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The Impact of AI-Powered Try-On Technology on Online Consumers' Impulsive Buying Intention: The Moderating Role of Brand Trust

Yanlei Gao and Jingwen Liang *

College of Fashion and Design, Donghua University, Shanghai 200051, China; 8220180@mail.dhu.edu.cn
* Correspondence: 1239108@mail.dhu.edu.cn; Tel.: +86-183-0751-6691

Abstract: Within the global wave of manufacturing intelligence, AI technologies are revolutionizing industrial frameworks through deep integration. As a resource-intensive sector, fashion has become a pivotal arena for assessing AI's role in sustainable development. China, the world's largest apparel producer, faces unique AI integration challenges, highlighting the intersection of innovation and sustainability. To further explore the impact of AI-powered try-on technology on the impulsive buying intentions of young Chinese consumers, this research utilizes a modified version of the stimulus–organism–response (SOR) model. From the lens of online shopping, the research investigates how key features of AI-powered try-on technology, such as visual vividness, interactive control, personalized configuration, and ease of use, affect impulsive buying intentions. Additionally, the study examines the mediating roles of perceived utilitarian value, perceived hedonic value, and perceived immersion, alongside the moderating role of brand trust. A structured online survey was conducted with 366 participants, and the data were analyzed using the partial least squares (PLS) method. The findings reveal that the four core attributes of AI-powered try-on technology have a positive effect on impulsive buying intentions. Furthermore, the mediating roles of perceived utilitarian value, perceived hedonic value, and perceived immersion, along with the moderating influence of brand trust, were substantiated. In the realm of online apparel shopping, AI-powered try-on technology effectively stimulates impulsive buying behavior and drives online purchases. These results offer valuable theoretical insights for enhancing AI-powered try-on applications, while also providing strategic guidance for fashion brands and e-commerce platforms in developing AI-driven sustainable marketing approaches.

Keywords: artificial intelligence; impulsive buying; brand trust; perceived value; try-on technology; sustainability

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1. Introduction

As one of the most pressing sectors in global manufacturing's sustainability transition, the fashion industry faces severe ecological challenges. Its massive production scale drives substantial resource consumption, creating environmental impacts that starkly contrast with the human-centered technological ethics of the Fifth Industrial Revolution [1]. Artificial intelligence is rapidly transforming the industry, with innovative AI technologies reshaping traditional paradigms from design to manufacturing and retail [2]. Among these, AI-powered try-on technology and fashion recommendation tools demonstrate unique potential for advancing sustainability. AI-powered try-on technology enables consumers to preview garment fit and aesthetics without physical contact [3], addressing three critical challenges in online fashion retail: (1) its precise matching algorithms reduce irrational stockpiling from size and style mismatches, decreasing resource waste [4]; (2) virtual wardrobe simulations extend product lifecycle utilization, minimizing raw material consumption [5]; (3) through precise visual representation, the technology enables users to preview fitting effects, reducing return rates and consequently lowering logistics-related carbon emissions [6]. Collectively, these capabilities advance sustainable transformation in digital fashion commerce. This study investigates how key characteristics of AI-powered try-on technology influence consumers' online impulsive purchasing intentions. The technology utilizes three-dimensional body scanning data and computer graphics principles to construct personalized 3D avatars, enabling users to virtually trial garments selected from extensive digital inventories, with real-time rendering of fitted apparel [7]. Integrated recommendation systems provide personalized, context-aware shopping suggestions based on individual user profiles [8]. The technological architecture typically comprises five core components: (1) 3D body measurement, (2) avatar modeling, (3) garment simulation, (4) fabric physics rendering, and (5) virtual fitting algorithms. Major retailers have implemented this technology across multiple domains, including Amazon's AR shoe fitting and virtual makeup applications and Nike's digital footwear trials, demonstrating its cross-category adaptability [9]. This study focuses specifically on the apparel sector within e-commerce retail platforms, a domain that represents one of the most emblematic consumer categories in digital commerce, characterized by its highly visual and experiential nature [10]. Unlike other product categories, apparel purchasing decisions involve multiple interdependent variables including style, color, and sizing, necessitating enhanced sensory engagement to reduce consumer uncertainty [11]. AI-powered try-on technology addresses this complexity by providing immersive, realistic experiences that simultaneously streamline decision-making processes and amplify purchasing impulses [12]. Given apparel's paradigmatic status in e-commerce, research into AI-powered try-on technology for this sector represents both methodological necessity and practical significance.

Previous research has examined the impact of AI-powered try-on technology adoption on consumer behavior in a fragmented manner. The existing literature predominantly explores the impact of AI-powered try-on technology on consumer satisfaction. For instance, Song and Bonanni found that, in the context of luxury shopping, this technology enhances consumer satisfaction within virtual environments [13]. Likewise, Nawaz et al. investigated how AI-powered try-on services in the beauty industry foster positive word-of-mouth and strengthen purchase intentions [14]. However, existing research has rarely explored how AI-powered try-on technology triggers impulse buying and other irrational consumption patterns. While previous studies mainly focused on its ability to improve sales conversion rates, its potential for creating sustainable value remains understudied. For example, promoting technological ethics could transform impulse consumption from quantity-driven expansion to quality-focused improvement [15]. Moreover, while some scholars have explored the relationship between AI technology and impulse buying, Widiatmo found that real-time interaction and virtual try-on features in livestream e-commerce directly enhance immersive experiences, thereby fostering impulse purchases among viewers [16]. However, these studies have not differentiated the effects across various value dimensions. This underscores the need for a deeper understanding of how multidimensional perceived value shapes impulsive behavior in AI-powered try-on scenarios. Rawal and Singh's study demonstrates that, in the beauty industry, the informational and hedonic values of virtual try-on features positively influence impulsive purchasing behavior [17]. Similarly, Le and Nguyen establish that virtual try-on technologies in cosmetics guide impulse buying by enhancing customers' hedonic values [18]. Although these studies offer valuable insights into the impact of virtual try-on technology on impulsive behavior, they focus exclusively on AR-based implementations, without considering AI-driven applications. They also overlook the apparel industry. Furthermore, existing literature has yet to elucidate how brand trust dynamically moderates the pathway between technological features and consumer behavior. Current research has not sufficiently examined how specific characteristics of AI-powered try-on technology, particularly visual vividness [19], interactive control [20], personalized configuration [21], and ease of use [22], directly or indirectly influence impulsive purchasing behavior. This study aims to address this critical gap by providing an integrative framework that elucidates the impact pathways of apparel virtual try-on technologies on impulse buying, incorporating the mediating roles of perceived value dimensions and the moderating effects of brand trust.

This study employs the SOR model to conduct an empirical analysis. Recognized for its ability to effectively capture the transmission mechanism through which technological stimuli shape behavioral responses via psychological states, the SOR framework is particularly suited for elucidating the real-time influence of highly interactive technologies such as AI-powered try-on technology on consumer decision making [18]. In this model, the key attributes of AI-powered try-on technology (visual vividness, interactive control, personalized configuration, and ease of use) are stimulus factors. The organism component reflects consumers' perceived value, which consists of three dimensions: perceived utilitarian value, perceived hedonic value, and perceived immersion. Brand trust is incorporated as a moderating variable. Visual vividness refers to the degree of realism and detail in the rendered try-on effects [23]. A highly vivid visual experience enhances consumers' perception of the try-on process by bridging the gap between virtual and physical experiences, fostering positive mental imagery of the apparel, and deepening immersion, ultimately driving impulse purchases [24]. Interactive control allows users to engage with the platform in real time through various input methods. This sense of autonomy enhances perceived utilitarian value, lowers the cognitive barriers to purchase decisions, and increases the likelihood of impulsive behavior [25]. Personalized configuration adapts the try-on experience to individual characteristics, preferences, and needs, improving both accuracy and enjoyment [26]. Ease of use reflects the convenience and fluidity of the try-on process. A seamless and effortless experience strengthens users' intention for continued engagement, which in turn influences impulse buying [27].

In summary, this study addresses critical empirical gaps in understanding how AI-powered try-on technologies influence consumers' impulsive purchasing behavior. Focusing on China's Generation Z online consumers (aged 18–30), we develop an analytical framework based on an enhanced SOR model. The research adopts a two-pronged approach: first, we conduct experimental studies to determine whether and how the technological characteristics of try-on systems induce online impulse buying through the mediating mechanisms of perceived value. Second, we investigate how varying levels of brand trust moderate the strength and directionality of these impact pathways. This study makes three significant contributions to the literature: (1) theoretical: it extends AI technology's impact framework by revealing transient psychological mechanisms behind impulse buying, examining parallel mediation of utilitarian value, hedonic value, and perceived immersion, and identifying brand trust's differential moderation. (2) Contextual: it shifts focus from cosmetics and footwear to China's apparel market, addressing a critical gap in AI-powered try-on technology research. (3) Practical: it offers actionable insights for optimizing virtual try-on features and supports AI-driven sustainable marketing strategies for fashion brands and e-commerce platforms. Therefore, our research questions are as follows:

1. How do the characteristics of AI-powered try-on technology (visual vividness, interactive control, personalized configuration, and ease of use) induce impulsive purchasing intentions through the mediating mechanisms of perceived value?
2. Which aspects of perceived value (utilitarian, hedonic, immersion) mediate the relationship between AI-powered try-on technology and impulsive buying behavior?
3. How do varying levels of brand trust reshape the strength and directionality of these impact pathways?

2. Theoretical Background

2.1. Stimulus–Organism–Response (SOR) Model

The SOR model, originally proposed by Mehrabian and Russell [28], posits that consumer purchasing behavior results from the interplay of external stimuli that trigger behavioral responses, the individual organism processing these stimuli, and the consequent behavioral outcomes [29]. This framework effectively integrates cognitive and affective processes to explain how perceptions and emotions toward external stimuli lead to subsequent positive or negative behaviors [30]. This study adopts the SOR model as its theoretical framework for three compelling reasons. First, the SOR theory demonstrates extensive applicability, with successful precedents in impulse buying, online e-commerce, and AI technology adoption research [31,32]. Notably, in the context of AI adoption, Yin and Qiu utilized the SOR model to demonstrate how AI marketing technologies on e-commerce platforms (characterized by accuracy, insightfulness, and interactivity) enhance perceived value and subsequently increase purchase intention [33]. Similarly, Vafaei-Zadeh et al. applied the SOR framework to examine how social influence and anthropomorphic stimuli in AI customer service affect user technology adoption [34]. The SOR model's applicability in explaining the diversity and complexity of user behavior influenced by AI technological stimuli has been empirically validated in prior research. Furthermore, Huo and Wang highlight the SOR framework's unique capacity to capture real-time emotional fluctuations triggered by technological stimuli, making it particularly suitable for investigating flow experience and situational variables' moderating effects [35]. This aligns with AI-powered try-on technology's core characteristic of millisecond-level synchronization between user actions and system feedback, which induces transient psychological state fluctuations in consumers [36]. The SOR model's chain effectively explains such millisecond-level behavioral triggering mechanisms. Additionally, the SOR framework's ability to integrate multidimensional stimuli enables the decomposition of AI technology features' compound effects while accommodating moderating variables. In contrast, although alternative information system theories such as the TAM model and UTAUT exist, their predefined focus on specific system characteristics like usefulness and ease of use limits their flexibility in explaining multidimensional cognitive and affective stimuli [37]. These models are better suited for static evaluations rather than capturing dynamic decision-making processes or precisely quantifying moderating effects [38].

Building on this foundation, we use the SOR framework to explain how AI-powered try-on technology stimulates emotional and cognitive states, driving impulsive purchases. The stimulus includes four AI features: visual vividness, interactive control, personalized configuration, and ease of use. The organism represents perceived value (utilitarian, hedonic, immersion), while the response is online impulsive buying.

2.2. AI-Powered Try-On Technology as Stimuli

AI-driven digital integration technologies have fundamentally transformed customer engagement [13]. Specifically, AI-powered try-on technology synthesizes computer vision, AI, and AR to digitally simulate the process of consumers trying on garments or accessories [12]. Integrated with big data analytics and machine learning, it analyzes consumer purchase histories, preferences, and browsing patterns to deliver personalized recommendations, creating tailored marketing experiences [39]. Existing research demonstrates that AI technological features such as visual realism [40], interactive control [21], social sharing [20], personalized needs [15], information quality [41], operational convenience [17], and immersive experiences [42] significantly influence consumer behavior. Based on this, our study focuses on the four most relevant features: visual vividness, interactive control, personalized configuration, and ease of use.

Visual vividness refers to AI-powered try-on technology's ability to authentically replicate garments' physical attributes (texture, sheen, drape) and dynamic behaviors (e.g., movement-induced sway) through high-fidelity image rendering, dynamic light simulation, and fabric detail reconstruction within digital interfaces [23]. As Heller et al. demonstrate, such vivid digital visualizations reduce cognitive imagination costs, enabling consumers to assess product fit without relying on textual descriptions, thereby enhancing decision-making efficiency [43].

Interactive control refers to users' ability to engage in real-time interactions with the platform through various input methods, enabling them to adjust try-on content, view different effects, share experiences socially, and even participate in customization and styling [25]. This participatory engagement enhances users' perceived control and satisfies their need for autonomy [44].

Personalized configuration involves the AI system's capacity to generate customized try-on solutions based on user data (body measurements, style preferences, purchase history), including intelligent size recommendations, style matching, and outfit suggestions [21]. The algorithmic objectivity of these recommendations effectively reduces decision-making uncertainty, while personalized style suggestions enhance self-expression satisfaction [45].

Ease of use refers to the system's ability to enable users to complete virtual try-on operations quickly without specialized guidance, characterized by intuitive interfaces, streamlined processes, and system stability [27]. This user-friendly design reduces cognitive load and mitigates negative emotional responses during interaction [46].

2.3. Consumer Perceived Value as Organism

When consumers interact with external environmental stimuli, cognitive and affective perceptions emerge [47]. Perceived value, defined as users' evaluation of products or services, serves as a critical prerequisite for purchasing behavior [48]. This multidimensional construct has been extensively studied in impulse buying research. For instance, Yang et al. examined how utilitarian and hedonic values influence impulsive purchasing in mobile commerce environments [49]. Similarly, Chih et al. utilized these value dimensions to investigate impulse buying within LINE community interactions [50]. Zhang et al. further demonstrated that utilitarian and hedonic values derived from online reviews enhance browsing behavior and positively impact impulse purchases [51]. Collectively, these studies establish perceived utilitarian and hedonic values as foundational and frequently employed dimensions in impulse buying research. In the context of AI-powered try-on technology, perceived utilitarian value represents consumers' rational evaluation of the technology's practicality, functionality, and efficiency. For example, the technology utilizes 3D body scanning and machine learning recommendations to provide intelligent style matching, reducing size uncertainty [52]. Its high-precision simulation of garment drape, elasticity, and other physical attributes offers superior product visualization, minimizing "image–text mismatch" cognitive biases [53]. Perceived hedonic value is defined as the pleasure, novelty, and self-expression satisfaction consumers experience during virtual try-on interactions [54]. For instance, the system's social sharing features enhance users' social fulfillment. Additionally, the technology enables low-cost experimentation with unlimited outfit combinations [55], stimulating consumer curiosity and entertainment experiences.

Moreover, perceived immersion has been extensively examined in consumer research on virtual reality technology [20]. AI-powered try-on technology delivers a highly interactive and immersive sensory shopping experience, featuring functions such as immersive try-on, intelligent outfit recommendations [24], and recognition-based imports. Feng et al. highlighted that, in virtual environments, key drivers of impulse buying behavior include the sense of immersion, interactivity, and imagination [56]. Therefore, this study incorporates perceived immersion as a key research construct. Perceived immersion in this study mainly refers to the psychological state in which consumers are deeply invested in the virtual try-on experience, temporarily detached from the real environment, and immersed in the virtual world. Through AI-powered try-on technology, users can watch a highly matched clothing effect display in the virtual environment and adjust the style and color of the clothing in real time, and this highly realistic visual display makes consumers feel as if they are in the real world [57]. AI-powered try-on technology makes personalized recommendations based on user data and creates a try-on experience that is highly matched to the user's needs, which reduces the distance between the virtual and the real and further enhances the sense of immersion [3].

2.4. Impulse Buying Behavior as Response

Applebaum defines impulse buying as an unplanned purchase driven by external stimuli [30]. Consumers frequently engage in impulse purchases, a widespread phenomenon characterized by spontaneity and triggered by external cues [58], often resulting in immediate decision making without prior intention [59]. Various factors influence online impulse buying behavior, including: (1) social influences, such as marketing interactions with livestream anchors, consumer reviews, and the number of social media likes [60]; (2) marketing strategies, such as scarcity tactics and product exclusivity [61]; (3) digital environment factors, including website design quality, operational efficiency, and personalization [62]; and (4) consumer characteristics, such as trust, brand awareness, and expertise [63]. While impulse buying remains a significant topic in consumer behavior research, little attention has been devoted to understanding how AI-powered try-on technology, as a product presentation tool, shapes and stimulates impulse purchasing behavior. Through 3D body shape matching and intelligent recommendations, AI-powered try-on technology streamlines the shopping process by eliminating the need for consumers to integrate multiple sources of information (such as reviews and product images) typically required in traditional e-commerce. This reduction in cognitive load makes purchasing decisions more intuitive [64]. When consumers encounter apparel that aligns with their preferences, they are more likely to make impulse-driven decisions rather than engaging in extended rational deliberation. Jain and Gandhi highlight that AI technology enhances product discovery, styling recommendations, and customer support by eliminating the complexities of filters, checkboxes, radio buttons, and sliders, allowing consumers to enjoy a seamless browsing experience. This streamlined interaction influences purchasing decisions and encourages impulse buying [65]. Unlike traditional strategies that rely heavily on customer reviews, AI-powered try-on technology employs predictive evaluation, physical simulation, and dynamic visualization to mitigate perceived risk [66]. By making the purchasing process more interactive and emotionally engaging, it shifts consumer decision making from rational assessment to intuitive and affective impulses. Furthermore, by leveraging data-driven algorithmic validation, the technology boosts consumer decision confidence. Real-time risk visualization through try-on comparisons shortens decision hesitation periods, increasing the likelihood of impulse purchases. Many e-retailers are adopting AI-driven innovations to stimulate impulsive buying emotions [67]. Given its potential to reshape consumer experiences and advance sustainable marketing, investigating the relationship between AI-powered try-on technology and impulse buying is both timely and necessary.

3. Hypotheses Development

3.1. AI-Powered Try-On Technology and Impulsive Buying

This study employs visual vividness, interactive control, personalized configuration, and ease of use as the environmental stimuli through which AI-powered try-on technology influences consumer impulse buying behavior. Baltezarevic suggests that AI technology stimulates consumers' visual senses, enabling them to experience product attributes within a virtual environment. This process affects perception, learning, and memory, thereby shaping consumer desires, motivations, and behaviors [68]. Through sensory stimulation, emotions are also triggered, leading consumers into a dopamine-driven response that disrupts rational judgment and encourages impulse buying [69]. Furthermore, based on the fear of missing out (FOMO) theory [70], AI-powered try-on technology enhances clothing styles, fabrics, and the user's body and wearing state through high-fidelity rendering and dynamic light and shadow tracking. This optimizes the virtual representation, shaping the user's ideal image and triggering the projection of their ideal self. This process intensifies the anxiety of missing out on their ideal self, which in turn suppresses rational evaluation and drives the consumer's impulse buying intention [71]. We thus propose the following hypothesis:

H1a. *Better visual vividness of AI-powered try-on technology has a positive impact on impulse buying.*

Interactive control enables consumers to autonomously select clothing styles, colors, and sizes while viewing real-time try-on effects and engaging in social sharing [72]. In AI-powered try-on technology, interactive control satisfies autonomy needs and creates instant feedback loops, deeply activating the neural mechanisms underlying impulse buying. Drawing on instant gratification theory, Liu et al. found that users can immediately view different outfit combinations without multiple clicks or page loading delays. This instant feedback fulfills users' psychological need for quick satisfaction, reducing decision-making time and accelerating purchase decisions [73]. Gesture-based controls (e.g., swiping, rotating, zooming) allow real-time manipulation of virtual avatars (e.g., adjusting clothing angles, switching scenes), enhancing perceived autonomy and competence, thereby satisfying self-determination needs. As Kathuria and Bakshi highlight, based on self-determination theory, both intrinsic and extrinsic motivations can trigger emotional responses that facilitate impulse buying [74]. We thus propose the following hypothesis:

H1b. *Better interactive control of AI-powered try-on technology has a positive impact on impulse buying.*

Compared to non-personalized virtual try-on technologies, personalized configuration provides greater self-consistency, leading to more positive consumer perceptions [26]. As Kathuria and Bakshi emphasize, retailers should leverage AI-driven tools and data analytics to create personalized product recommendations aligned with individual consumer behaviors and preferences. This satisfies intrinsic autonomy needs, capitalizes on emotional responses, and shifts consumers from rational analysis to intuitive reactions, thereby stimulating impulse buying [74]. Furthermore, personalization-induced scarcity effects and social comparison anxiety (e.g., system displays showing "10,000 favorites" or "limited stock") amplify users' fear of missing out (FOMO), accelerating purchase decisions [75]. We thus propose the following hypothesis:

H1c. *Better personalized configuration of AI-powered try-on technology has a positive impact on impulse buying.*

According to Csikszentmihalyi's flow theory, when users face a moderate level of challenge, such as selecting outfit combinations, and their skills align with the task, they enter a state of deep focus where the sense of time fades. In this state, rational control is diminished, and behavior becomes more driven by intuition [76]. Enhancing ease of use reduces the cognitive load on users, allowing them to focus more on the product itself and enter a flow state, making them more likely to rely on intuition for impulse buying [41]. Furthermore, simplifying the process effectively reduces self-control, weakening the restraints during the purchasing decision, and compelling consumers to rely on impulsive intuition in their choices [77]. We thus propose the following hypothesis:

H1d. *Better ease of use of AI-powered try-on technology has a positive impact on impulse buying.*

3.2. Perceived Value and Impulse Buying

Previous research has demonstrated that perceived value positively influences consumers' impulse buying behavior [49]. In the context of AI-powered try-on technology, utilitarian value reflects consumers' perceptions of practicality, convenience, and efficiency gains. As Park et al. highlight, improved shopping efficiency and seamless website performance lead consumers to browse more products [78], significantly increasing the likelihood of encountering stimuli that trigger impulse purchases [79]. Consumers perceive AI technology as enabling faster decision making, reducing shopping risks, and saving time and effort. This high utilitarian value experience lowers decision costs, boosts purchase confidence, and ultimately drives impulse buying [80]. We thus propose the following hypothesis:

H2a. *The utilitarian value perceived by customers using AI-powered try-on technology has a positive impact on their impulse buying.*

Perceived hedonic value refers to the enjoyment and entertainment that consumers experience when using mobile commerce platforms, and it is regarded as an important precursor to purchasing behavior [81]. Previous studies have shown that consumers who derive pleasure and emotional satisfaction from using a website are more inclined to make impulse purchases [49]. Furthermore, research by Verhagen and van Dolen indicates that positive emotions play a key role in driving impulse buying behavior [82]. We thus propose the following hypothesis:

H2b. *The hedonic value perceived by customers using AI-powered try-on technology has a positive impact on their impulse buying.*

Fortin and Dholakia's research highlights that immersion plays a key role in creating the ideal online shopping experience and enhances consumers' belief in the authenticity of the product and the overall shopping journey [19]. When customers experience the realism and engagement of the virtual try-on process, they become more absorbed in the shopping experience, which triggers emotional reactions and increases their propensity for impulse buying [20]. We thus propose the following hypothesis:

H2c. *The immersion perceived by customers using AI-powered try-on technology has a positive impact on their impulse buying.*

3.3. Perceived Value, AI-Powered Try-On Technology, and Impulse Buying

The visual vividness of AI-powered try-on technology delivers high-fidelity visual information, accurately presenting clothing materials, cuts, and fit. Through the try-on interface, consumers access three-dimensional spatial details that traditional images and text cannot convey. This reduces cognitive costs, enabling users to intuitively evaluate products without relying on textual descriptions or external reviews. The resulting transparency shortens decision-making cycles [83]. Interactive control allows users to verify product suitability through rotation, size adjustment, and social sharing, achieving exponential gains in try-on efficiency and precise demand matching. Seamless interactions reduce cognitive load, shifting consumers from theoretical evaluation to emotional decision making [20]. Ease of use minimizes learning costs, streamlining processes so that consumer attention remains focused on the products themselves. By enhancing shopping efficiency and reducing decision costs, these features increase the likelihood of impulse buying behavior [27]. We thus propose the following hypotheses:

H3a: *Perceived utilitarian value plays a mediating role between the visual vividness and impulse buying.*

H3b: *Perceived utilitarian value plays a mediating role between the interactive control and impulse buying.*

H3c: *Perceived utilitarian value plays a mediating role between the ease of use and impulse buying.*

Interactive control provides users with an immersive, engaging, and personalized try-on experience, enhancing the novelty and entertainment value of shopping [25]. This enjoyable experience makes consumers more emotionally driven in their purchasing behavior, prompting them to make decisions based on emotions and intuition, thereby increasing the likelihood of impulse buying [84]. Personalized AI-powered try-on technology generates unique virtual representations of users and offers customized outfit recommendations, improving satisfaction with the fit and fostering a sense of identity and exclusivity. This, in turn, shifts consumers from rational analysis to intuitive responses, stimulating impulse purchases [74]. We thus propose the following hypotheses:

H3d: *Perceived hedonic value plays a mediating role between the interactive control and impulse buying.*

H3e: *Perceived hedonic value plays a mediating role between the personalized configuration and impulse buying.*

AI-powered try-on technology with high visual vividness enhances realism through dynamic simulations and interactive experiences, deepening user immersion in the try-on process [85]. As immersion increases, users become more captivated by their projected self-image and shopping experience, leading to emotion-driven decisions that override rational thinking and accelerate purchase choices [24]. Personalized configurations foster a strong alignment with individual styles, strengthen emotional connections, and increase user focus [86]. In this state, users are more likely to overlook rational factors such as price and functionality. The instant gratification provided by personalized configuration amplifies shopping impulses [58]. Furthermore, high ease of use reduces learning costs and operational burdens, allowing users to focus entirely on the try-on experience. This heightened immersion further facilitates impulse buying behavior [87]. We thus propose the following hypotheses:

H3f: *Perceived immersion plays a mediating role between the visual vividness and impulse buying.*

H3g: *Perceived immersion plays a mediating role between the personalized configuration and impulse buying.*

H3h: *Perceived immersion plays a mediating role between the ease of use and impulse buying.*

3.4. Brand Trust

Brand trust is defined as the consumer's confidence in a brand's ability to reliably deliver on its promises [88]. Previous studies have shown that when a brand holds a dominant position in a consumer's mind and is trusted, consumers are more inclined to make an immediate purchase [89]. Putir et al. suggest that the degree of trust in a brand can enhance the propensity for impulse buying [90]. Brand trust strengthens consumers' positive perceptions of the brand, making it easier for perceived value to translate into impulse purchases [91]. Research by Suhyar and Pratminingsih indicates that brand trust influences impulse buying, as consumers tend to view the information and marketing from trusted brands as more authentic and credible, thus increasing their likelihood of impulse buying [92].

Brand trust serves as a powerful market signal, representing a company's reliability, product quality consistency, and commitment fulfillment [93]. It positively influences consumer perceptions of security [94]. As a quality signal, brand trust reduces consumer skepticism toward AI-powered try-on technology and product quality. For instance, when consumers have high brand trust, they are more likely to believe that the AI-powered try-on technology is meticulously designed and optimized to accurately reflect product outcomes, ensuring that products meet expectations. This lowers perceived risk and reduces the cognitive effort required to assess technical reliability, thereby enhancing utilitarian value [95]. Moreover, because brand trust itself acts as a strong signal, consumers more quickly internalize the utilitarian value provided by AI try-on, shortening rational evaluation processes and increasing purchase immediacy. According to the need for cognitive closure theory, brand trust reduces consumers' need for additional information search [96], streamlining the decision-making process and increasing the likelihood of making quick, impulse purchases based on utilitarian value. In this context, brand trust functions as a cognitive shortcut, easing the cognitive load [64]. As a result, consumers can make decisions more swiftly, leading to impulse buying that is quicker, more intuitive, and driven by utilitarian value. We thus propose the following hypothesis:

H4a. *Brand trust positively moderates the relationship between utilitarian value and impulse buying, meaning that, when brand trust is higher, the impact of utilitarian value on impulse buying becomes stronger.*

In the context of AI-powered try-on, perceived hedonic value primarily manifests through novel experiences, immersive interactions, entertainment, and pleasure. Brand trust amplifies the perception of hedonic value through emotional transfer mechanisms [97]. When consumers have high brand trust, they experience psychological security, satisfaction, and a sense of belonging. These positive emotions transfer to their virtual try-on experiences [98]. For example, consumers may perceive the try-on process as more enjoyable and interactive, reducing cognitive dissonance and making it easier to immerse themselves in the fun and entertainment of virtual try-on [99]. We posit that brand trust, through emotional transfer mechanisms, enhances consumers' perception of hedonic value during AI-powered try-on. This heightened hedonic experience reduces rational deliberation and increases the likelihood of impulse buying. We thus propose the following hypothesis:

H4b. *Brand trust positively moderates the relationship between hedonic value and impulse buying, meaning that, when brand trust is higher, the impact of hedonic value on impulse buying becomes stronger.*

Brand trust strengthens the impact of immersive experiences on impulse buying through flow protection mechanisms [100]. According to flow theory, consumers in immersive states can mitigate cognitive distractions, decision anxiety, and privacy concerns [101]. However, high brand trust reduces these external disruptions, enabling consumers to enter flow states more quickly and sustain immersive experiences longer [102]. For instance, consumers with strong brand trust are more likely to believe in the accuracy of AI-powered try-on results without repeatedly comparing virtual and actual outcomes, thereby enhancing immersion. Strong brand trust can also diminish consumers' need for additional information, such as user reviews or return policies, allowing them to concentrate fully on the try-on experience without external distractions [103]. The immersive experience induced by the flow state leads to a loss of time perception, reducing the level of thoughtful consideration typical in traditional shopping settings, thus enabling consumers to make faster purchasing decisions. We thus propose the following hypothesis:

H4c. *Brand trust positively moderates the relationship between perceived immersion and impulse buying, meaning that, when brand trust is higher, the impact of immersion on impulse buying becomes stronger.*

4. Research Methods

4.1. Research Model

Eroglu et al. first applied the SOR model to online shopping platforms, exploring how consumer preferences and cognitive states shape purchasing behavior within virtual retail environments [104]. Building on prior literature and the SOR model, this research develops a new theoretical model. As illustrated in Figure 1, AI-powered try-on technology, as the antecedent variable, is categorized into four key dimensions: visual vividness, interactive control, personalized configuration, and ease of use. Perceived consumer value, serving as a mediating variable, comprises three dimensions: perceived utilitarian value, perceived hedonic value, and perceived immersion. Brand trust moderates the relationship between perceived value and impulsive buying intention, which is the outcome variable.

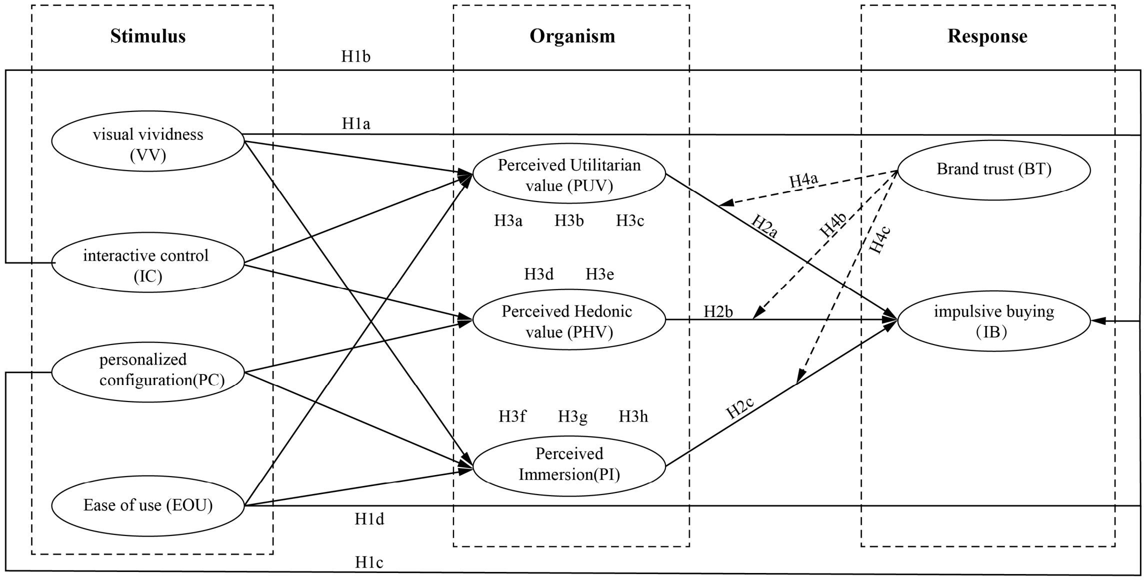


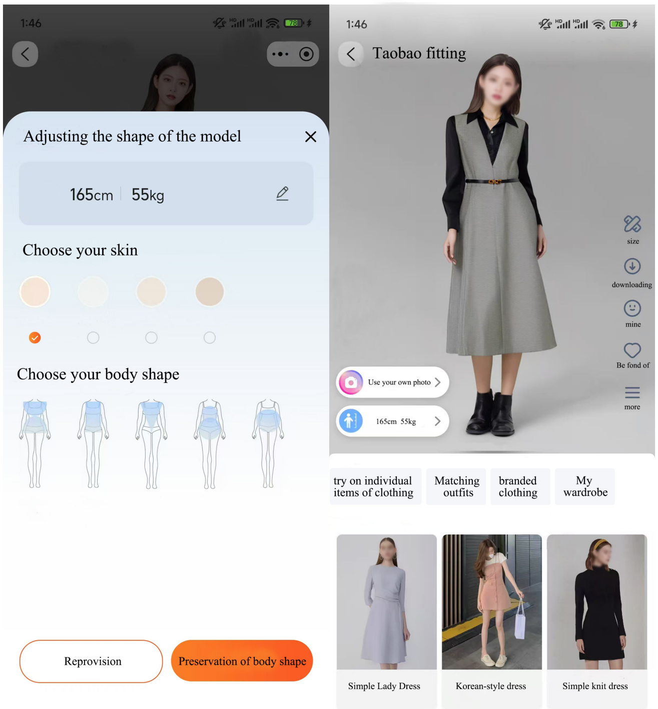
Figure 1. Research model.

4.2. Participants and Procedure

Taobao stands as China's premier e-commerce platform and one of the largest globally [105]. Within its ecosystem, apparel is a cornerstone category, with a widely implemented AI-powered try-on technology that spans numerous brands and product types, serving a vast consumer base [106]. This technology integrates personalized adjustments, intelligent size recommendations, dynamic try-on, styling suggestions, and social sharing, all supported by advanced technology and a highly optimized user experience [83,107]. Given its extensive adoption and technological maturity, this research selects Taobao's virtual try-on application as the research subject. The interface of Taobao's AI-powered try-on technology is illustrated in Figure 2.

In the preparatory phase of the study, 20 participants were invited for an on-site trial aimed at validating the authenticity of AI-powered try-on technology and assessing the quality of its user experience. After uploading personal photos, participants observed that the virtual model images, try-on effects, and virtual garment representations displayed exceptionally high fidelity and realism. The trial process is illustrated in Figure 2. Based on participants' feedback, the survey instrument underwent semantic revisions and reliability analysis to ensure the validity of the data and the accuracy of the research findings. This preliminary experiment not only provided reliable technical validation for subsequent research but also facilitated necessary optimizations in the research design, offering valuable insights, particularly regarding the impact of AI-powered try-on technology on impulse buying intentions.

According to the 2024 China College Student Consumer Behavior Report, the annual consumption expenditure of Chinese university students reached approximately CNY 850 billion, underscoring their substantial purchasing power. The university demographic remains a key driver of China's e-commerce market. Additionally, iiMedia Research data reveal that Taobao continues to be the preferred shopping platform among college students, capturing 39.7% of their total online purchases. Moreover, university students, being in a critical stage of socialization, are particularly susceptible to the influence of social media recommendations. As a result, they are more prone to impulse buying when exposed to visually driven marketing strategies [108]. Strong hedonic motivations often drive their consumption behavior, as they tend to exhibit heightened interest in emerging technologies and fashion trends. Consequently, they are more likely to make spontaneous and non-rational purchasing decisions during the shopping process [109].



(a) (b)

Figure 2. Taobao AI-powered application mobile interface. (**a**) Body adjustment interface; (**b**) Try-on interface.

In conclusion, the selection of university students as the target demographic is particularly justified given the distinctive nature of their decision-making processes and the representative nature of their impulse buying behavior. By focusing on this cohort, the study aims to examine the influence of AI-powered try-on technology on impulse purchasing and to gain deeper insights into their psychological responses to such innovations. To ensure the precision and reliability of the findings, subsequent analyses employ structural equation modeling (SEM) for a rigorous evaluation of the collected data. Before the survey, participants watched an instructional video detailing the functionality and operation of Taobao's virtual fitting room. The video showcased key features such as virtual avatar customization, AI-powered try-on, outfit recommendations, and social media sharing. Following the video, participants were required to download the application on their smartphones and engage with it for 15 min. During this time, they were free to explore the app's features and select clothing items for virtual try-on.

During the experiment, participants' interactions and engagement were closely monitored. Initially, participants were asked to complete virtual try-ons for more than ten different styles of clothing and provide screenshots. Subsequently, they were required to submit records of at least 50 virtual try-ons. By monitoring the completion of these tasks, we were able to objectively assess each participant's level of engagement, ensuring the reliability of the experimental results and the validity of the data [110]. After submitting their try-on images, participants were invited to respond to a survey using WeChat, a popular communication tool in China, on the online platform WenJuanXin (https://www.wjx.cn/). In total, 400 questionnaires were collected. In the first section of the survey, participants were asked, "Did you use the virtual try-on feature again after submitting your screenshots?" If the answer was "Yes", they were prompted to continue answering the subsequent questions. If the answer was "No", they were instructed to end the survey. The second section of the questionnaire gathered demographic information, while the final section focused on the research data. In the final step, incomplete and duplicate responses were removed. A total of 34 responses were deemed unsuitable for the study, leaving 366 valid questionnaires for analysis. Table 1 provides detailed demographic information of the survey participants.

Table 1. Demographic statistics.

Measures	Value	Frequence	(%)
Gender	Male	153	41.8
	Female	213	58.2
Age (years)	18–21	111	30.33
	22–24	134	36.61
	Over 24 years old	121	33.06
Education	Post-secondary education	121	33.06
	Bachelor's degree	165	45.08
	Master's degree or above	80	21.86
Major	Engineering	155	42.35
	Management	54	14.75
	Arts	46	12.57
	Literature	69	18.85
	Others	42	11.48
Online shopping experience	6 months to 1 year	33	9.02
	1–2 years	115	31.42
	3–4 years	146	39.89
	More than 5 years	72	19.67
Average monthly expenditure on clothing	Less than 1000	145	39.62
	1000–2000		26.5
	2000–3000	99	27.05
	More than 3000	25	6.83
Pre-awareness of virtual dress fitting APP	Yes	366	100
	No	0	0
Total		366	100

4.3. Measurement

The questionnaire measures used in this research were derived from a review of existing literature and adapted to fit the specific research context (see Table 2 for details). The four items measuring visual vividness (VV) were adapted from Yim et al. [40], McLean et al. [111], and Hyo Jeong Kang et al. [112]. Items assessing interactive control (IC) were modified from the works of Huang et al. [113], Yu et al. [21], Voicu et al. [20], and Song et al. [13]. The personalized configuration (PC) was adapted from Yu et al. [21], Song et al. [13], Li et al. [114], and Gao et al. [115]. The four items measuring ease of use (EOU) were adapted from Zhang et al. [116] and Lee et al. [27]. Perceived utilitarian value (PUV) was assessed using four items modified from the studies of Lee et al. [117], Alimamy et al. [118], and Hsu et al. [119]. Similarly, the four items for perceived hedonic value (PHV) were adapted from the research of Hsu et al. [119], Huang et al. [120], and Yin et al. [33]. Perceived immersion (PI) was measured using four items derived from prior studies by Daassi et al. [121], Song et al. [122], and Arghashi et al. [123]. Impulse buying (IB) was assessed through five items adapted from the works of Chen et al. [124], Chen et al. [24], Miranda et al. [125], Kimiagari et al. [126], and Trivedi et al. [127]. Lastly, brand trust (BT) was measured using four items drawn from the studies of Sohaib et al. [88], Joshi et al. [128], and Villagra et al. [129]. All items were measured on a seven-point Likert scale, ranging from "strongly disagree" (1) to "strongly agree" (7).

Table 2. Measurement.

Constructs	Items	Reference
Visual Vividness (VV)	VV1: The overall image of the virtual model created by this technology is very similar to the real image.	[40]
	VV2: This technology creates a virtual model whose body characteristics (such as circumference, leg shape, proportion, etc.) are very similar to the real image.	[111]
	VV3: The visual display of the product presented by this technology is very clear.	[40]
	VV4: The visual effect presented by this technology is vivid, novel and impressive.	[112]
Interactive Control (IC)	IC1: I have certain control over the technology and can freely choose the information I want.	[113]
	IC2: I can control the rhythm and navigation of my product browsing.	[21]
	IC3: I can comment through this virtual fitting APP and see others' comments.	[20]
	IC4: I can share the virtual fitting experience link on social media.	[13]
Personalized Configuration (PC)	PC1: This technology allows me to modify the overall body characteristics (such as fat, thin, etc.) and see the modified clothing effect.	[21]
	PC2: This technology allows detailed correction of the local body characteristic index and can see the changed clothing effect.	[13]
	PC3: This technology allows me to modify my hair style, etc, and see the effect of matching clothes.	[114]
	PC4: I can mix and match clothes according to my interests and see the effect after matching.	[115]
Ease of Use (EOU)	EOU1: I think the interface of VFRs will be clear and understandable.	[116]
	EOU2: I think the virtual fitting APP is easy to use.	[116]
	EOU3: I am easily adept at using virtual fitting apps.	[27]
	EOU4: I feel like the virtual fitting app runs fast.	[27]
Perceived Utilitarian Value (PUV)	PUV1: Using the virtual fitting app, I can shop for clothes online very easily.	[119]
	PUV2: Using the virtual fitting app, I can very easily combine a varied range of products and choose more easily what suits me better.	[119]
	PUV3: Using the virtual fitting APP, I can very easily combine a varied range of products and change the way I arrange myself more easily.	[120]
	PUV4: Using the virtual fitting APP is practical for me.	[33]
Perceived Hedonic Value (PHV)	PHV1: Shopping with virtual fitting apps makes me happy	[119]
	PHV2: Shopping with virtual fitting apps makes me feel relaxed.	[119]
	PHV3: Shopping with a virtual fitting app where I can find ways to enjoy myself.	[120]
	PHV4: Shopping with virtual fitting apps it can surprise and intrigue me.	[33]
Perceived Immersion (PI)	PI1: I forget the reality of the outside world when using virtual fitting apps.	[121]
	PI2: While using the virtual fitting app, I was immersed in the task at hand.	[122]
	PI3: The virtual fitting app stimulated my thinking.	[123]
	PI4: The clothing seemed to exist in real-time.	[121]
Impulse Buying (IB)	IB1: I often think "buy now, think later" when using a virtual fitting app.	[124]
	IB2: After seeing so many people share trying on the product, I feel like I can't wait to want it.	[24]
	IB3: It's hard to resist the temptation to do this purchase.	[125]
	IB4: I buy clothes on the virtual fitting app without thinking twice.	[126]
	IB5: I wasn't planning on purchasing this dress, but after having a virtual fitting, I ended up buying it.	[127]
Brand Trust (BT)	BT1: I trust the quality of my favourite brand' s products.	[88]
	BT2: My preferred fashion brand is honest and truthful with me about its products and services.	[128]
	BT3: My favourite brand's products make me feel safe	[129]
	BT4: Buying my favourite brand's products is guarantee	[129]

5. Data Analysis and Results

This research investigates the impact of AI-powered try-on technology on impulse buying intentions while examining the mediating role of perceived value between AI-powered try-on technology and impulse buying intentions. Finally, it explores the moderating effect of brand trust on the relationship between perceived value and impulse buying intentions. Partial least squares structural equation modeling (PLS-SEM) is employed to analyze models involving both mediating and moderating variables. Compared to other methods, PLS imposes fewer restrictions on sample size [130]. PLS-SEM is frequently used across various disciplines, including marketing, organizational, and strategic management. It allows for modeling multiple dependent and independent variables, addresses multicollinearity, robustly handles data disturbances and missing values, and constructs latent independent variables based on cross-product matrices of response variables, thereby enabling compelling predictions [131].

Therefore, this study utilized SPSS 27.0 for descriptive statistical analysis of the sample. Smart PLS 4.0 was employed for multivariate statistics and analysis for structural equation modeling and hypothesis testing, as it is particularly effective in handling moderating and mediating variables.

5.1. Descriptive Statistics

Descriptive statistics were employed to characterize respondents' answers [132]. The results include mean values, standard deviations, skewness, and kurtosis. As shown in Table 3, PI2 recorded the highest mean score (4.21), while IBI5 had the lowest (2.70), indicating that most responses leaned toward affirmative answers. The kurtosis values ranged from −0.047 (PI2) to 1.111 (IBI4), while skewness varied between −1.412 (PI1) and 0.143 (IBI4). According to prior research, acceptable thresholds for skewness and kurtosis are ∣2.3∣ [133]. Since the obtained values fall within this standard range, the dataset exhibits high quality, thereby enhancing the reliability of subsequent model testing.

Table 3. Descriptive statistics.

Constructs	Mean Statistic	Mean Statistic	Std. Dev. Statistic	Skewness Statistic	Kurtosis Statistic
Brand Trust (BT)	BT1	3.08	2.024	0.631	−0.917
	BT2	3.08	2.037	0.612	−0.951
	BT3	3.10	2.002	0.629	−0.864
	BT4	3.02	1.998	0.652	−0.863
Ease of Use (EOU)	EOU1	3.09	1.895	0.594	−0.972
	EOU2	3.01	1.929	0.726	−0.759
	EOU3	3.04	1.943	0.650	−0.901
	EOU4	3.05	1.911	0.649	−0.859
Impulse Buying Intent (IBI)	IBI1	2.72	1.811	1.022	−0.022
	IBI2	2.71	1.881	1.078	−0.029
	IBI3	2.73	1.870	1.013	−0.146
	IBI4	2.72	1.872	1.111	0.143
	IBI5	2.70	1.834	1.084	0.123
Interactive Control (IC)	IC1	2.96	1.850	0.755	−0.675
	IC2	2.85	1.778	0.912	−0.297
	IC3	3.01	1.865	0.773	−0.646
	IC4	3.05	1.893	0.795	−0.638
Perceived Hedonic Value (PHV)	PHV1	3.05	2.029	0.784	−0.660
	PHV2	3.13	2.067	0.668	−0.909
	PHV3	3.02	1.962	0.723	−0.731
	PHV4	3.06	2.039	0.789	−0.693
Perceived Immersion (PI)	PI1	3.76	2.200	0.285	−1.412
	PI2	4.21	2.247	−0.047	−1.538
	PI3	3.96	2.228	0.085	−1.504
	PI4	3.34	2.037	0.493	−1.108
Personalized Provision (PP)	PP1	3.33	2.027	0.584	−1.044
	PP2	3.26	1.970	0.573	−0.975
	PP3	3.19	1.970	0.628	−0.935
	PP4	3.00	1.951	0.783	−0.661

Table 3. *Cont.*

Constructs	Mean Statistic	Mean Statistic	Std. Dev. Statistic	Skewness Statistic	Kurtosis Statistic
Perceived Utilitarian Value (PUV)	PUV1	2.98	1.995	0.750	−0.868
	PUV2	3.01	2.049	0.737	−0.934
	PUV3	3.02	2.019	0.739	−0.899
	PUV4	3.05	2.012	0.696	−0.952
Vivid Visual Image (VVI)	VVI1	3.20	1.973	0.568	−1.050
	VVI2	3.23	1.946	0.571	−0.967
	VVI3	3.17	1.922	0.587	−0.907
	VVI4	3.22	1.954	0.600	−0.942

5.2. Evaluation of Measurement and Structural Model

Before evaluating the structural model in PLS-SEM, the measurement model is validated by assessing its reliability and validity. The results indicate that all factor loadings range from 0.823 to 0.953, all exceeding the threshold of 0.7, confirming the satisfactory measurement quality for each construct. Additionally, the reliability of the constructs is examined using both Cronbach α and composite reliability (CR), with both values expected to exceed 0.700 [134]. The results reveal that Cronbach α values range from 0.846 to 0.958, and CR values range from 0.894 to 0.968, indicating that all constructs exhibit good reliability and internal consistency.

Subsequently, this research assesses the validity of the measurement scale from convergent and discriminant validity perspectives. Convergent validity is first evaluated using the average variance extracted (AVE), which reflects the extent to which each construct is explained by its indicators [135]. As shown in Table 4, the AVE values for all constructs range from 0.679 to 0.873, all exceeding the recommended threshold of 0.5 and consistently remaining below their respective Cronbach α values. These results confirm that the scale demonstrates a high level of convergent validity. Regarding discriminant validity, according to the Fornell–Larcker criterion, the square roots of the AVE for each latent factor are more significant than the correlations between that factor and any other latent factors (see Table 5), indicating that the measurement model exhibits good discriminant validity [136]. Moreover, the HTMT values are below 0.9 [137], further supporting the conclusion that the measurement model possesses satisfactory discriminant validity.

Table 4. Results of construct validity and reliability analysis.

Constructs	Items	Factor Loading	Cronbach's α	(rho_a)	Composite Reliability (CR)	AVE
Brand Trust (BT)	BT1	0.928	0.951	0.953	0.965	0.873
	BT2	0.941				
	BT3	0.931				
	BT4	0.937				
Ease of Use (EOU)	EOU1	0.924	0.942	0.943	0.959	0.853
	EOU2	0.924				
	EOU3	0.919				
	EOU4	0.926				
Impulse Buying (IB)	IB1	0.917	0.958	0.958	0.968	0.856
	IB2	0.940				
	IB3	0.935				
	IB4	0.922				
	IB5	0.913				

Table 4. *Cont.*

Constructs	Items	Factor Loading	Cronbach's α	(rho_a)	Composite Reliability (CR)	AVE
Interactive Control (IC)	IC1 IC2 IC3 IC4	0.922 0.935 0.917 0.932	0.945	0.946	0.960	0.858
Perceived Hedonic Value (PHV)	PHV1 PHV2 PHV3 PHV4	0.899 0.909 0.924 0.926	0.935	0.936	0.954	0.837
Perceived Immersion (PI)	PI1 PI2 PI3 PI4	0.808 0.832 0.837 0.820	0.846	0.865	0.894	0.679
Personalized Configuration (PC)	PC1 PC2 PC3 PC4	0.891 0.918 0.900 0.823	0.906	0.910	0.934	0.780
Perceived Utilitarian Value (PUV)	PUV1 PUV2 PUV3 PUV4	0.919 0.938 0.926 0.917	0.944	0.946	0.960	0.856
Visual Vividness (VV)	VV1	0.953	0.944	0.946	0.960	0.857

Table 5. Discriminant validity (Fornell–Larcker criterion).

Construct	BT	EOU	IB	IC	PHV	PI	PC	PUV	VV
BT	0.934								
EOU	0.428	0.923							
IB	0.550	0.618	0.925						
IC	0.492	0.537	0.642	0.927					
PHV	0.534	0.502	0.615	0.554	0.915				
PI	0.265	0.324	0.458	0.400	0.313	0.824			
PC	0.443	0.476	0.625	0.528	0.477	0.365	0.883		
PUV	0.408	0.461	0.596	0.517	0.458	0.351	0.509	0.925	
VV	0.424	0.470	0.571	0.544	0.399	0.258	0.459	0.465	0.926

5.3. Hypothesis Testing

Before conducting the path coefficient analysis, it is essential to assess whether multicollinearity exists among the latent variables in the structural model. Regarding model diagnostics, multicollinearity among the latent factors is evaluated using the variance inflation factor (VIF), with VIF values exceeding 5 indicative of multicollinearity. This study's highest VIF is 2.107, suggesting that multicollinearity is not a concern. To ensure the stability of the estimated parameters for each construct, this study employs the bootstrap resampling method, performing 5000 iterations of sample extraction and analysis to determine the validity of the paths. If $t \geq 1.96$ and the significance level (p-value) is less than 0.05, the hypothesis is supported [116]. The path coefficients are presented in Figure 3, while the p-values and t-values are shown in Table 6.

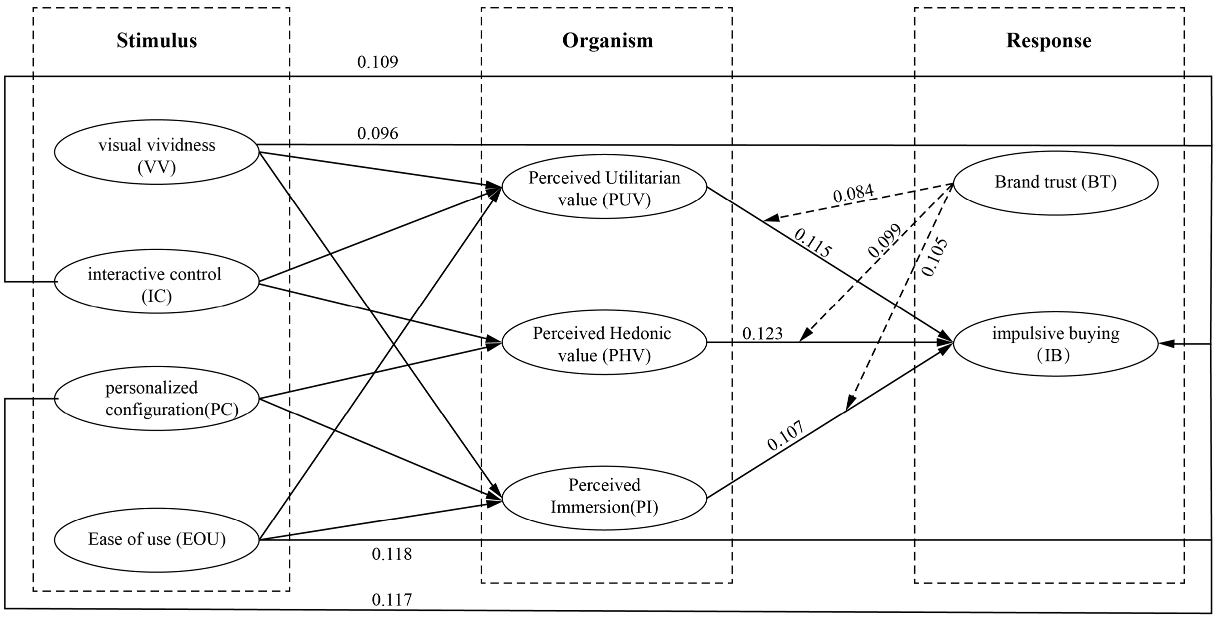


Figure 3. Results of PLS-SEM analysis.

Table 6. Result of structural equation modeling.

Structural Model Paths	Original Sample	Sample Mean	Standard Deviation	*t*-Value	*p*-Value	Result
H1a VV → IB	0.096	0.096	0.042	2.292	0.022	Accepted
H1b IC → IB	0.109	0.109	0.042	2.601	0.009	Accepted
H1c PC → IB	0.117	0.116	0.043	2.689	0.007	Accepted
H1d EOU → IB	0.118	0.116	0.046	2.558	0.011	Accepted
H2a PUV → IB	0.115	0.114	0.040	2.895	0.004	Accepted
H2b PHV → IB	0.123	0.124	0.042	2.957	0.003	Accepted
H2c PI → IB	0.107	0.107	0.033	3.197	0.001	Accepted

H1a investigates the relationship between visual vividness (VV) and impulse buying (IB). This significant relationship ($\beta = 0.096$, $t = 2.292$, $p < 0.05$) indicates that a more visual vividness in AI-powered try-on technology positively influences impulse buying. The relationship between interactive control (IC) and IB is also significant ($\beta = 0.109$, $t = 2.601$, $p < 0.01$), suggesting that better interactive control in AI-powered try-on technology positively affects impulse buying. Similarly, the relationship between personalized configuration (PC) and IB is significant ($\beta = 0.117$, $t = 2.689$, $p < 0.01$), implying that a higher level of personalized configuration in AI-powered try-on technology positively influences impulse buying. Furthermore, the relationship between ease of use (EOU) and IB is significant ($\beta = 0.118$, $t = 2.558$, $p < 0.05$), suggesting that greater ease of use in AI-powered try-on technology positively affects impulse buying. Therefore, the hypotheses H1a, H1b, H1c, and H1d are all supported, confirming the validity of H1. As shown in Table 5, the positive influence of perceived utilitarian value (PUV) on IB is significant ($\beta = 0.115$, $t = 2.895$, $p < 0.01$). Similarly, the relationship between perceived hedonic value (PHV) and IB is significant ($\beta = 0.123$, $t = 2.957$, $p < 0.01$), indicating that a higher perceived utilitarian value in AI-powered try-on technology positively influences impulse buying. Finally, the relationship between perceived immersion (PI) and IB is significant ($\beta = 0.107$, $t = 3.197$, $p < 0.01$), suggesting that a more substantial perceived immersion in AI-powered try-on technology positively impacts impulse buying. Consequently, hypotheses H2a, H2b, and H2c are supported, thereby confirming the validity of H2.

This research employs Smart-PLS 4.0 with bootstrap resampling (5000 samples) to test the mediating effects of perceived utilitarian value (PUV), perceived hedonic value (PHV), and perceived immersion (PI). The results of these mediating effects are presented in Table 7. Perceived utilitarian value (PUV) plays a significant mediating role between visual vividness (VV) and impulse buying (IB) (β = 0.024, t = 2.193, $p < 0.05$), between interactive control and IB (β = 0.034, t = 2.531, $p < 0.05$), and between ease of use and IB (β = 0.019, t = 2.012, $p < 0.05$). Therefore, hypotheses H3a, H3b, and H3c are supported. Perceived hedonic value (PHV) plays a significant mediating role between interactive control and IB (β = 0.052, t = 2.819, $p < 0.01$), as well as between personalized configuration (PC) and IB (β = 0.032, t = 2.342, $p < 0.05$). Hence, hypotheses H3d and H3e are supported. However, perceived immersion (PI) does not significantly mediate the relationship between visual vividness and impulse buying (β = 0.006, t = 2.440, $p > 0.05$). Thus, hypothesis H3f is not supported. Nevertheless, PI plays a significant mediating role between personalized configuration and IB (β = 0.027, t = 2.440, $p < 0.05$), as well as between ease of use and IB (β = 0.019, t = 2.012, $p < 0.05$). Consequently, hypotheses H3g and H3h are supported.

Table 7. Mediation effects.

Structural Model Paths	Original Sample	Sample Mean	Standard Deviation	*t*-Value	*p*-Value	Result
H3a VV → PUV → IB	0.024	0.024	0.011	2.193	0.028	Accepted
H3b IC → PUV → IB	0.034	0.033	0.013	2.531	0.011	Accepted
H3c EOU → PUV → IB	0.019	0.019	0.009	2.012	0.044	Accepted
H3d IC → PHV → IB	0.052	0.052	0.018	2.819	0.005	Accepted
H3e PC → PHV → IB	0.032	0.032	0.013	2.342	0.019	Accepted
H3f VV → PI → IB	0.006	0.006	0.007	0.967	0.334	Rejected
H3g PC → PI → IB	0.027	0.027	0.011	2.440	0.015	Accepted
H3h EOU → PI → IB	0.019	0.019	0.009	2.012	0.044	Accepted

This research employs Smart-PLS 4.0 to test the moderating effect of brand trust. The results of the moderating effect of brand trust are presented in Table 8. H4 tests the moderating effect of brand trust on the relationship between perceived utilitarian value (PUV) and impulse buying (IB). The results indicate a significant moderating effect in the relationship between perceived utilitarian value and IB (β = 0.084, t = 2.080, $p < 0.05$). Similarly, the impact of perceived hedonic value (PHV) on IB is significantly moderated by brand trust (β = 0.099, t = 2.896, $p < 0.01$). Brand trust also significantly moderates the relationship between perceived immersion (PI) and IB (β = 0.105, t = 2.990, $p < 0.01$). Therefore, hypotheses H4a, H4b, and H4c are supported, confirming the validity of H4.

Table 8. Moderating effects of brand trust.

Structural Model Paths	Original Sample	Sample Mean	Standard Deviation	*t*-Value	*p*-Value	Result
H4a BT × PUV → IB	0.084	0.082	0.040	2.080	0.038	Accepted
H4b BT × PHV → IB	0.099	0.100	0.034	2.896	0.004	Accepted
H4c BT × PI → IB	0.105	0.106	0.035	2.990	0.003	Accepted

6. Discussion

Existing research suggests that virtual reality significantly impacts marketing effectiveness and user satisfaction [24,138]. A growing body of literature has provided insights into the applications of virtual technologies in enhancing user experience, customer satisfaction, and marketing activities [13,139,140]. However, prior studies have rarely examined the relationships between AI-powered try-on technology, consumers' perceived value, impulse buying intentions, and brand trust. Accordingly, the primary objective of this study is to investigate the impact of AI-powered try-on technology on online consumers' impulse buying intentions, with a particular focus on the mediating role of perceived value and the moderating role of brand trust. Drawing upon a modified stimulus–organism–response (SOR) model, this study seeks to explain how AI-powered try-on technology influences consumers' impulse buying behavior. Specifically, we identify four key features of AI-powered try-on technology—vivid visual imagery, interactive control, personalized configuration, and ease of use—and examine their effects on consumers' impulse buying intentions. These features not only exert a direct positive influence on impulse buying behavior but also operate through critical mediating mechanisms, including perceived utilitarian value, perceived hedonic value, and perceived immersion.

The study demonstrates that the vividness of visual imagery and personalized interactive control in AI-driven virtual try-on technology has a significant positive impact on consumers' impulse buying intentions. Perceived utilitarian value and perceived hedonic value, as mediating variables, further amplify the influence of these technological features. Specifically, perceived utilitarian value enhances consumers' purchase motivations by offering convenience and practicality in the shopping process, while perceived hedonic value stimulates impulse buying by increasing the enjoyment and entertainment value of the shopping experience. Additionally, the role of perceived immersion was also validated, indicating that consumers are more prone to impulsive purchasing behaviors when immersed in an engaging and interactive experience.

The moderating role of brand trust was also validated in this study. The results indicate that, in high brand trust contexts, the influence of various features of AI-powered try-on technology on impulse buying intentions is significantly stronger. These findings are consistent with prior research, where scholars have suggested that strong brand trust can effectively drive consumers' impulse buying tendencies [90]. This suggests that, once consumers have established a trust relationship with a brand, they are more likely to be influenced by the stimuli provided by try-on technology, leading to impulsive purchasing behaviors. This finding highlights the pivotal role of brand trust in the consumer decision-making process, particularly in the context of emerging technological applications.

7. Conclusions

7.1. Theoretical and Managerial Implications

This study, grounded in the SOR model, explores how AI-powered try-on technology influences consumers' impulse buying intentions through perceived value (utilitarian value, hedonic value, and immersion experience). While the SOR model has been extensively applied to online shopping behavior research, there remains a limited understanding of how AI-powered try-on experiences shape consumer psychology and decision making. The primary contribution of this study lies in extending the SOR model to the emerging context of AI-powered virtual try-on, thereby enhancing its explanatory power in AI-enabled e-commerce. Additionally, this study deconstructs perceived value into three dimensions—utilitarian value, hedonic value, and immersion experience—and elucidates their distinct pathways in shaping impulse buying intentions. Unlike previous research that predominantly focuses on conventional purchase drivers, such as price discounts and social influences, this study underscores how technology-driven shopping experiences influence consumer decision-making processes. This contribution not only broadens the conceptualization of perceived value in digital shopping environments but also provides a more granular framework for future research to interpret technology-driven consumer decision behaviors precisely. Finally, this study further validates the critical moderating role of brand trust in the relationship between virtual try-on technology and consumer purchasing behavior. It enriches the theoretical understanding of brand trust within digital consumption contexts, particularly as intelligent technologies and virtual experiences increasingly become mainstream shopping modalities.

In practical applications, AI-powered try-on technology enhances consumers' perceived value through its key features—visual vividness, interactive control, personalized configuration, and ease of use—thereby stimulating impulse buying. For instance, in terms of interactive control, brands can integrate visual displays of sustainable materials within the virtual try-on interface, offering interactive information such as carbon footprint and supply chain transparency. By leveraging augmented reality (AR) technology, consumers can virtually "experience" the texture of eco-friendly fabrics. These optimizations not only increase consumer interest but also heighten hedonic emotions, suppress rational deliberation, and elevate the likelihood of impulse purchases. Regarding personalized provision, brands can utilize AI to analyze consumers' purchase histories and browsing behaviors to deliver tailored recommendations for sustainable fashion. Platforms can highlight curated selections with labels such as "Eco-friendly picks based on your style" or "Low-carbon footprint essentials", while simultaneously emphasizing product features during the AI-powered try-on process. This strategy enhances consumers' immersive shopping experiences and further stimulates impulse buying tendencies.

Additionally, strengthening brand trust can mitigate perceived purchase risks, thereby facilitating consumer adoption of AI-powered try-on technology. Brands should implement measures that reinforce consumer confidence in AI-generated try-on results. For example, integrating a "real buyer try-on comparison" feature would allow consumers to cross-reference AI-generated visuals with real-user wear experiences, reducing uncertainty. Moreover, brands could incorporate "official certification" labels within the virtual try-on interface, clearly indicating verified technology sources, fabric compositions, and quality assurances. Enhancing transparency and credibility can effectively alleviate consumer hesitation and increase purchase likelihood.

7.2. Limitations

Despite the theoretical and practical contributions made by this study in exploring the impact of AI-powered try-on technology on consumers' impulse buying intentions and the moderating role of brand trust, several limitations remain. First, this study primarily focuses on the online shopping behavior of young consumers in China. However, consumers from different cultural backgrounds may have varying reactions to try-on technology. Future studies could explore cross-cultural differences to provide a more global perspective on the adoption and impact of such technologies. Second, this study employs a cross-sectional research design, with data collected at a specific point in time. Longitudinal studies that track changes in consumer attitudes and behaviors over time could offer deeper insights into how perceptions of virtual try-on technology evolve. Finally, although this study emphasizes several key features of AI-powered try-on technology and their effects on consumer purchase intentions, some factors were not considered. For instance, the potential influence of try-on technology on consumers' social interactions and emotional responses has not been explored. Moreover, this research targets Chinese university students as participants. While this group represents a significant portion of online shoppers and tends to have a high acceptance of AI technologies, their consumption behavior may not fully capture the behaviors of consumers from other age groups, professions, or cultural backgrounds. Therefore, future research could extend to a more diverse sample, encompassing different age groups, socioeconomic classes, and countries, to enhance the external validity of the findings.

7.3. Future Research Directions

Future research could extend to consumer groups in different countries and regions to explore the acceptance of AI-powered try-on technology across various cultural contexts. For example, cultures with high uncertainty avoidance (such as Japan and the Republic of Korea) may rely more heavily on brand trust to reduce the perceived risks associated with AI-powered try-on technology. In contrast, cultures with low uncertainty avoidance (such as the United States and the United Kingdom) may be more open to technological innovations and enhance purchase intention through immersive experiences. Additionally, collectivist cultures (such as China) may be more influenced by social factors, whereas individualistic cultures (such as the United States) may place greater value on personalized customization.

Although this study focused on Chinese university students, investigating the broader applicability of AI-powered try-on technology's impact on impulse buying across different populations is important. For instance, younger consumers (such as Generation Z) may be more receptive to AI technology and view its immersive experience and personalized recommendations as significant drivers of purchasing decisions. In comparison, older consumers may exhibit higher levels of technological anxiety and rely more on brand trust for reassurance. Moreover, gender differences may also influence consumers' perceived value of AI-powered try-on technology. Female consumers might be more attuned to the visual appeal and personalized recommendations that AI-powered try-on technology provides. In contrast, male consumers may prioritize the utility of increased shopping efficiency.

As consumers become more concerned with sustainability, AI-powered try-on technology could play a pivotal role not only in enhancing the shopping experience but also in promoting sustainable fashion consumption. Future studies could draw on sustainable consumption behavior theories to investigate how AI-powered try-on technology impacts consumers' sustainable purchasing decisions. For example, how AI-powered try-on technology influences the acceptance of sustainable fabrics (such as recycled fibers or organic cotton). Furthermore, the research could examine whether AI recommendation systems, based on consumers' historical purchase behavior and environmental awareness, can effectively promote the selection of sustainable fashion items (e.g., second-hand or circular fashion).

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