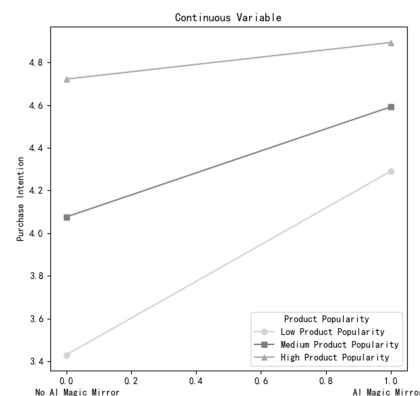
Variable	Item	Factor Loading	Cronbach's α
Perceived Value	PerceivedValue1	0.865	0.884
	PerceivedValue2	0.850	
	PerceivedValue3	0.891	
	PerceivedValue4	0.849	
Perceived Risk	PerceivedRisk1	0.840	0.912
	PerceivedRisk2	0.895	
	PerceivedRisk3	0.909	
	PerceivedRisk4	0.900	
	PerceivedRisk5	0.750	

Table A3. Main effect in Study 3.

Variable	Square Sum	Freedom	F Value	p
AI Magic Mirror	45.333	1	35.381 ***	<0.001
Procedure Type	6.358	1	4.962 *	0.027
Gender	0.419	1	0.327	0.568
Age	14.401	5	2.248 *	0.049
Education	5.895	4	1.150	0.333
Occupation	9.809	7	1.094	0.366
Consumer experience	35.636	1	27.813 ***	<0.001
Adj R ²			0.245	
N			395	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.**Table A4.** Moderating effect of product popularity.

Variable	Coefficient	Standard Error	t-Value	p -Value	95% Confidence Interval
Constant	2.9350 ***	0.5416	5.4191	0.0000	[1.8702, 3.9999]
AI Magic Mirror	1.3019 ***	0.1637	7.9507	0.0000	[0.9799, 1.6238]
Product Popularity	0.8462 ***	0.1720	4.9183	0.0000	[0.5079, 1.1844]
AI Magic Mirror $\times$ Product Popularity	−1.0751 ***	0.2275	−4.7254	0.0000	[−1.5224, −0.6278]
ΔR^2	0.0414 ***			0.0000	
Low Product Popularity	1.3019 ***	0.1637	7.9507	0.0000	[0.9799, 1.6238]
High Product Popularity	0.2268	0.1598	1.4191	0.1567	[−0.0874, 0.5411]

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.**Figure A2.** Moderating effects of procedure popularity.

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