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The Benefit–Sacrifice Trade-Off of AI-Powered Fashion Services: Effects on Perceived Value and Intention to Use

Seunghyun Woo and Jinsook Hwang *

Department of Apparel Design, Konkuk University, Seoul 05029, Republic of Korea; shwoo92@konkuk.ac.kr
* Correspondence: jsh@konkuk.ac.kr

Abstract

This study investigates the benefit–sacrifice trade-off of artificial intelligence (AI)-powered fashion services by examining how perceived benefits (usefulness, timeliness, enjoyment) and perceived sacrifices (technical effort, privacy risk, lack of personalization) shape consumers' perceived value and intention to use, drawing on the Value-based Adoption Model (VAM). Survey data were collected from 420 Millennial and Generation Z (MZ) consumers with prior experience using online fashion platforms, and the measurement and structural models were evaluated using SPSS 25.0 and AMOS 25.0 through confirmatory factor analysis, structural equation modeling, mediation analysis, and multi-group analysis. The results show that timeliness and enjoyment significantly increased perceived value, whereas usefulness and enjoyment directly increased intention to use. Technical effort negatively affected both perceived value and intention to use, while privacy risk showed no significant effect. Unexpectedly, lack of personalization positively influenced intention to use, suggesting that young consumers favor exposure to broad market trends over restrictive, narrowly tailored recommendations. Perceived value mediated the effects of the benefit–sacrifice factors, and consumer trust moderated the value–intention relationship, strengthening it among high-trust consumers. By integrating VAM with a benefit–sacrifice trade-off perspective, this study offers theoretical and practical insights for designing effective AI-driven fashion commerce strategies.

Keywords: artificial intelligence (AI); AI-powered fashion services; benefit–sacrifice trade-off; value-based adoption model (VAM); intention to use; consumer trust

1. Introduction

Rapid advances in artificial intelligence (AI) have positioned information technology (IT) as indispensable across all industrial sectors, making digital integration a prerequisite for sustainable growth. This shift is particularly critical in the fashion industry, where trends and rapid market adaptation are paramount. The convergence of fashion and IT has long been highlighted as a pivotal issue that continues to exert a profound impact on the fashion ecosystem, and the digital transformation accelerated by the COVID-19 pandemic has triggered sweeping changes across various sectors, including fashion [1].

Among the technologies driving this transformation, artificial intelligence (AI) has advanced particularly rapidly, alongside developments in the Internet of Things (IoT), virtual reality (VR), and robotics, which are expected to permeate daily life ever more deeply. Since the emergence of generative AI (GenAI) in 2022, AI has attracted unprecedented scholarly and managerial attention for its capacity to automate creativity, personalize services at scale, and enhance operational efficiency [2]. Among these, global enterprises

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are concentrating their strategic efforts on developing diverse AI-driven services. AI is no longer merely a tool for convenience; it has become seamlessly integrated into personal life, as seen in conversational AI assistants, generative AI tools that create customized content, autonomous driving systems that analyze real-time environments, and smart-home systems that optimize energy use and security based on user behavior patterns. By delivering hyper-personalized services, AI is rapidly expanding its footprint across manufacturing, finance, healthcare, and retail.

However, despite this technological sophistication and rapid diffusion, successful service implementation and stable consumer adoption require a user-centric approach that systematically addresses consumer needs and points of friction, rather than focusing solely on technical performance. The fashion industry is no exception to this trend: AI is increasingly embedded across the consumer journey through personalized styling recommendations, virtual try-on and fitting technologies, and AI-powered chatbots that assist with product search and purchase decisions. While more advanced AI paradigms—such as generative and conversational AI—are rapidly emerging, these foundational AI touchpoints (recommendations, virtual try-on, and chatbots) remain the most widely adopted in fashion e-commerce. Clarifying how consumers form value judgments around these established services provides an essential basis for understanding the adoption of next-generation generative AI applications, which are considered in the concluding discussion. Because fashion consumption is closely tied to individual identity and aesthetic preference, consumer responses to these AI-driven services are likely to be more nuanced and varied than in other product categories. Identifying the specific needs and pain points that fashion consumers experience when engaging with AI is therefore of particular importance for both academic understanding and practical service design.

These consumer-level concerns are no less relevant in the fashion context. At the same time, as AI systems acquire increasingly human-like cognitive and perceptual capabilities, concerns over technology misuse and unintended negative consequences have intensified [3]. The emergence of new technologies inherently has a dual-sided nature, offering unprecedented opportunities while simultaneously posing significant risks [4]. Consumers evaluating new technologies weigh anticipated functional benefits against potential sacrifices [5], and this trade-off often generates resistance rooted in data inaccuracies, the opaque nature of AI algorithms [6], and concerns over data breaches and privacy infringement. Furthermore, the "filter bubble" phenomenon—in which consumers are repeatedly exposed to algorithmically biased information—can undermine autonomous choice [7]; yet other research suggests that reduced personalization may instead support exploratory consumption: some consumers actively resist highly personalized curation to preserve their individual style [8], a tendency that is particularly salient among younger consumers for whom fashion serves as a vehicle for identity exploration [9]. Understanding how fashion AI users—particularly the Millennial and Generation Z (MZ) consumers who constitute a dominant share of this market—actually respond to such algorithmic curation, whether as a threat to autonomy or an opportunity for exploration, is therefore an important empirical question.

In response to these challenges and tensions, a growing body of research has sought to examine the ethical dilemmas and potential risks associated with AI [10,11]. Sustainable AI development requires a holistic perspective that accounts for both perceived benefits and hidden drawbacks. A recent systematic and bibliometric review of AI-driven consumer research in fashion (2022–2025) shows that empirical attention has concentrated primarily on AI-powered chatbots and general AI services, most often explained through the Technology Acceptance Model (TAM) and the Stimulus-Organism-Response (SOR) framework, while studies explicitly examining the trade-off between perceived benefits and sacrifices

remain scarce [2]. Indeed, this review reports that the personalization-privacy trade-off has been examined in only a single study to date, and even then only within a physical retail context, leaving the broader benefit-sacrifice structure of consumer perceptions in AI-powered fashion services largely unexplored. Because this benefit-sacrifice trade-off manifests differently depending on the industry context and service type, empirical investigation is needed to identify the specific barriers perceived by fashion consumers and to delineate future directions for AI-powered fashion services.

Accordingly, this study adopts the Value-Based Adoption Model (VAM) as a theoretical framework to empirically examine the causal relationships among the benefit-sacrifice trade-off of AI-powered fashion services, perceived value, and intention to use. VAM posits that consumers form an overall perception of value by weighing perceived benefits against perceived sacrifices, and that this perceived value, in turn, shapes adoption behavior. Furthermore, given the interplay of expectation and anxiety surrounding AI, consumer trust is a critical determinant of long-term technology acceptance [12]. This study therefore also investigates the moderating role of trust in the relationship between perceived value and intention to use, thereby re-examining the centrality of consumer trust in the fashion AI context.

By identifying how specific benefit and sacrifice factors shape consumer value perceptions and adoption intentions, this study aims to extend the literature on AI-driven commerce and to offer practical implications for AI-powered fashion service providers seeking to design user-centric strategies that balance technological innovation with consumer trust.

2. Literature Review and Hypothesis Development

2.1. Concept and Benefit–Sacrifice Trade-Off of Artificial Intelligence

Artificial Intelligence (AI) refers to systems capable of solving complex problems and supporting decision-making processes through data-driven learning, characterized by continuous performance enhancement via iterative training. Beyond basic problem-solving, modern AI technology has advanced toward sophisticated predictive and evaluative capabilities, seeing widespread integration across diverse consumer service domains [13]. Concurrently, these technological strides have elevated consumer expectations for heightened decision-making efficiency and convenience.

AI-driven services deliver various perceived benefits to consumers. Specifically, they optimize efficiency during task performance and information retrieval, enabling expedited decision-making through rapid data processing and analytical capabilities [14–16]. Moreover, AI-powered recommendation and curation features alleviate cognitive overload amid information abundance, allowing users to experience hedonic enjoyment and interest during service engagement. Jang [17] empirically confirmed that efficiency and hedonic value serve as primary motivators for AI service adoption, demonstrating that consumers recognize entertaining elements as a distinct benefit. Thus, AI services possess the intrinsic capability to concurrently deliver functional efficiency and emotional enjoyment.

Conversely, AI services inherently encompass non-negligible negative attributes. Because data analytics form the operational foundation of AI services, personal data collection and utilization are indispensable prerequisites, inadvertently triggering concerns regarding privacy infringement and data breaches [18]. The proliferation of AI applications leveraging voice recognition and image processing has further amplified user anxiety surrounding privacy preservation [19]. Additionally, technical glitches and system reliability issues represent salient risk factors during service interaction [20]. Furthermore, algorithmic recommendation and filtering functions risk constraining consumer autonomy. Although filtering mechanisms enhance search efficiency by delivering preference-tailored

content, continuous exposure to homogenous information can exacerbate confirmation bias [21]. This algorithmic constraint ultimately restricts autonomous decision-making and leads to unfavorable service evaluations [22]. Indeed, Kim [23] demonstrated that when AI recommendation systems undermine perceived autonomy, consumer happiness and word-of-mouth intentions are significantly diminished.

Current AI systems remain at an augmented, human-collaborative stage rather than full automation, constrained by lingering issues in accuracy, safety, and security [24]. Consumers thus experience psychological ambivalence, anticipating functional benefits while harboring concerns over potential sacrifices. Because this benefit-sacrifice trade-off shapes overall service value and intention to use, examining consumer perception structures is essential to understanding AI diffusion in the fashion industry.

2.2. AI-Powered Fashion Services and the Benefit–Sacrifice Trade-Off

The rapid development of Artificial Intelligence (AI) technology has transformed the broader fashion industry, influencing every stage from product design and production to distribution and marketing [25,26]. Initially restricted to unidirectional information delivery such as basic product searches, AI-powered fashion services have evolved alongside the popularization of online shopping. Today, AI leverages big data to analyze consumer characteristics, taste preferences, and behavioral patterns, serving as a core mechanism for customized service delivery and optimized information processing [13,27].

In online fashion retail environments, AI-powered fashion services manifest through various interactive customer touchpoints, predominantly including personalized recommendation algorithms, virtual try-on (VTO) services, and conversational chatbots. These applications mitigate information search friction, streamline shopping efficiency, and support purchasing decisions in digital settings where human interaction is inherently absent [27–29]. Recent empirical studies demonstrate that these AI-driven features enhance shopping convenience, brand trust, decision confidence, and overall customer satisfaction [30].

Importantly, rather than being restricted to a single isolated feature, the perceived benefits and sacrifices evaluated in this study represent pervasive dimensions experienced across AI-powered fashion services as a whole:

- Perceived Benefits across AI-powered fashion services: The functional utility of optimizing choices (usefulness), the accelerated speed of search and decision-making (timeliness), and the interactive, novel shopping engagement (enjoyment) constitute ubiquitous benefits that consumers derive from diverse AI interactions, including recommendations, VTO, and chatbots.
- Perceived Sacrifices across AI-powered fashion services: Conversely, potential risks and operational friction points permeate all fashion AI touchpoints. For instance, privacy risks arise not only from the collection of biometric body images in VTO, but also from continuous tracking of personal preferences in recommendation systems and conversational data harvesting in chatbots [31]. Similarly, a lack of personalization reflects a systemic concern across AI-powered fashion services—where consumers perceive that algorithms, whether in recommendations, VTO, or chatbots, deliver generic, trend-focused, or standardized responses rather than capturing nuanced, individual aesthetic preferences [32]. Furthermore, adapting to varying AI user interfaces and managing operational glitches pose a universal cognitive burden (technical effort) across all AI-powered fashion service touchpoints [33].

In summary, while specific AI applications may accentuate certain features, AI-powered fashion services inherently operate as a double-edged sword within online decision-making processes. Consumers simultaneously evaluate multidimensional benefits (usefulness, timeliness, and enjoyment) and sacrifices (technical effort, privacy risks, and lack of personalization)

across their overall fashion AI experience. Consequently, this holistic evaluation of benefit–sacrifice trade-off serves as a decisive antecedent shaping overall perceived service value and subsequent intention to use.

2.3. Theoretical Framework: Value-Based Adoption Model (VAM)

Understanding consumer adoption intention is essential for the commercialization and diffusion of novel technologies. Davis [34] proposed the Technology Acceptance Model (TAM), centered on perceived usefulness and ease of use. Later extensions—the Extended TAM and the Unified Theory of Acceptance and Use of Technology (UTAUT)—further developed the understanding of user behavior. However, these models focus primarily on the positive utilities of technology use, overlooking the sacrifices and friction points consumers must endure [35,36].

In practice, consumers evaluating new technologies weigh benefits—convenience, efficiency—against sacrifices such as financial cost, perceived risk, and effort. To address this limitation, Kim et al. [37] introduced the Value-Based Adoption Model (VAM), which posits that perceived value—formed through the cognitive trade-off between benefits and sacrifices—determines intention to use [37,38]. By integrating positive drivers (e.g., usefulness, enjoyment) with negative inhibitors (e.g., technical burden, risk), VAM is well suited to explaining AI-driven service adoption, where functional gains and psychological burdens coexist [28].

This study therefore adopts VAM as its theoretical framework to capture the benefit–sacrifice trade-off of AI-powered fashion services. Building on the premise that benefits enhance value perception while sacrifices diminish it [37], the sub-dimensions of perceived benefits and sacrifices are operationalized in the following sub-sections.

2.3.1. Perceived Benefits of AI-Powered Fashion Services

Perceived benefits refer to the overall rewards and positive expectations consumers seek when purchasing or using a product or brand [39]. In the Value-Based Adoption Model (VAM), Kim et al. [37] conceptualize perceived benefits through two dimensions: usefulness, an extrinsic and cognitive factor, and enjoyment, an intrinsic and emotional factor. Grounded in Rogers' [40] Innovation Diffusion Theory, this structure reflects how both functional utility and emotional experience jointly shape technology adoption and behavioral intention.

Usefulness represents a cognitive evaluation of the performance gains offered by a new technology [40], defined as consumers' belief that using the technology enhances task performance [34]. As a fundamental determinant in the technology adoption literature, usefulness is a prerequisite for positive value creation [35]. In AI-powered fashion services, usefulness manifests when algorithms process catalog data to deliver accurate recommendations, sizing insights, and coordination suggestions, streamlining consumer decision-making. This aligns with recent findings that perceived usefulness remains a primary driver of favorable attitudes toward AI-based services, even as trust and ease of use exert comparatively weaker influence on continued engagement [41].

Enjoyment reflects the intrinsic fun, pleasure, and emotional engagement experienced during technology interaction [42]. Consumers who perceive hedonic pleasure while engaging with new technologies display more favorable attitudes and adoption behaviors [42]. In AI-powered fashion service environments, enjoyment is driven by interactive features—virtual try-on (VTO) simulations, dynamic style transformations, and conversational AI—that transform routine shopping into engaging experiences [25].

This study also incorporates timeliness (efficiency) as a domain-specific benefit beyond conventional VAM dimensions. A primary motivation for firms deploying AI is to optimize

operational efficiency for users [43]. Given the fast pace of the fashion market and the abundance of online choices, AI-powered fashion services deliver utilitarian value by rapidly identifying preferences, accelerating data processing, and reducing information search time.

Accordingly, this study operationalizes perceived benefits as a multidimensional construct—usefulness, timeliness, and enjoyment—each positively influencing perceived value. The following hypotheses are proposed:

H1a. *Usefulness has a positive effect on perceived value.*

H1b. *Timeliness has a positive effect on perceived value.*

H1c. *Enjoyment has a positive effect on perceived value.*

These benefit dimensions are also posited to directly influence intention to use. When consumers recognize high utility, speed, and pleasure, these attributes directly drive intention to use. The following hypotheses are proposed:

H4a. *Usefulness has a positive effect on intention to use.*

H4b. *Timeliness has a positive effect on intention to use.*

H4c. *Enjoyment has a positive effect on intention to use.*

2.3.2. Perceived Sacrifices of AI-Powered Fashion Services

Perceived sacrifices encompass the monetary and non-monetary costs consumers incur during service acquisition and use [37]. In the original VAM, Kim et al. [37] conceptualized sacrifices as monetary cost (perceived fee) and non-monetary cost (technicality)—the psychological strain, time, and effort required to adapt to a new technology or system [40]. When a service interface is perceived as complex or burdensome relative to its utility, this negatively affects value evaluation and behavioral intention.

In fashion e-commerce, AI-driven features—recommendation algorithms, virtual try-on, chatbots—are typically offered as complimentary value-added services without direct user fees. Monetary cost is therefore excluded from this study as contextually irrelevant, and non-monetary sacrifice is instead operationalized through technical effort as a primary dimension. Because fashion products are particularly prone to size- and fit-related returns, accurately conveying detailed product information and ensuring that AI-powered interfaces process and present this information efficiently become especially important in this category [44]. Interface complexity and inefficient technical interactions are therefore likely to be perceived as a particularly burdensome sacrifice in AI-powered fashion services.

Given the data-driven nature of AI, privacy risk is also a critical non-monetary sacrifice inhibiting adoption [45]. AI-powered fashion services collect personal preferences, purchase histories, and biometric data (e.g., in virtual try-on). Heightened privacy anxiety undermines perceived value and acts as a barrier to service engagement [46]. Because such data often extends beyond conventional consumer identifiers to include body measurements, physical appearance, and personal style preferences, privacy risk may be particularly salient in the fashion domain compared to other e-commerce categories [47,48].

This study further introduces lack of personalization as a sacrifice salient to the fashion domain. Although AI algorithms draw on extensive data, they risk imposing algorithmically curated trends that constrain consumer autonomy [21]. According to psychological

reactance theory, when individuals perceive their freedom of choice to be threatened or restricted, they experience a motivational drive to reassert that freedom, often resulting in negative evaluations of the restricting agent [49,50]. Because fashion consumption centers on personal identity and aesthetic expression, standardized recommendations that fail to capture nuanced preferences can feel restrictive rather than helpful, limiting autonomous exploration. This tension echoes the personalization–privacy paradox identified in the broader AI service literature, where consumers simultaneously desire tailored recommendations yet grow wary of the data practices such personalization entails [51]. Nonetheless, consumer responses to reduced personalization may vary across segments: some consumers actively resist highly personalized recommendations to preserve stylistic distinctiveness [8], a tendency that is particularly pronounced among younger consumers for whom fashion serves as a vehicle for identity exploration [9]. Given this possibility of segment-dependent variation, empirical examination is warranted to determine whether lack of personalization operates as a sacrifice factor as hypothesized below.

Accordingly, this study operationalizes perceived sacrifices as a multidimensional construct—technical effort, privacy risk, and lack of personalization—each acting as a negative inhibitor of perceived value. The following hypotheses are proposed:

H2a. *Technical effort has a negative effect on perceived value.*

H2b. *Privacy risk has a negative effect on perceived value.*

H2c. *Lack of personalization has a negative effect on perceived value.*

These sacrifice dimensions are also posited to directly inhibit intention to use: heightened perceptions of effort and risk directly diminish consumers' readiness to adopt AI-powered fashion services. The following hypotheses are proposed:

H5a. *Technical effort has a negative effect on intention to use.*

H5b. *Privacy risk has a negative effect on intention to use.*

H5c. *Lack of personalization has a negative effect on intention to use.*

2.4. Perceived Value, Intention to Use, and Mediating Role

Perceived value is broadly defined as consumers' overall evaluation of a product or service's utility, formed by weighing perceived benefits against total monetary, temporal, and psychological costs [52]. McDougall and Levesque [53] similarly conceptualized it as the overall advantage gained relative to the sacrifices incurred during service acquisition. Grounded in trade-off theory, consumers seek to maximize utility within constrained resources—a core principle of the Value-Based Adoption Model [37]. In this process, consumers weigh multi-attribute benefits against perceived sacrifices to form their value evaluation, which in turn shapes behavioral intention [52]. This pattern is consistent with recent research on AI-generated fashion products, which similarly finds that consumers' purchase intentions are driven primarily by perceived value dimensions—such as perceived design effort and price value—rather than by technological novelty alone [54].

Intention to use reflects an individual's subjective likelihood and readiness to engage with a specific service, encompassing repeat use, continued engagement, and willingness to recommend [55]. Grounded in the Theory of Reasoned Action [56], positive cognitive evaluations and favorable attitudes toward a service translate into stronger behavioral commitment to continued use [57].

In fashion e-commerce, when consumers perceive that the benefits of AI-powered fashion services (usefulness, timeliness, enjoyment) outweigh accompanying sacrifices (technical effort, privacy risk, lack of personalization), their elevated perceived value directly drives intention to use. Within the VAM framework, perceived value serves as a central cognitive mechanism that transmits the effects of both benefits and sacrifices to intention to use: while benefit and sacrifice factors may also exert direct effects on intention to use, they simultaneously shape perceived value, which in turn influences adoption behavior. Perceived value thus functions as a key mediator within the benefit–sacrifice trade-off framework. The following hypotheses are proposed:

H3. *Perceived value has a positive effect on intention to use.*

H6a. *Perceived value mediates the relationship between usefulness and intention to use.*

H6b. *Perceived value mediates the relationship between timeliness and intention to use.*

H6c. *Perceived value mediates the relationship between enjoyment and intention to use.*

H6d. *Perceived value mediates the relationship between technical effort and intention to use.*

H6e. *Perceived value mediates the relationship between privacy risk and intention to use.*

H6f. *Perceived value mediates the relationship between lack of personalization and intention to use.*

2.5. The Moderating Role of Consumer Trust

Trust is a foundational construct across disciplines, traditionally used to explain the quality of interpersonal relationships. With the evolution of digital environments, trust has extended beyond human actors to encompass corporations, brands, platforms, and technological systems [58]. From a technology adoption perspective, trust represents consumers' belief that a technology will reliably deliver expected performance, along with a willingness to depend on it [12]. In service settings, trust reflects confidence that a provider acts in the consumer's best interest [59]—a mechanism especially vital under high risk and uncertainty [60]. Trust reduces perceived risk, mitigates transactional uncertainty, and drives intention to use, whereas a lack of trust triggers service avoidance [61,62]. This pattern is consistent with recent evidence from AI-powered fashion platforms, where the absence of a trust-integrated framework has been noted as a limitation for fully explaining consumer adoption behavior [63], underscoring the continued relevance of trust as a boundary condition in this domain.

In AI-driven service settings, trust gains heightened significance due to the opacity of algorithmic decision-making, automated recommendations, and extensive data collection. In fashion e-commerce specifically, AI applications rely on biometric measurements, preference tracking, and purchase histories, raising ethical concerns—algorithmic bias, corporate transparency, data misuse—that can induce consumer anxiety. Trust in AI-powered fashion services thus functions not only as a belief in technical competence but also as an ethical contract regarding organizational integrity and responsible data stewardship.

Applying this perspective to the VAM framework, even when consumers perceive high functional value from AI-powered fashion services, a deficiency in trust—particularly regarding data ethics—can hinder intention to use. Conversely, robust consumer trust acts as a psychological safety net that amplifies the translation of perceived value into intention to use. Trust thus operates as a contingent mechanism that strengthens or weakens the relationship between perceived value and intention to use.

Accordingly, this study proposes the following hypothesis:

H7. *Consumer trust positively moderates the relationship between perceived value and intention to use, such that the positive effect is stronger when consumer trust is high.*

2.6. Research Model

To empirically examine the benefit-sacrifice acceptance mechanism of AI-powered fashion services, this study establishes an extended research framework based on the Value-Based Adoption Model (VAM). The framework conceptualizes perceived benefits (usefulness, timeliness, enjoyment) and perceived sacrifices (technical effort, privacy risk, lack of personalization) as multi-attribute antecedents influencing both perceived value and intention to use.

Perceived value is further posited to directly drive intention to use while serving as a central mediator transmitting the effects of the benefit and sacrifice antecedents. Finally, consumer trust is incorporated as a moderating factor that shapes the relationship between perceived value and intention to use. Figure 1 illustrates the proposed research model and hypothesized relationships.

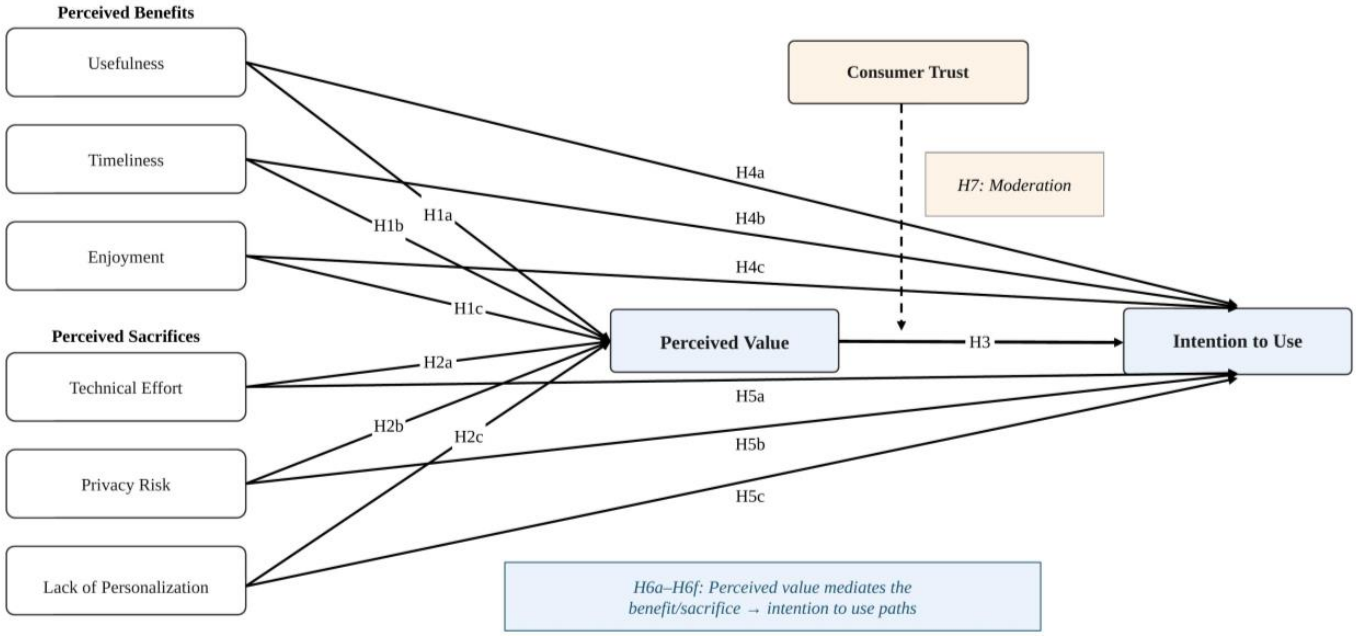


Figure 1. Proposed Research Model. Note: H1a–H5c denote hypothesized direct paths. H6a–H6f denote hypothesized mediating effects of perceived value. H7 denotes the hypothesized moderating effect of consumer trust; the dashed arrow represents this moderating path.

3. Materials and Methods

3.1. Research Design and Data Collection

To empirically validate the proposed research model, an online survey was conducted targeting Millennial and Generation Z (MZ) consumers. This cohort holds strong academic and practical value as a core segment in the online fashion market, given their favorable disposition toward new technologies and their pursuit of value-driven consumption based on firm personal preferences [32,64].

The target population was restricted to adults born between 1981 and 2003 (aged 19 or older) who had purchased or browsed fashion products through online shopping malls within the past six months. To ensure data accuracy, respondents were further limited to those with a basic awareness of artificial intelligence (AI); a clear definition of AI was

provided at the start of the survey, and only respondents confirming their understanding were allowed to proceed.

Data were collected through Macromill Embrain, a professional online survey agency, from respondents meeting the screening criteria. Of the 429 questionnaires initially completed, unfaithful responses—such as straight-lining or excessively short completion times—were excluded, yielding a final sample of 420 valid responses for analysis.

3.2. Operational Definitions and Measurement of Variables

The measurement items utilized in this study were adapted and modified from established prior research to align with the specific research objectives. Except for demographic characteristics and usage behavior items, all variables were measured using a 5-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree").

First, perceived benefits were adapted from [37,65–67], consisting of 15 items tailored to the AI-powered fashion service context. Similarly, perceived sacrifices were reconstructed based on [37,67–69], also measured using 15 items. Perceived value was evaluated with 5 items modified and supplemented from [37,66,68,70]. Intention to use was assessed using 5 items adapted from [37,66,69] to fit the current research context. Furthermore, consumer trust for the moderation analysis was measured using items adapted from [61,69]. Finally, nominal scale items were included to capture respondents' demographic characteristics (e.g., region of residence, occupation, education level, household income, and monthly clothing expenditure) as well as their online shopping and AI-powered fashion service usage behaviors.

3.3. Data Analysis Strategy

Survey data were analyzed using SPSS 25.0 and AMOS 25.0 according to the following procedures. First, frequency analysis examined respondents' demographic characteristics and their online shopping and AI-powered fashion service usage behaviors. Second, exploratory factor analysis (EFA) and reliability analysis (Cronbach's α) assessed the preliminary validity and internal consistency of the measurement tools, followed by independent samples t-tests to examine mean differences across groups. Third, confirmatory factor analysis (CFA) established the convergent and discriminant validity of the measurement model. Finally, structural equation modeling (SEM) tested the hypothesized relationships among variables. The bootstrapping method was applied to verify the significance of direct, indirect, and total effects for the mediation analysis, and multi-group SEM was conducted to examine the moderating role of consumer trust.

In addition, Harman's single-factor test was conducted to assess the potential threat of common method bias.

4. Empirical Results and Analysis

4.1. Demographic Characteristics of the Sample

Table 1 presents the demographic characteristics of the 420 valid respondents used for analysis. The sample was evenly split by gender (49.3% male, 50.7% female) and well distributed across the MZ generation in terms of age, ranging from 20.2% (19–24) to 30.0% (25–29). Respondents were concentrated in the Seoul metropolitan area, with Gyeonggi-do (30.0%) and Seoul (28.8%) together accounting for over half the sample. Office/professional workers formed the largest occupational group (42.2%), and the majority held a university degree (62.1%). Monthly household income was most frequently in the 2–3 million KRW range (24.0%), while monthly clothing expenditure was concentrated between 100,000 and 300,000 KRW (57.2% combined).

Table 1. Demographic Characteristics of the Sample (N = 420).

Category	*n*	%	Category	*n*	%
Gender			**Education**		
Male	207	49.3	High school graduate	45	10.7
Female	213	50.7	Currently enrolled (university)	75	17.9
Age			University graduate	261	62.1
19–24	85	20.2	Graduate school (enrolled/completed)	39	9.3
25–29	126	30.0	**Monthly household income (KRW)**		
30–35	102	24.3	Less than 1 million	18	4.3
36–40	107	25.5	1–2 million	20	4.8
Region			2–3 million	101	24.0
Seoul	121	28.8	3–4 million	77	18.3
Gyeonggi-do	126	30.0	4–5 million	50	11.9
Busan	28	6.7	5–6 million	51	12.1
Incheon	24	5.7	6–7 million	29	6.9
Others	121	28.8	7 million or more	74	17.6
Occupation			**Monthly clothing expenditure (KRW)**		
Office/professional worker	117	42.2	Less than 100,000	96	22.9
Student	89	21.2	100,000–200,000	141	33.6
Freelancer	26	6.2	200,000–300,000	99	23.6
Public official	25	6.0	300,000–400,000	42	10.0
Sales/service worker	23	5.5	400,000–500,000	20	4.8
Others	80	18.9	500,000 or more	22	5.2
Total	**420**	**100.0**	**Total**	**420**	**100.0**

4.2. Measurement Model Evaluation and Validity

To verify the validity and internal consistency of the measurement variables, exploratory factor analysis (EFA) and reliability analysis were conducted first, using principal component analysis (PCA) with eigenvalues greater than 1.0 and Varimax rotation.

The EFA revealed that perceived benefits comprised three sub-dimensions: usefulness (shopping efficiency), timeliness (time-saving and prompt response), and enjoyment (fun and interest derived from service use). Perceived sacrifices likewise comprised three sub-dimensions: technical effort (complexity of initial adoption), privacy risk (anxiety over data security), and lack of personalization (concern that data-driven AI overlooks individual aesthetic traits). Perceived value, intention to use, and consumer trust were each extracted as single-factor structures.

Following item purification—dropping items that undermined validity or internal consistency—confirmatory factor analysis (CFA) was performed on the overall measurement model, comprising nine latent constructs. The results are presented in Table 2.

The measurement model showed a good fit to the data: χ^2 = 531.584 (df = 314, $p < 0.001$), Normed χ^2 = 1.693, RMR = 0.024, GFI = 0.918, RMSEA = 0.041, CFI = 0.966, NFI = 0.922, RFI = 0.907, IFI = 0.967, TLI = 0.960, indicating an overall excellent fit. Convergent validity was established, as standardized factor loadings exceeded 0.70 for all indicators. Average variance extracted (AVE) for the nine latent factors ranged from 0.561 to 0.798, and composite reliability (CR) ranged from 0.779 to 0.944, both exceeding standard

thresholds. Internal consistency was also confirmed, with Cronbach's alpha ranging from 0.737 to 0.907, well above the 0.70 benchmark.

Table 2. Results of Confirmatory Factor Analysis.

Construct	Item	Std. Loading	t-Value	Cronbach's α	AVE	CR
Usefulness	AI services provide useful information for my online fashion shopping.	0.858	—	0.907	0.772	0.944
	AI services seem helpful for shopping for fashion products online.	0.830	21.367 ***			
	AI services are expected to be helpful for my fashion shopping on online platforms.	0.811	20.585 ***			
	AI services are useful.	0.808	20.433 ***			
	I believe that using AI services enables efficient fashion shopping online.	0.771	18.984 ***			
Timeliness	I believe that using AI services helps me make faster purchasing decisions for fashion products online.	0.837	—	0.807	0.616	0.827
	AI services provide only the information relevant to my fashion shopping needs.	0.733	15.486 ***			
	AI services are expected to reduce the time spent shopping for fashion products online.	0.718	15.137 ***			
Enjoyment	I am willing to use AI services for the enjoyment of shopping for fashion products online.	0.796	16.548 ***	0.824	0.687	0.868
	It would be interesting to use AI services when shopping for fashion products online.	0.792	—			
	AI services are expected to enhance the enjoyment of my fashion shopping experience.	0.756	15.668 ***			
Technical Effort	I believe that using AI services for online fashion shopping would be inconvenient.	0.733	—	0.758	0.561	0.793
	Shopping for fashion products in person seems more convenient than using AI services.	0.721	12.991 ***			
	I feel that using AI services for online fashion shopping is still unstable.	0.697	12.619 ***			
Privacy Risk	I am concerned that the security systems of AI services on online platforms are vulnerable.	0.841	17.034 ***	0.842	0.684	0.866
	I am concerned that AI-driven online shopping sites are insecure against spam or hacking attempts.	0.810	—			
	I am afraid that my personal information could be leaked if I use AI services for online shopping.	0.749	15.513 ***			
Lack of Personalization	I am concerned that AI services provide the same or similar information to every consumer.	0.834	9.879 ***	0.737	0.640	0.779
	I feel that AI services focus more on global fashion trends than on my own personal taste.	0.700	—			
Perceived Value	I think the value gained from using AI services for online fashion shopping is worth the effort I put in.	0.805	—	0.810	0.695	0.872
	Using AI services provides greater benefits than the costs of using them for online fashion shopping.	0.760	15.484 ***			
	I am willing to invest time to use AI services for my fashion shopping online.	0.742	15.092 ***			

Table 2. *Cont.*

Construct	Item	Std. Loading	t-Value	Cronbach's α	AVE	CR
Intention to Use	I plan to use AI services in the future when shopping for fashion products online.	0.831	—	0.867	0.798	0.922
	If the online fashion platform I frequently use offers an AI service, I would like to use it.	0.828	19.121 ***			
	I am willing to use artificial intelligence services when shopping for fashion products online.	0.824	18.996 ***			
Consumer Trust	I believe that AI services are trustworthy when shopping for fashion products online.	0.756	—	0.813	0.590	0.887
	I trust the information provided by AI services when shopping for fashion products online.	0.760	15.151 ***			
	I believe that AI services will fulfill my expectations when shopping for fashion products online.	0.787	15.687 ***			

Note: *** $p < 0.001$. Loadings without a t-value served as the reference indicator for scale identification. Model fit: $\chi^2 = 531.584$ (df = 314, $p < 0.001$), Normed $\chi^2 = 1.693$, RMR = 0.024, GFI = 0.918, RMSEA = 0.041, CFI = 0.966, NFI = 0.922, RFI = 0.907, IFI = 0.967, TLI = 0.960.

Discriminant validity was assessed by comparing squared correlations between construct pairs against each construct's AVE. As all squared correlations were lower than the corresponding AVE values, discriminant validity was established (Table 3).

To assess the potential threat of common method bias, Harman's single-factor test was conducted. An unrotated exploratory factor analysis was performed on all observed items measuring the study constructs. The results indicated that the first factor accounted for 33.315% of the total variance, which is well below the recommended threshold of 50% [71]. Therefore, common method bias is unlikely to be a serious concern in this study.

Table 3. Squared Correlations and Average Variance Extracted (AVE) of Constructs.

Construct	USE	TIM	ENJ	TE	PR	LOP	PV	ITU	CT
USE	**0.772**								
TIM	0.561 (0.749)	**0.616**							
ENJ	0.642 (0.801)	0.454 (0.674)	**0.687**						
TE	0.198 (−0.445)	0.150 (−0.387)	0.129 (−0.359)	**0.561**					
PR	0.052 (−0.228)	0.043 (−0.208)	0.023 (−0.150)	0.454 (0.674)	**0.684**				
LOP	0.049 (−0.222)	0.088 (−0.297)	0.014 (−0.117)	0.389 (0.624)	0.176 (0.420)	**0.640**			
PV	0.430 (0.656)	0.511 (0.715)	0.403 (0.635)	0.176 (−0.419)	0.033 (−0.182)	0.057 (−0.238)	**0.695**		
ITU	0.537 (0.733)	0.355 (0.596)	0.529 (0.727)	0.219 (−0.468)	0.047 (−0.217)	0.021 (−0.144)	0.506 (0.711)	**0.798**	
CT	0.484 (0.696)	0.423 (0.650)	0.401 (0.633)	0.172 (−0.415)	0.086 (−0.294)	0.075 (−0.274)	0.576 (0.759)	0.539 (0.734)	**0.590**

Note: Diagonal values (bold) represent the AVE for each construct. Off-diagonal values represent the squared correlation between constructs, with the corresponding correlation coefficient shown in parentheses. Discriminant validity is supported, as all squared correlations are smaller than the AVE values of the corresponding constructs. USE = Usefulness; TIM = Timeliness; ENJ = Enjoyment; TE = Technical Effort; PR = Privacy Risk; LOP = Lack of Personalization; PV = Perceived Value; ITU = Intention to Use; CT = Consumer Trust.

4.3. Hypothesis Testing: Direct Effects

To examine the causal relationships among the latent constructs and test H1 through H5, structural equation modeling (SEM) was performed on the structural model comprising the eight constructs directly involved in the hypothesized paths (i.e., excluding consumer trust, which was examined separately through multi-group analysis in Section 4.5). The structural model showed a good fit to the data: $\chi^2 = 420.088$ ($df = 247$, $p < 0.001$), Normed $\chi^2 = 1.701$, RMR = 0.023, GFI = 0.928, RMSEA = 0.041, CFI = 0.970, NFI = 0.931, TLI = 0.963.

4.3.1. Effects of Perceived Benefits and Sacrifices on Perceived Value (H1 and H2)

Among perceived benefits, timeliness had a significant positive effect on perceived value ($\beta = 0.470$, $p < 0.001$), supporting H1b. This suggests that consumers evaluate service value more favorably when AI services shorten shopping time or provide prompt responses. Enjoyment also had a significant positive effect ($\beta = 0.192$, $p < 0.05$), supporting H1c, which aligns with Lee [18], who found that perceived entertainment value was significantly associated with more favorable attitudes toward AI. Usefulness, however, had no significant effect on perceived value ($\beta = 0.082$, $p = 0.443$), rejecting H1a. This diverges from prior studies (e.g., [37,72]), suggesting that the utility of AI-powered fashion services may be evaluated post-purchase rather than during initial engagement. H1 was thus partially supported.

Among perceived sacrifices, technical effort had a significant negative effect on perceived value ($\beta = -0.221$, $p < 0.05$), supporting H2a and confirming that complex or inconvenient procedures generate negative perceptions, consistent with Zhao et al. [67]. Privacy risk had no significant effect ($\beta = 0.095$, $p = 0.195$), rejecting H2b, consistent with [68,73]; for MZ consumers, who are highly accustomed to online platforms, security concerns may not constitute a decisive sacrifice. Lack of personalization likewise had no significant effect ($\beta = 0.040$, $p = 0.590$), rejecting H2c. H2 was thus partially supported.

4.3.2. Effect of Perceived Value on Intention to Use (H3)

Perceived value had a significant positive effect on intention to use ($\beta = 0.364$, $p < 0.01$), fully supporting H3. This corroborates Kim and Song [38], confirming that positive consumer value derived from AI-powered fashion services directly translates into intention to use.

4.3.3. Direct Effects of Perceived Benefits and Sacrifices on Intention to Use (H4 and H5)

Among perceived benefits, usefulness had a significant positive effect on intention to use ($\beta = 0.288$, $p < 0.01$), supporting H4a and indicating that accumulated shopping experience and product satisfaction enhance future intention. Timeliness had no significant effect ($\beta = -0.107$, $p = 0.095$), rejecting H4b. Enjoyment had a significant positive effect ($\beta = 0.270$, $p < 0.01$), supporting H4c and aligning with [74,75].

Among perceived sacrifices, technical effort had a significant negative effect on intention to use ($\beta = -0.249$, $p < 0.05$), supporting H5a and underscoring the need for user-friendly interfaces. Privacy risk had no significant effect on intention to use ($\beta = 0.041$, n.s.), rejecting H5b, consistent with [18]. Unexpectedly, lack of personalization had a significant *positive* effect on intention to use ($\beta = 0.145$, $p < 0.05$), rejecting H5c. This unexpected direction suggests that consumers use AI-powered fashion services not merely for hyper-personalized recommendations, but as a broad information-seeking tool for monitoring trends and peer behavior.

The SEM results and hypothesis testing summary for H1–H5 are presented in Table 4.

Table 4. Results of Hypothesis Testing (H1–H5).

Hypothesis	Path	β	S.E.	C.R.	Result
H1a	Usefulness → Perceived Value	0.082	0.113	0.766	Not Supported
H1b	Timeliness → Perceived Value	0.470	0.074	5.231 ***	Supported
H1c	Enjoyment → Perceived Value	0.192	0.102	1.969 *	Supported
H2a	Technical Effort → Perceived Value	−0.221	0.109	−2.049 *	Supported
H2b	Privacy Risk → Perceived Value	0.095	0.065	1.297	Not Supported
H2c	Lack of Personalization → Perceived Value	0.040	0.077	0.539	Not Supported
H3	Perceived Value → Intention to Use	0.364	0.074	4.810 **	Supported
H4a	Usefulness → Intention to Use	0.288	0.091	3.322 **	Supported
H4b	Timeliness → Intention to Use	−0.107	0.085	−1.320	Not Supported
H4c	Enjoyment → Intention to Use	0.270	0.084	2.898 **	Supported
H5a	Technical Effort → Intention to Use	−0.249	0.093	−2.442 *	Supported
H5b	Privacy Risk → Intention to Use	0.041	0.050	0.541	Not Supported
H5c	Lack of Personalization → Intention to Use	0.145	0.064	1.961 *	Not Supported (significant, opposite direction)

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Model fit: $\chi^2 = 420.088$ (df = 247, $p < 0.001$), Normed $\chi^2 = 1.701$, RMR = 0.023, GFI = 0.928, RMSEA = 0.041, CFI = 0.970, NFI = 0.931, TLI = 0.963.

4.4. Mediating Effects of Perceived Value (H6)

To examine whether perceived value significantly mediates the relationships between perceived benefits/sacrifices and intention to use, bootstrapping analysis (5000 resamples, 95% bias-corrected confidence intervals) was conducted using AMOS. The results are presented in Table 5.

Among the six hypothesized paths, only timeliness exerted a statistically significant indirect effect on intention to use through perceived value (indirect effect = 0.171, $p < 0.05$), supporting H6b. Because timeliness had no significant direct effect on intention to use (β = −0.107, n.s.), this pattern indicates full mediation: timeliness enhances intention to use entirely through its contribution to perceived value, rather than through any direct pathway.

The remaining paths (H6a, H6c–H6f) were not supported, as their indirect effects did not reach statistical significance. For usefulness (H6a) and lack of personalization (H6f), this is consistent with their non-significant first-stage effects on perceived value observed in the preceding analysis (H1a and H2c, respectively). For enjoyment (H6c) and technical effort (H6d), although both exerted significant effects on perceived value and directly on intention to use, their indirect effects through perceived value did not reach significance, suggesting that these factors influence intention to use primarily through direct rather than value-mediated pathways. Privacy risk (H6e) showed no significant effect at any stage, consistent with its non-significant impact on both perceived value (H2b) and intention to use (H5b). Overall, these findings suggest that perceived value functions as a selective, rather than universal, mediating mechanism—transmitting the effect of timeliness specifically, while benefit and sacrifice factors such as enjoyment and technical effort operate more directly on consumers' intention to use AI-powered fashion services.

Table 5. Mediating Effects of Perceived Value (H6a–H6f).

Hypothesis	Path	Direct Effect	Indirect Effect	Total Effect	Result
H6a	Usefulness → Perceived Value → Intention to Use	0.288 **	0.030	0.318 **	Not Supported
H6b	Timeliness → Perceived Value → Intention to Use	−0.107	0.171 *	0.064	Supported (Full Mediation)
H6c	Enjoyment → Perceived Value → Intention to Use	0.270 **	0.070	0.340 **	Not Supported
H6d	Technical Effort → Perceived Value → Intention to Use	−0.249 *	−0.080	−0.330 **	Not Supported
H6e	Privacy Risk → Perceived Value → Intention to Use	0.041	0.035	0.076	Not Supported
H6f	Lack of Personalization → Perceived Value → Intention to Use	0.145 *	0.015	0.159 *	Not Supported

Note: * $p < 0.05$, ** $p < 0.01$. Indirect effects were tested using bootstrapping (5000 resamples) with 95% bias-corrected confidence intervals in AMOS.

4.5. Moderating Effects of Consumer Trust (H7)

To examine the moderating role of consumer trust in the relationship between perceived value and intention to use, a moderation analysis was conducted. Respondents were divided into a low-trust group and a high-trust group based on their measured trust scores. An independent samples t-test confirmed a statistically significant difference between the two groups ($p < 0.001$), with mean trust scores of 2.93 (low-trust group) and 3.92 (high-trust group).

Prior to multi-group structural equation modeling, configural and metric invariance were tested by comparing the unconstrained and measurement-weight-constrained models across the two groups. The comparison yielded a non-significant chi-square difference ($\Delta\chi^2 = 11.224$, $\Delta df = 16$, $p = 0.795$), confirming measurement invariance and establishing that the two groups could be validly compared.

The moderating effect of trust was then tested by comparing the unconstrained model ($\chi^2 = 799.991$, $df = 511$) with a model in which the path from perceived value to intention to use was constrained to be equal across groups ($\chi^2 = 805.324$, $df = 512$). This constraint produced a significant chi-square difference ($\Delta\chi^2(1) = 5.334$, $p = 0.021$), indicating that the perceived value–intention to use path differs significantly between the two groups and confirming the moderating role of consumer trust (H7 supported).

Specifically, perceived value had no significant effect on intention to use in the low-trust group ($\beta = 0.144$, $p > 0.05$), whereas it had a strong, significant positive effect in the high-trust group ($\beta = 0.573$, $p < 0.001$). This pattern indicates an enhancing moderating effect, whereby higher consumer trust amplifies the positive impact of perceived value on intention to use. These results are summarized in Table 6.

Table 6. Moderating Effect of Consumer Trust (H7).

Model	Path	Trust-Low Group (β)	Trust-High Group (β)	χ^2	*df*	$\Delta\chi^2(1)$	*p*
Unconstrained Model	—	—	—	799.991	511	—	—
Constrained Model	Perceived Value → Intention to Use	0.144	0.573 ***	805.324	512	5.334	0.021

Note: *** $p < 0.001$. The constrained model fixes the perceived value → intention to use path to be equal across the trust-low and trust-high groups; a significant χ^2 difference indicates a significant moderating effect.

These findings corroborate Zhang and Lee [76], who highlighted the positive role of consumer trust in adoption intention toward AI assistants, and Park and Jung [77], who showed that perceived usefulness influences usage intention through cognitive and affective trust. Ultimately, these results underscore that establishing reliable consumer trust is a critical boundary condition and a decisive success factor for fashion companies implementing AI-powered services.

Figure 2 provides a comprehensive visual summary of the structural model, presenting the standardized path coefficients and significance levels for all hypothesized relationships, including the full mediation of timeliness through perceived value (H6b) and the moderating effect of consumer trust (H7).

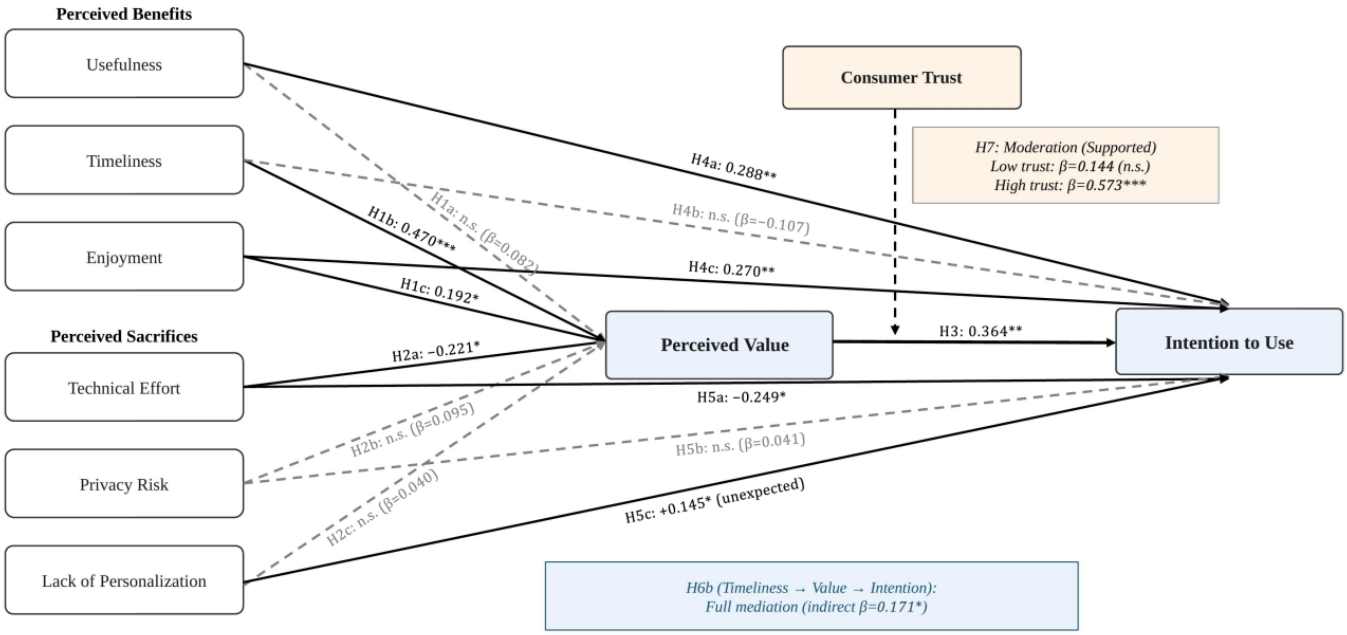


Figure 2. Structural Model with Standardized Path Coefficients. Note: Solid lines indicate statistically significant paths; gray dashed lines indicate non-significant paths; the black dashed arrow from Consumer Trust indicates the moderating path (H7). * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

5. Discussion and Conclusions

5.1. Summary of Findings

This study applied the Value-Based Adoption Model (VAM) to the context of AI-powered fashion services, empirically examining how consumers' perceived benefits and sacrifices influence perceived value and intention to use. The primary findings can be summarized as follows.

Regarding the determinants of perceived value (H1 and H2), among perceived benefits, timeliness and enjoyment exerted significant positive effects on perceived value, whereas usefulness was statistically insignificant. Among perceived sacrifices, technical effort significantly reduced perceived value, while privacy risk and lack of personalization showed no significant effects.

With respect to the effects of perceived value and the direct effects of benefit and sacrifice factors on intention to use (H3–H6), perceived value strongly drove intention to use. The direct effects analysis further revealed that usefulness and enjoyment positively influenced intention to use directly, whereas timeliness exerted no significant direct effect on intention to use. Instead, perceived value fully mediated the relationship between timeliness and intention to use (H6), indicating that timeliness enhances usage intention entirely through its contribution to consumers' overall value perception rather than through

any direct pathway. Technical effort acted as a major barrier, significantly decreasing intention to use. Interestingly, a lack of personalization unexpectedly exerted a positive effect on intention to use, reflecting consumers' tendency to use AI as a tool for broad trend exploration rather than narrowly tailored recommendations.

Finally, the moderating effect of consumer trust (H7) was confirmed through multi-group analysis. Perceived value significantly influenced intention to use only within the high-trust group, whereas the low-trust group showed no significant effect, underscoring consumer trust as a critical boundary condition and catalyst for translating perceived value into behavioral intention.

5.2. Theoretical and Managerial Implications

Building upon these empirical insights, this study offers several important contributions to both academic literature and industry practice.

5.2.1. Theoretical Implications

This study offers several important theoretical contributions to the literature on technology adoption and fashion marketing. First, by applying the Value-Based Adoption Model (VAM) to the emerging context of AI-powered fashion services, this study validates its robustness in retail environments where consumers simultaneously weigh technological benefits against cognitive and psychological sacrifices.

Second, unlike prior studies that treated benefits and sacrifices as monolithic constructs, this research unpacks their multi-dimensional structure—usefulness, timeliness, and enjoyment versus technical effort, privacy risk, and lack of personalization—offering a more nuanced understanding of consumer psychology in digital fashion platforms. This dimensional divergence is further illustrated by usefulness, which—unlike timeliness and enjoyment—exerted a significant direct effect on intention to use but not on perceived value. Whereas timeliness and enjoyment are experienced in real time during the shopping process and thus readily inform consumers' overall value judgment, usefulness is more fully appraised only after the shopping task is completed, a post-usage character consistent with the Expectation-Confirmation Model [78], in which perceived usefulness operates as a post-adoption belief that directly predicts behavioral intention.

Third, and most notably, this study finds that a lack of personalization positively influenced intention to use, contrary to the conventional assumption that greater personalization uniformly enhances adoption. This counterintuitive result suggests that young fashion consumers may value exposure to broad market trends over restrictive, narrowly tailored recommendations, extending VAM by revealing boundary conditions under which a conventionally negative sacrifice factor can operate as a latent benefit. This interpretation is also consistent with characterizations of Korean MZ (Millennial and Generation Z) consumers as exhibiting a dual orientation toward both individuality and trend conformity: although these consumers seek to express a distinctive personal identity, their extensive engagement with social media appears to heighten their sensitivity to prevailing fashion trends and their responsiveness to peer- and influencer-driven style cues [79]. Within this framework, reduced algorithmic personalization may be valued not because it opposes self-expression, but because it supports the trend-conscious, socially attuned mode of identity construction that is particularly salient among younger fashion consumers.

Fourth, by empirically verifying the moderating role of consumer trust between perceived value and intention to use, this study bridges cognitive value evaluation and actual behavioral adoption.

Finally, by comprehensively incorporating both the positive and negative dimensions of AI-powered fashion services and integrating consumer trust as a boundary condition,

this study outlines a theoretical foundation for sustainable, ethical human–AI coexistence in retail ecosystems, moving beyond short-term adoption metrics to address broader socio-technical implications.

5.2.2. Managerial Implications

To satisfy evolving consumer needs and establish differentiated marketing strategies, this study provides several practical and strategic guidelines for fashion enterprises and online retailers.

First, fashion consumers place greater emphasis on benefit factors than sacrifice factors, with enjoyment emerging as a core driver of AI-powered fashion service adoption. Practitioners should therefore develop engaging, emotionally stimulating content and differentiated gamification strategies—such as augmented reality (AR) and metaverse integration—to deliver immersive shopping experiences. For emerging brands struggling to build immediate consumer trust, offering innovative and entertaining AI shopping experiences may be the most effective way to secure intention to use.

Second, the finding that a lack of personalization positively influences intention to use suggests that fashion AI platforms should avoid over-narrowing their recommendations. Rather than pursuing hyper-personalization at the expense of variety, platforms should balance tailored suggestions with curated exposure to broader trends, allowing consumers to discover styles beyond their established preferences. In practical terms, recommendation services that incorporate prevailing fashion trends into personal styling suggestions—rather than relying solely on individual purchase history—are likely to resonate more strongly with MZ consumers, who place high value on staying attuned to current style movements [79]. Building platform features that enable users to share trend-conscious styling choices with one another, such as community-based style boards or trend-following feeds, may also serve as an effective marketing strategy, allowing consumers to satisfy both their desire for personal relevance and their interest in collective fashion sensibility.

Third, as technical effort was identified as a key factor requiring improvement, platforms should prioritize interface simplicity and system responsiveness. Because fashion content is inherently visual and image-intensive, slow loading times can be particularly detrimental to the user experience; optimizing image rendering and minimizing latency in recommendation delivery are therefore essential for sustaining consumer engagement. Complex input procedures should be replaced with one-click curation and intuitive, minimal-step interfaces that allow consumers to navigate AI-powered features without requiring extensive technical familiarity. Fourth, transparently disclosing privacy protection policies and applying professional verification badges can alleviate cognitive anxiety, thereby playing a critical role in building consumer trust and driving intention to use.

Finally, beyond pursuing short-term adoption rates, fashion enterprises should maintain a balanced perspective that weighs both the positive and negative dimensions of AI services. By leveraging consumer trust as a key moderating mechanism and ensuring ethical, transparent operations, businesses can establish a practical roadmap for long-term, sustainable coexistence between humans and AI within the digital retail ecosystem. As generative AI and other rapidly emerging technologies continue to reshape the fashion retail landscape, practitioners should proactively monitor these developments and adapt their AI strategies accordingly, particularly with respect to safety, transparency, and reliability, which are likely to become increasingly salient concerns for consumers.

5.3. Limitations and Future Research Directions

Despite its theoretical and managerial contributions, this study has several limitations that offer meaningful directions for future research.

First, this study focused its consumer survey exclusively on online-based AI-powered fashion services, reflecting the rapid growth trajectory and scale of the e-commerce market. However, the advancement of artificial intelligence and the expansion of smart services are not confined to the digital sphere; offline retail environments are undergoing similar transformations, and retail services are projected to diversify increasingly through omni-channel frameworks in which the boundaries between online and offline channels seamlessly dissolve. Consequently, a notable limitation of this study is its lack of investigation into AI-powered fashion services applicable within offline retail channels. Future research should extend beyond the digital domain to encompass both online and offline contexts, thereby providing valuable insights and foundational data for developing and optimizing advanced, boundary-spanning retail services.

Second, this study sampled Millennial and Generation Z (MZ) consumers, given their status as core digital-native adopters of AI-powered fashion services. While this focus provided valuable insights into the perceptions of a technologically engaged and trend-sensitive cohort, it also limits the generalizability of the findings to other consumer segments. Older generations, who may exhibit different risk perceptions, technology adoption patterns, and value priorities, were not represented in this study. Future research should extend the investigation to a broader range of age groups and conduct cross-generational comparisons to examine whether the benefit-sacrifice factors identified in this study operate consistently across different consumer cohorts, or whether generation-specific adoption mechanisms emerge.

Third, data collection for this study preceded the rapid diffusion of generative AI technologies in fashion retail, and the benefit and sacrifice dimensions examined here may not fully capture how consumers perceive these more recent AI capabilities. As AI technologies continue to evolve rapidly, new dimensions of perceived benefit and sacrifice are likely to emerge alongside them. Future research should therefore incorporate emerging constructs such as AI safety, transparency, and reliability, which are becoming increasingly salient as generative and more autonomous AI systems become embedded in fashion retail.

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