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Generational differences in AI adoption among fashion curation platform users

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Abstract

This study investigates consumer acceptance of artificial intelligence (AI)-enabled fashion curation platforms by integrating the Task–Technology Fit (TTF) and Technology Acceptance Model (TAM) frameworks. Building on contemporary research that emphasizes the transformative role of AI in retail and fashion, the study examines how the alignment between AI functionalities and user needs strengthens perceived usefulness and ease of use, enhancing satisfaction and behavioral intention. Using a survey-based quantitative design with adapted TTF and TAM scales, we analyzed data from fashion curation platform users via structural equation modeling (SEM), including multi-group comparisons across Generation Z, Millennials, and Generation X. Results show cohort-sensitive pathways: Generation Z responds more to technological fit and usefulness, whereas Generation X prioritizes ease of use and experiential satisfaction; intention mechanisms converge once upstream beliefs are formed, aligning with broader AI acceptance patterns and moderators noted in consumer contexts. The findings extend technology acceptance scholarship by localizing generational heterogeneity primarily in the formation of perceived usefulness and satisfaction within AI curation contexts, while offering actionable guidance for task–technology alignment and journey design in digital fashion retail. The study motivates future multi-cohort investigations that incorporate evolving AI capabilities and examine trust and governance considerations in fashion platforms.

Keywords: Artificial intelligence, Fashion curation technology, Digital platform, Task–technology fit, Technology acceptance model

Introduction

Artificial intelligence (AI) is reshaping the fashion industry across design, production, retail, and consumer experience by embedding capabilities such as recommendation, visual search, virtual try-on, conversational agents, and generative design into digital channels, thereby scaling personalization, efficiency, and creativity (Choi et al., 2023; Goti et al., 2023; Lee et al., 2025; Shi et al., 2025). Within this landscape, AI curation technology refers to systems that integrate behavioral signals (e.g., clicks, purchases), product attributes (e.g., style, compatibility), visual content (e.g., images, videos), and contextual cues to produce coordinated outfits, bundled product sets, dynamic sequencing, and visually guided, conversational support tailored to users (Guo et al., 2023).

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Distinct from generic recommenders, fashion curation emphasizes inter-item compatibility and domain-specific visual reasoning, often realized through multimodal interfaces that enrich designer–consumer and system–user interactions (Guo et al., 2023; Shirkhani et al., 2023).

Industry evidence highlights the centrality of curation to fashion commerce, where AI enhances experience and purchase intention while also supporting sustainability goals through improved forecasting, quality assessment, and resource stewardship (Goti et al., 2023; Zaman et al., 2025). Generative methods accelerate visual synthesis and trend workflows, extending applications in images, 3D, and video (Shi et al., 2025). Related work in sustainable fashion shows AI's role in waste reduction, quality control, and reverse logistics, advancing circular models and ethical practices (Nisa et al., 2025; Ramos et al., 2023).

Despite rapid diffusion, mechanisms driving consumer acceptance, satisfaction, and continued use of AI-enabled curation remain underexplored. The Technology Acceptance Model (TAM) consistently identifies perceived usefulness and perceived ease of use as antecedents of intention in fashion and related digital settings (Milanesi et al., 2024; Watchravesringkan et al., 2010; Zaman et al., 2025). Complementing TAM, Task–Technology Fit (TTF) highlights how alignment between task requirements and technology capabilities shapes perceived utility and performance, thereby influencing adoption (Chakraborty, 2025; Pillai & Sivathanu, 2020). In fashion curation, where users assess styling compatibility and interact through visual, multimodal interfaces, poor alignment risks undermining both perceived usefulness and perceived ease of use, and ultimately engagement (Guo et al., 2023; Shirkhani et al., 2023).

Two gaps remain. First, there is little empirical testing of an integrated TTF–TAM framework in AI fashion curation, though adjacent domains show that combining fit constructs with acceptance beliefs is fruitful (Al-Emran, 2021; Vanduhe et al., 2020). In fashion, rapidly evolving AI–GAN-enabled design, sequential and content-level recommendation, metaverse-centric intelligence—reshapes evaluation and choice but is rarely modeled in terms of task–technology alignment and acceptance outcomes (Ding et al., 2022; Divitiis et al., 2022; Mu et al., 2024; Sohn et al., 2020). Second, evidence on cohort heterogeneity is scarce, despite signs that Generation Z, as digital natives with strong orientation toward AI-enabled utility, differ in adoption patterns from older cohorts (Ruis-Viñals et al., 2024). Broader digital fashion studies also suggest that technology exposure conditions perceptions and intentions, implying generational asymmetries that remain underexamined in curation (Zhang et al., 2023).

To address these gaps, this study integrates TTF and TAM into a unified framework and tests it with Korean users of digital fashion platforms. Specifically, we examine: (i) how TTF influences perceived usefulness and perceived ease of use and, in turn, behavioral intention, and (ii) generational differences in these mechanisms through multi-group structural equation modeling (SEM) comparing Generation Z, Millennials, and Generation X. By theorizing curation-specific alignment and validating cohort heterogeneity, the study advances adoption theory in AI-enabled fashion commerce and offers practical guidance for tailoring curation strategies across consumer segments. Theoretically, it situates AI curation within acceptance paradigms and bridges fragmented literatures on AI-enhanced recommendation and adoption; practically, it informs the design

of fit-centric and value-forward curation features for increasingly immersive, algorithmically mediated shopping environments.

Literature Review

AI fashion curation platforms

AI fashion curation platforms are consumer-facing digital systems that algorithmically recommend and sequence fashion items to support styling and purchase decisions. These systems integrate behavioral signals (e.g., clicks, dwell time), product attributes (e.g., silhouette, fabric), and visual information to generate coordinated outfits, capsule collections, and personalized discovery paths via visual search or conversational interfaces. Unlike generic recommenders, which emphasize similarity, curation systems prioritize inter-item compatibility and stylistic coherence (Goti et al., 2023; Shirkhani et al., 2023). Advances in multimodal methods now enable richer fashion understanding, image/3D/video synthesis, and scalable styling visualization (Ngai et al., 2025; Shi et al., 2025). Beyond conversion, curation can reduce returns by improving fit confidence and also support resale and recycling models through AI-enabled quality assessment (Goti et al., 2023; Nisa et al., 2025). Consumer studies further highlight usability, usefulness, reliability, enjoyment, and personalization as key drivers of continued use, underscoring the need to align curation functions with user-perceived value in fashion e-commerce (Shin & Hwang, 2022).

Task–Technology Fit

Task–Technology Fit (TTF) explains technology outcomes through the alignment between task requirements and technology capabilities. High fit allows users to perform tasks more effectively and efficiently, thereby enhancing adoption (Schrier et al., 2010). Studies consistently model TTF by linking task and technology characteristics to perceived fit and subsequent outcomes in services such as hotel self-service, HR, and AI consumer platforms (Chakraborty, 2025; Pillai & Sivathanu, 2020; Schrier et al., 2010). For instance, in talent acquisition, both task and technology factors shape TTF, which predicts AI tool usage (Pillai & Sivathanu, 2020). In online food delivery, personalization and efficiency strengthen fit, boosting adoption (Chakraborty, 2025).

In fashion, tasks involve unique requirements—such as visual compatibility, multi-modal interaction, and style-coherence reasoning—that go beyond similarity-based logic. Misalignment may disproportionately reduce user value, yet few studies have explicitly applied TTF to fashion curation, leaving its role in shaping perceptions and intentions underexplored (Shirkhani et al., 2023).

Technology Acceptance Model

The Technology Acceptance Model (TAM) posits that perceived usefulness and perceived ease of use drive intention, offering a parsimonious account of adoption (Davis, 1989). While the role of attitude is sometimes debated, the belief–intention pathway remains robust (Teo, 2009). In consumer settings, extended TAM research shows that contextual and platform features strengthen perceived usefulness and perceived ease of use, enhancing use. For example, social networking capabilities and perceived mass affect acceptance on social platforms (Rauniar et al., 2014).

Fashion studies similarly demonstrate that perceived usefulness, perceived ease of use, and experiential factors (e.g., enjoyment, innovativeness, fashionability) shape attitudes and intentions toward technology-enhanced products (Watchravesringkan et al., 2010). In mobile fashion shopping, perceived usefulness, perceived ease of use, and enjoyment increase perceived value, which mediates adoption (Ko et al., 2009). Overall, TAM remains powerful in technology-driven retail, though domain-specific features such as coordination and multimodality condition how perceived usefulness and perceived ease of use form and influence satisfaction, loyalty, and continued use (Goti et al., 2023).

Integrating TTF into the TAM framework

While TAM explains how beliefs influence intention, it does not clarify how those beliefs originate. Integrating TTF addresses this by positioning fit as an antecedent to perceived usefulness and perceived ease of use. Evidence across contexts shows that high fit enhances perceived usefulness—and sometimes perceived ease of use—thereby strengthening satisfaction, intention, and continued use in line with TAM (Al-Emran, 2021; Schrier et al., 2010). In AI-enabled services, TTF also influences trust, highlighting pathways from alignment to beliefs and behavior (Chakraborty, 2025; Pillai & Sivathanu, 2020).

Applied to AI fashion curation, this integration is compelling because tasks such as assessing item compatibility, navigating visual catalogs, and using multimodal interfaces are highly sensitive to alignment between user goals and system capabilities (Goti et al., 2023; Shirkhani et al., 2023). When curation features match task demands (e.g., coordinated styling sets, transparent visual rationales, responsive personalization), users are more likely to perceive systems as useful and easy to use, leading to greater satisfaction and stronger adoption intentions (Shin & Hwang, 2022). Yet empirical tests of this integration in fashion remain limited, motivating the present study's model that examines how TTF shapes perceived usefulness and perceived ease of use and, through them, satisfaction and behavioral intention.

Hypothesis development

The positive relationship between TTF and perceived usefulness is supported by adequate interdisciplinary research, demonstrating that when consumers encounter technologies tailored to their task needs, their perceived benefits from those technologies increase markedly. In the specific context of AI fashion curation platforms, the TTF framework emphasizes the importance of aligning platform algorithms and features—such as personalized recommendations, multimodal interfaces, and adaptive curation—with the unique demands of fashion consumers (Goti et al., 2023). Al-Maatouk et al. (2020) affirmed that in academic social media environments, TTF significantly correlates with improved customer satisfaction with the AI fashion curation platform and learning outcomes, with perceived usefulness mediating these effects. Similarly, in the domain of business analytics, Muchenje et al. (2024) established that a high TTF between analytic solutions and business problem-solving tasks leads to substantial gains in user-perceived value and practical benefits (Muchenje et al., 2024). Moreover, Yang et al. (2025) confirmed using structural modeling that TTF significantly influences the perceived usefulness of technology applications in real estate, serving

as a strong parallel for anticipated effects in fashion curation. In practical terms, when AI curation platforms cater effectively to the essential transactional and experiential needs of fashion shoppers, consumers' perceptions of usefulness markedly increase—this result strongly supports Hypothesis 1.

H1 TTF positively influences perceived usefulness.

A robust TTF indicates that technological features are specifically designed to meet users' operational requirements, minimizing cognitive barriers and facilitating intuitive use of the platform. In AI-driven fashion curation, high TTF means that features such as personalized recommendations and a dynamic interface are effectively integrated, aiding consumers in assessing and choosing fashion products. This integration results in lower perceived complexity and facilitates easier system adoption (Goti et al., 2023). Empirical research shows that users who feel a strong connection between technology and their objectives experience heightened perceived ease of use. For example, studies on self-service analytics have found that high TTF corresponds with improved perceptions of system simplicity and ease of navigation (Daradkeh, 2019). In digital training settings, aligning gamified elements with training goals directly enhances users' perceptions of usability, further confirming TTF's key role in influencing perceived ease of use (Vanduhe et al., 2020). Recent research into blockchain adoption in real estate also reveals a significant positive impact of TTF on perceived ease of use, indicating the principle's relevance across various digital platforms, including AI fashion curation services (Yang et al., 2025). These findings from different sectors support the idea that high TTF in an AI fashion curation platform strongly and positively impacts users' perceived ease of use.

H2 TTF positively influences perceived ease of use.

According to the well-established TAM framework, perceived ease of use acts as a foundational predictor of perceived usefulness, an effect that has been extensively demonstrated in the context of digital platforms and, by extension, AI-powered fashion curation services. Goti et al. (2023) reveal that, in fashion e-commerce, user-friendly AI features facilitate item discovery and directly lead to heightened perceptions of system benefits. This correlation is not confined to the retail domain. In a structural equation model examining e-learning technologies, Yan et al. (2024) observed that ease of use significantly mediated the relationship between motivational stimuli (such as flow experience) and perceived usefulness, establishing perceived ease of use as a strong cognitive lever for maximizing the perceived value of technology (Yan et al., 2024). Furthermore, empirical analysis in higher education gamification systems confirms that enhancing perceived ease of use drives adoption and increases users' recognition of technology's practical benefits (Vanduhe et al., 2020). For AI fashion curation platforms aiming to increase engagement, prioritizing intuitive design and simple workflows can directly enhance perceived usefulness and users' behavioral intention to use the AI fashion curation platform continually.

H3 Perceived ease of use positively influences perceived usefulness.

In AI fashion curation platforms, when users find the system useful—indicating it successfully improves their shopping efficiency, offers relevant recommendations, and aids in making more accurate fashion choices—their satisfaction with the experience increases accordingly. This connection is theoretically supported and extensively documented in digital service and retail literature. For example, studies on self-service analytics show that perceived usefulness has a direct and significant impact on satisfaction, as tools delivering relevant and actionable insights enhance the perceived value for users (Daradkeh, 2019). Similarly, in the wider context of fashion e-commerce, extensive literature reviews reveal that the usefulness of AI-driven features—such as recommendation engines and personalized content—are crucial in boosting satisfaction by meeting specific, context-driven needs in digital retail settings (Goti et al., 2023). Moreover, behavioral intention and satisfaction with intelligent retail systems are influenced by perceived usefulness in TAM (Yan et al., 2024). When applying these insights to AI fashion curation, focusing on delivering tangible, personally relevant utility is vital for achieving higher levels of consumer engagement satisfaction.

H4 Perceived usefulness positively influences satisfaction.

Behavioral intention refers to an individual's deliberate plan or willingness to use a technology in the near future (Wu & Lederer, 2009); it functions as a proximal predictor of actual usage within the technology acceptance tradition, where perceived usefulness and perceived ease of use shape intentions that, in turn, predict use across diverse educational and consumer platforms (Rauniar et al., 2014). In fashion-relevant digital environments, behavioral intention thus captures consumers' readiness to engage with AI-enabled curation platforms in subsequent interactions (Ko et al., 2009; Watchravesringkan et al., 2010). Perceived usefulness serves as a crucial antecedent to users' behavioral intention, a relationship thoroughly supported in TAM and confirmed by empirical studies across AI-enabled fashion retail and broader digital contexts. When users recognize that an AI fashion curation platform enhances their decision-making efficiency, provides relevant style suggestions, and effectively streamlines the fashion discovery process, they develop a stronger inclination toward long-term engagement with the technology. This connection is evident in large-scale systematic reviews of AI in fashion e-commerce, where perceptions of utility significantly underpin user loyalty and ongoing system use (Goti et al., 2023). Moreover, research on technology adoption of self-service has validated that perceived usefulness is directly and strongly associated with behavioral intention (Daradkeh, 2019). Therefore, ensuring AI fashion curation platforms provide tangible, user-centered benefits is essential for fostering persistent behavioral intention.

H5 Perceived usefulness positively affects behavioral intention.

The ease with which consumers can interact with an AI fashion curation platform strongly predicts their overall satisfaction, aligning with the TAM premise that user-friendly technologies yield more favorable perceptions and emotional responses (Rachmi et al., 2023). Empirical analyses show that perceived ease of use correlates

with satisfaction and acts as a crucial antecedent, facilitating efficient discovery and selection processes for online shoppers. Research in online retailing in India found that dimensions such as ease of purchase, navigation, and understanding contribute meaningfully to satisfaction (Tandon et al., 2016). Furthermore, in research settings beyond fashion—such as digital libraries and information systems—usability and system quality are consistently identified as prominent drivers of satisfaction (Soltani-Nejad et al., 2020). In AI curation, delivering a seamless user experience thus becomes an operational imperative for satisfaction and long-term engagement.

H6 Perceived ease of use positively influences satisfaction.

Perceived ease of use is consistently identified as a foundational construct driving users' continuous intention to use digital platforms, including AI-powered fashion curation services. When platforms offer streamlined interactions—minimizing operational effort and maximizing user clarity—users are more inclined to integrate these solutions into their daily routines. In e-commerce, for example, structural equation modeling analysis has confirmed that perceived ease of use and perceived usefulness are significant predictors of behavioral intention, with usability directly promoting longer-term engagement (Värzaru et al., 2021). Complementing these findings, interface characteristics such as screen design and navigation clarity are empirically linked to higher perceived ease of use. Beyond commerce and information management, studies in e-learning environments have further demonstrated that perceived ease of use is predictive of initial acceptance and persistent system use, identifying ease as a central enabler of sustained digital experiences (Yan et al., 2024). These insights collectively reinforce that for AI fashion curation platforms, elevating perceived usability is essential for facilitating ongoing satisfaction.

H7 Perceived ease of use positively affects behavioral intention.

The relationship between consumer satisfaction and behavioral intention is well substantiated by theoretical models and empirical studies. Satisfaction serves as an outcome of positive platform experiences, such as high service reliability, responsiveness, and ease of use, and a critical antecedent to behavioral intention. For instance, studies in e-retailing and electronic commerce confirm that when users are satisfied with the quality and convenience of services provided, their likelihood of repeat purchase or continued engagement increases markedly (Dhingra et al., 2020; Kumar et al., 2020). Even in dynamic contexts such as social media, empirical data reveal that greater satisfaction yields a significantly higher probability of recurrent platform use, substantiating the hypothesis that satisfaction is a decisive predictor of sustained behavioral intention (Sharabati et al., 2022). These findings collectively reinforce the importance of satisfaction as a leverage point for enhancing long-term user engagement.

H8 Satisfaction positively influences behavioral intention.

Moderation effects of generations

Generational cohort theory posits that formative socio-technological experiences shape stable patterns in technology perceptions and usage, warranting explicit cross-cohort modeling in technology acceptance research (Sox et al., 2016). Prior evidence shows substantial heterogeneity in belief–intention pathways by cohort: age moderates core Technology Acceptance Model relationships to behavioral intention, with perceived usefulness and perceived ease of use exhibiting cohort-contingent strengths (Tarhini et al., 2014). Generational categories reflected validated birth-year conventions, with Generation X (1965–1980), Millennials (1981–1996), and Generation Z (1997–2012) operationalized as distinct segments (Sox et al., 2016; Tsai et al., 2016).

Generation Z, often classified as “digital natives,” tends to emphasize advanced functionalities, technological novelty, and perceived usefulness when interacting with online fashion and AI-enhanced e-commerce platforms, directly impacting their behavioral intention and purchase behavior (Pu et al., 2025; Ruis-Viñals et al., 2024; Singh, 2024). Conversely, older generations, such as Generation X, typically demonstrate a utilitarian focus, prioritizing perceived ease of use and practical efficiency, making these constructs more prominent predictors of satisfaction and behavioral intention for this group (Figá-Talamanca et al., 2022). For instance, structural equation modeling in robo-advisor adoption reveals that, while perceived ease of use drives technology uptake among younger cohorts (Generations Z and Millennials), perceived usefulness serves as a critical determinant for Generation X+, who are more likely to integrate technology when its functional value is evident (Figá-Talamanca et al., 2022). Furthermore, cross-sectional studies in digital banking and e-learning suggest that generational differences impact the underlying mechanisms of technology engagement and sustained use, reinforcing the importance of modeling generation as a moderator when examining the pathways from TTF, perceived ease of use, and perceived usefulness to satisfaction and behavioral intention (Tarhini et al., 2014; Vărzaru et al., 2021). Collectively, various studies underscore the significant role of generational cohorts in moderating the relationships between TAM constructs and behavioral intention, and these findings support the hypothesis that the strength and direction of associations between TTF, perceived ease of use, perceived usefulness, satisfaction, and behavioral intention depend on generational context, necessitating a cohort-sensitive approach to understanding technology acceptance and utilization.

H9 Generation moderates key structural paths in the integrated model, such that path coefficients differ across cohorts (Gen X, Millennials, Gen Z) for the core relationships among TTF, perceived usefulness, perceived ease of use, satisfaction, and behavioral intention.

Therefore, a research model was constructed, reflecting all hypotheses, as shown in Fig. 1.

Methods

Measurement scales and analysis method

This study utilized a robust quantitative design to develop measurement scales by systematically adapting and expanding established items from foundational TTF and TAM research, ensuring theoretical integrity and relevance to the sector. TTF indicators

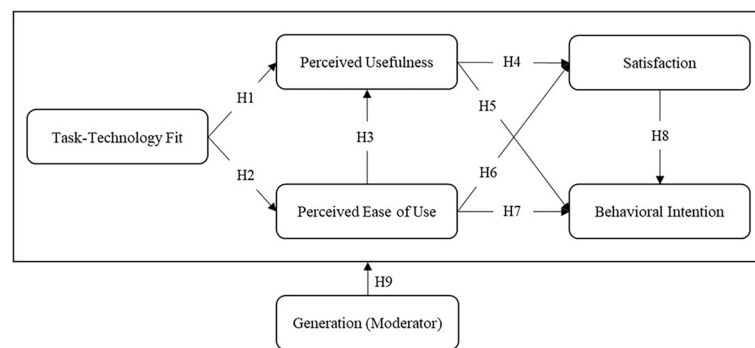


Fig. 1 Research model

were recalibrated based on the essential question sets from Goodhue and Thompson (1995), while TAM constructs—such as perceived usefulness, ease of use, satisfaction, and behavioral intentions—were derived from the validated language and framework of Davis (1989) and subsequent research tailored to e-services and AI applications. As shown in Table 1, each item was specifically revised to encapsulate features of AI fashion curation, in line with recent survey studies directed at digital-native and mall platform users. The survey adopted a seven-point Likert scale, recognized for effectively capturing nuanced attitudes in technology adoption contexts (Singh, 2024). To ensure clarity and contextual alignment, survey items were pilot tested with a subgroup of the target population, following pretest validation protocols commonly recommended in TAM/TTF research literature (Tsai et al., 2016).

An initial analysis incorporating descriptive statistics and reliability tests was conducted to assess data quality. Measurement reliability was evaluated using Cronbach's alpha, and items were retained if they met the appropriate thresholds. To test the hypothesized relationships among the constructs, structural equation modeling (SEM) was utilized. Statistical validation included structural equation modeling and multi-group comparison to evaluate overall model fit and generational moderation, in line with state-of-the-art practices in TAM and TTF research (Al-Emran, 2021; Al-Maatouk et al., 2020; Sox et al., 2016; Tarhini et al., 2014; Vărzaru et al., 2021). Therefore, SEM was selected for its ability to test multiple dependencies simultaneously and comprehensively validate the theoretical model involving latent constructs derived from TTF and TAM. The analysis was performed using SPSS and AMOS software that supports confirmatory factor analysis and structural modeling—convergent validity and discriminant validity were adequately tested.

Sampling frame and contextual justification

We purposefully sampled Korean consumers because Korea is an advanced, high-adoption market for digital fashion commerce and mobile shopping, offering a theoretically rich and policy-relevant setting for studying AI-enabled curation on a scale (Ko et al., 2009). Prior fashion and retail technology studies conducted with Korean consumers demonstrate both methodological feasibility and substantive relevance for international readers, including mobile fashion shopping adoption (Ko et al., 2009), online VR fashion stores (Won et al., 2024), and digital fashion design and AI-driven systems published in

Table 1 Questionnaire items

Construct	Questionnaire	References
Task-Technology Fit	The FCP effectively recommends items that match my fashion preferences	Al-Emran (2021); Goodhue and Thompson (1995)
	The FCP helps me easily find the information I want	
	The FCP supports me in selecting fashion items that suit me	
	The FCP fulfills my fashion-related needs	
	The FCP provides information that fits my fashion preferences and shopping purposes	
Perceived usefulness	Using the FCP makes my fashion item selection process more efficient	Bunea et al. (2024); Davis (1989); Vărzaru et al. (2021)
	Using the FCP improves the quality of my fashion-related decisions	
	Using the FCP helps me easily find items that match my fashion preferences	
	Using the FCP enhances my ability to coordinate fashion outfits	
	Using the FCP provides up-to-date information on the latest fashion trends	
Perceived ease of use	The FCP has an intuitive interface that is easy to use	Bunea et al. (2024); Davis (1989); Vărzaru et al. (2021)
	The FCP requires little effort to use	
	The FCP offers functions that are easy to understand	
	The FCP enables me to find desired fashion items easily	
	The FCP provides a simple and convenient navigation process	
Behavioral intention	I intend to shop through the FCP in the future	Pu et al. (2025); Ruis-Viñals et al. (2024)
	I plan to continue using the FCP for shopping	
	I will recommend the FCP to people around me	
	I will share positive aspects of the FCP with others	
Satisfaction	I am overall satisfied with the FCP	Jeong (2024); Vărzaru et al. (2021)
	I feel that the FCP meets my expectations	
	I consider using the FCP to be a generally positive experience	
	I am satisfied with my shopping experience on the FCP	

FCP Fashion Curation Platform

fashion and design outlets with global readership (Choi et al., 2023). Given the international growth of AI and personalization in fashion, evidence from a digitally mature consumer base in Korea can generate insights that generalize to broader markets while illuminating cohort-specific patterns (Prashar & Prashar, 2024; Shi et al., 2025).

Data were collected through a professional online panel agency specializing in Korean consumer research, consistent with established practice in fashion and e-commerce studies (Ko et al., 2009; Lee & Huang, 2020; Won et al., 2024). Screening ensured respondents had prior experience using digital fashion platforms (e.g., fashion shopping

Table 2 General information about the sample

Variable	Category	% (n)
Gender	Male	25.3 (76)
	Female	74.7 (224)
Age group by Generation	Z (1997 ~ 2012)	18.3% (55)
	M (1981 ~ 1996)	45.7% (137)
	X (1965 ~ 1980)	36.0% (108)
Average monthly purchase cost (Unit: Won)	Less than 200,000	16.0 (168)
	200,000 ~ less than 500,000	24.1 (253)
	500,000 ~ to less than 1 million	6.5 (68)
	1 million ~ less than 1.5 million	9.6 (101)
	1.5 million or more	8.6 (90)
Average monthly shopping time	Less than 1 h	16.0 (48)
	Less than 1 to 3 h	44.3 (133)
	Less than 3 to 5 h	28.3 (85)
	Less than 5 to 7 h	7.0 (21)
	More than 7 h	4.3 (13)

apps or sites offering algorithmic recommendations), so they could meaningfully evaluate Task–Technology Fit (TTF) and downstream constructs (Al-Emran, 2021). This approach aligns with multi-group and cross-sectional designs commonly used to examine technology adoption mechanisms and cohort differences (Mičik et al., 2025; Theocharis et al., 2025).

The survey was conducted online and all participation was voluntary. Only minimal demographics (gender and birth year) were collected to support generational analyses; no personally identifying information was requested. All responses were captured anonymously at source by the panel platform. The study obtained IRB approval (Approval No. 1041078–20250403-HR-106).

Sample profile

The final analytic sample comprised 300 eligible respondents balanced across gender and generational cohorts (Gen X, Millennials, Gen Z), enabling robust cohort-sensitive modeling consistent with recent generational research in technology-mediated commerce (Mičik et al., 2025; Moon et al., 2025; Ruis-Viñals et al., 2024; Theocharis et al., 2025). This balance supports multi-group analyses of acceptance mechanisms central to AI-enabled retail contexts (Mičik et al., 2025; Prashar & Prashar, 2024; Theocharis et al., 2025).

Table 2 presents the demographic characteristics of the study sample. Most respondents were female (74.7%), while male participants accounted for 25.3%. In terms of age distribution, respondents were relatively evenly spread across various age groups, with the largest proportion in their 50 s (28.6%), followed by those in their 30 s (25.0%), 40 s (23.7%), and 20 s (22.7%). When categorized by generation, Millennials comprised the largest group (45.7%), followed by Generation X (36.0%) and Generation Z (18.3%). These results suggest that the sample represents a diverse range of consumers, allowing for meaningful analysis of AI-driven fashion curation across different demographic segments.

Table 3 Correlation between variables

Variables	TTF	PU	PEU	BI	SF
TTF	1				
PU	.761**	1			
PEU	.544**	.666**	1		
BI	.587**	.727**	.670**	1	
SF	.675**	.746**	.708**	.803**	1

** $p < .01$

Results and Discussion

Descriptive statistics and normality test

Descriptive statistics for the primary constructs under investigation—including TTF, Perceived Usefulness (PU), Perceived Ease of Use (PEU), Behavior Intention (BI), and Satisfaction (SF)—are based on responses from 300 individuals. The observed range (2–7) is consistent across all variables, indicating effective use of the full scale. Mean scores cluster closely around 5, with relatively low standard deviations, reflecting moderate agreement among participants. Skewness values ranged from -0.425 to -0.263 and kurtosis from -0.012 to 0.372, all well within established thresholds for normality ($|\text{skewness}| < 1$, $|\text{kurtosis}| < 1$). These results indicate that the variables are approximately normally distributed, supporting the use of means and standard deviations as appropriate summary statistics. Overall, the distributional properties of the sample suggest that the data are suitable and reliable for subsequent inferential statistical analyses.

Correlation analysis

Based on the correlation matrix presented in Table 3, all observed variables exhibit significant and positive inter-correlations. Specifically, TTF demonstrates robust associations with PU ($r = .761^{**}$), PEU ($r = .544^{**}$), BI ($r = .587^{**}$), and SF ($r = .675^{**}$). PU also correlates strongly with PEU ($r = .666^{**}$), BI ($r = .727^{**}$), and SF ($r = .746^{**}$). Furthermore, PEU, BI, and SF are notably interconnected, with the highest correlation observed between BI and SF ($r = .803^{**}$). All correlations are statistically significant at the $p < .01$ level, indicating consistent and meaningful relationships between the constructs. The observed pattern of relationships aligns with previous research, which highlights the centrality of TTF, PU, and PEU in shaping BI and SF within TAM (Al-Maatouk et al., 2020; Presti et al., 2021; Vanduhe et al., 2020). These results further substantiate the integrative role of these constructs in explaining technology adoption and usage behaviors in educational and organizational settings.

Confirmatory factor analysis and model fit

The model's fit was assessed using multiple indices to ensure a nuanced evaluation, as recommended in recent confirmatory factor analysis (CFA) literature (Goretzko et al., 2023; Howard et al., 2024). The chi-square value was significant ($\chi^2 = 411.050$, $df = 199$, $p < .001$); however, reliance on this statistic alone is discouraged, given its over-sensitivity in large or complex models (Zheng & Bentler, 2023). Both CFI (.963) and TLI (.957) met or exceeded suggested cutoffs for acceptable fit, aligning with contemporary reporting

Table 4 Confirmatory factor analysis

χ^2	df	<i>p</i>	TLI	CFI	RMSEA			SRMR
					Value	Lower Bound	Upper Bound	
411.050	199	.000	.957	.963	.060	.052	.068	.036

standards (Goretzko et al., 2023; Howard et al., 2024). The RMSEA was .060, with its confidence interval (.052–.068) supporting the model's adequacy (Goretzko et al., 2023; Savalei, 2012). The SRMR of .036 indicates that the residual differences between observed and model-implied covariances are minimal—a sign of a strong fit (Shi et al., 2021). As shown in Table 4, all reported fit indices consistently indicate that the CFA model demonstrates a good fit to the data.

Confirmatory factor analysis was conducted to verify the measurement model, with all observed variables demonstrating standardized factor loadings ($\beta \geq 0.5$) that were statistically significant as shown in Table 5. This outcome provides robust evidence that the measurement items reliably reflect their respective latent constructs, fulfilling criteria for indicator relevance and conceptual clarity (Gagné & Hancock, 2006; Tarhini et al., 2014).

Construct reliability (CR) and average variance extracted (AVE)—best-practice metrics for convergent validity—were calculated for all constructs. Table 6 presents each CR value exceeded the established threshold of 0.70, and every AVE was above 0.50, substantiating the internal consistency and convergent validity of the measurement model (Gagné & Hancock, 2006; Goretzko et al., 2023). Such consistently high values confirm that each latent construct is adequately measured and captures substantial variance from its observed indicators.

Regarding the structural model, a multi-index approach was utilized to assess model fit in accordance with contemporary methodological standards guidance (Fan & Sivo, 2005; McNeish & Wolf, 2023). As shown in Table 7, despite a significant overall chi-square—often a byproduct of increased sample sizes—the normed chi-square value ($\chi^2/\text{df} = 1.559$) and fit indices (GFI = .918, AGFI = .893, CFI = .981, NFI = .948, IFI = .981, TLI = .977) signal excellent fit, far surpassing conventional cut-off values (Goretzko et al., 2023; McNeish & Wolf, 2023). Furthermore, residual-based indices, RMR and RMSEA, were notably low (0.036 and 0.043, respectively), indicating extremely limited model approximation error (Savalei, 2012). Therefore, the collective results strongly support the measurement and structural integrity of the AI-based fashion curation model, validating the proposed pathways for subsequent analysis.

Table 8 presents the results of the path analysis, evaluating the hypothesized relationships in the research model. Seven out of eight hypotheses were supported, with significant path coefficients at $p < .01$ or $p < .05$ levels. TTF had a strong positive effect on PU ($\beta = .656$, $p < .01$) and PEU ($\beta = .584$, $p < .01$), supporting H1 and H2. Additionally, PEU positively influenced PU ($\beta = .337$, $p < .01$), confirming H3. PU significantly impacted SF ($\beta = .586$, $p < .01$) and BI ($\beta = .204$, $p < .05$), supporting H4 and H5. PEU also had a significant effect on SF ($\beta = .341$, $p < .01$), validating H6. Nevertheless, the direct path from PEU to BI ($\beta = .072$, $p = .254$) was not significant, leading to the rejection of H7.

Table 5 Confirmatory factor analysis

Latent Variable	Observed variable	Estimate		S.E	C.R	
		B	β			
Task-Technology Fit	TTF5	1.000	.892			
	TTF4	.982	.846	.049	20.057	***
	TTF3	.844	.816	.045	18.737	***
	TTF2	.806	.798	.045	17.955	***
	TTF1	.819	.789	.047	17.611	***
Perceived usefulness	PU5	1.000	.777			
	PU4	1.078	.821	.070	15.439	***
	PU3	1.049	.798	.070	14.892	***
	PU2	1.100	.816	.072	15.306	***
	PU1	.957	.809	.063	15.147	***
Perceived ease of use	PEU5	1.000	.805			
	PEU3	1.129	.915	.060	18.891	***
	PEU2	1.061	.874	.060	17.747	***
	PEU1	1.064	.826	.065	16.390	***
Satisfaction	SF4	1.000	.885			
	SF3	.918	.866	.044	21.031	***
	SF2	.954	.823	.050	19.058	***
	SF1	1.028	.866	.049	21.070	***
Behavior intention	BI4	1.000	.851			
	BI3	1.043	.852	.056	18.720	***
	BI2	.905	.835	.050	18.110	***
	BI1	.915	.850	.049	18.658	***

* C.R.: Critical Ratio

Table 6 Construct reliability and average variance extracted

Variables	CR (Construct Reliability)	AVE (Average Variance Extracted)
TTF	.917	.689
PU	.902	.649
PEU	.906	.708
SF	.919	.738
BI	.899	.689

Table 7 Results of verification of research model fit

Model	CMIN	CMIN/df	CFI	TLI	GFI	AGFI	IFI	NFI	RMR	RMSEA
	304.066	1.559	.981	.977	.918	.893	.981	.948	.036	.043

Finally, SF strongly influenced BI ($\beta = .684$, $p < .01$), confirming H8 as the most substantial predictor of BI. These findings highlight the importance of TTF and usability factors in shaping consumer perceptions, ultimately leading to greater SF and BI for AI-driven fashion curation platforms.

Table 8 Results of hypothesis verification

Path				Estimate	S.E	β	C.R	p	Result
H1	TTF	→	PU	.560	.051	.656	10.944	.000**	Accept
H2	TTF	→	PEU	.552	.058	.584	9.446	.000**	Accept
H3	PEU	→	PU	.304	.046	.337	6.600	.000**	Accept
H4	PU	→	SF	.673	.077	.586	8.766	.000**	Accept
H5	PU	→	BI	.245	.096	.204	2.569	.010*	Accept
H6	PEU	→	SF	.354	.063	.341	5.624	.000**	Accept
H7	PEU	→	BI	.079	.069	.072	1.140	.254	Reject
H8	SF	→	BI	.716	.095	.684	7.507	.000**	Accept

* $p < .05$, ** $p < .01$ **Table 9** Results of measurement invariance analysis across groups

Model	χ^2	$\Delta\chi^2$	p	TLI	CFI	RMSEA
Unconstrained model	984.315	–	–	.922	.933	.047
Metric invariance model	1010.039	25.725	.845	.928	.934	.045
Scalar invariance model	1050.497	66.182	.000	.919	.927	.048
Strict invariance model	1099.756	115.441	.000	.920	.924	.047
Residual invariance model	1199.079	214.764	.000	.916	.914	.049

Moderating effect of generation Z, millennials and generation X

The results of the measurement invariance test across Generation Z, Millennials, and Generation X are presented in Table 9. The configural invariance model indicated an acceptable fit ($\chi^2=984.315$, CFI=.933, TLI=.922, RMSEA=.047), suggesting that the basic factor structure was consistent across the groups. The metric invariance model, which constrained factor loadings to be equal across groups, showed a non-significant χ^2 difference ($\Delta\chi^2=25.725$, $p=.845$) and acceptable fit indices, indicating that factor loadings were equivalent across generations.

Although the scalar invariance model, which further constrained item intercepts, yielded a significant χ^2 difference ($\Delta\chi^2=66.182$, $p<.001$), changes in fit indices were minimal (CFI=.927, RMSEA=.048), suggesting that partial scalar invariance could be assumed. The strict invariance model, adding constraints on residual variances, also showed a significant χ^2 change ($\Delta\chi^2=115.441$, $p<.001$) but fit indices remained within acceptable ranges. Even the factor variance/covariance invariance model, which imposed additional constraints on factor variances and covariances, demonstrated acceptable fit (CFI=.914, RMSEA=.049). Overall, the measurement invariance results indicate that metric invariance was satisfied, confirming that factor loadings were equivalent across generations. Despite the significant χ^2 changes in more restrictive models, the minimal changes in CFI and RMSEA suggest that partial scalar invariance is acceptable, and therefore, conducting a multi-group analysis is appropriate.

To test cohort differences in structural paths, we implemented pairwise constrained-model comparisons in AMOS. For each hypothesized path, we fitted a freely estimated baseline model and three constrained models imposing equality of the focal path between two cohorts (Gen Z–Millennials, Gen Z–Gen X, Millennials–Gen X). Pairwise differences were evaluated using the chi-square difference with 1 df,

Table 10 Multiple group analysis result (H9)

Path	β			χ^2	p	Z vs M		Z vs X		M vs X	
	Z	M	X			diff	p	diff	p	diff	p
TTF → PEU	.571**	.528**	.728**	2.371	.306	.043	.627	.157	.418	.200	.126
TTF → PU	.869**	.683**	.357**	8.998	.011*	.186	.435	.326	.003**	.326	.019*
PEU → PU	.167*	.301**	.576**	9.874	.007**	.134	.123	.406	.002**	.275	.080
PU → SF	.774**	.469**	.357**	7.168	.028*	.305	.041*	.417	.012*	.112	.439
PU → BI	.313	.134	.334*	1.492	.474	.179	.370	.021	.981	.200	.307
PEU → SF	.133	.416**	.618**	7.879	.019*	.283	.038*	.485	.007**	.202	.392
PEU → BI	-.089	.237*	-.332	8.260	.016*	.148	.022*	.243	.351	.095	.019*
SF → BI	.681**	.630**	.942**	1.364	.506	.051	.806	.261	.383	.312	.242

* $p < .05$, ** $p < .01$; Z Generation Z, M Millennials, X Generation X

$\Delta\chi^2 = \chi^2_{\text{constrained}} - \chi^2_{\text{free}}$, and p -values are reported alongside the magnitude of standardized differences ($|\Delta\beta|$). Structural comparisons are justified by established measurement invariance results (metric invariance and acceptable partial scalar invariance) (Byrne et al., 1989; Luong & Flake, 2021; Vandenberg & Lance, 2000; Yuan & Chan, 2016).

Table 10 reports group-specific standardized path coefficients together with pairwise constrained-model tests ($|\Delta\beta|$ and $\Delta\chi^2$ -based p). TTF → PU was significantly weaker in Gen X than in Gen Z and Millennials (Z–X: $p = .003$; M–X: $p = .019$), whereas PEU → PU was significantly stronger in Gen X than in Gen Z (Z–X: $p = .002$). PU → SF was significantly stronger in Gen Z than in Millennials and Gen X (Z–M: $p = .041$; Z–X: $p = .012$), while PEU → SF was significantly stronger in Millennials and Gen X than in Gen Z (Z–M: $p = .038$; Z–X: $p = .007$). For behavioral intention, PEU → BI was significantly stronger for Millennials than for Gen Z and Gen X (Z–M: $p = .022$; M–X: $p = .019$); no significant cohort differences were detected for PU → BI or SF → BI. These results provide explicit pairwise evidence on which cohorts differ and by how much, addressing heterogeneity in the usefulness/ease–satisfaction/intention pathways. Given known limitations of χ^2 -difference tests and multiplicity, we report unadjusted p -values in Table 10.

Key findings and interpretation of results

Analysis of the overall results confirmed that eight of the nine proposed hypotheses were accepted (H9 was partially accepted) and one was rejected. Task–Technology Fit (TTF) exerted strong positive effects on both Perceived Usefulness (PU; H1) and Perceived Ease of Use (PEU; H2). PEU also positively influenced PU (H3). In turn, PU significantly predicted Satisfaction (SF; H4) and Behavioral Intention (BI; H5), while PEU significantly shaped SF (H6). SF emerged as the strongest predictor of BI (H8). These results suggest that within AI-enabled fashion curation, fit characteristics and core TAM beliefs remain central to consumer evaluations, with usefulness and ease of use shaping downstream satisfaction and adoption intentions (Choung et al., 2022; Ding et al., 2022; Divitiis et al., 2022; Mu et al., 2024; Pillai & Sivathanu, 2020; Vorm & Combs, 2022).

On the other hand, only path from PEU to BI (H7) was not significant. The non-significance of the direct path from PEU to BI indicates that ease of interaction, by itself, is not the proximal driver of adoption in AI-based fashion curation. In

performance-centric, visually complex decision tasks, users appear to weigh the quality and relevance of curated outcomes more heavily than interface simplicity. Therefore, it can be inferred that intentions are primarily formed based on whether the system provides useful and satisfactory recommendations rather than on the ease of system operation. This pattern is theoretically consistent with evidence that PU tends to dominate intention formation in many IT adoption settings, while the influence of PEU is frequently indirect or contingent on context and task characteristics (Wu & Lederer, 2009).

The multi-group structural analysis with additional pairwise comparisons clarified which cohorts differ on specific paths while preserving the overall narrative of the integrated TTF–TAM model. The path from TTF to PU was significant across all cohorts but significantly stronger for Generation Z and Millennials than for Generation X, indicating that younger consumers translate system–task alignment into usefulness beliefs more readily, consistent with their greater comfort with technology-forward, contactless retail experiences and performance-mapping tendencies (Kim & Forsythe, 2008; Kim et al., 2021).

By contrast, the path from TTF to PEU remained non-significant and statistically comparable across cohorts, aligning with prior arguments that fit-related judgments do not uniformly generalize to perceived simplicity in use across settings (Howard & Rose, 2019; Mathieson & Keil, 1998). The relationship between PEU and PU was significant in all cohorts but notably stronger for Generation X than for Generation Z, implying that older users rely more on ease-of-use cues when evaluating usefulness in AI-enabled curation workflows, consistent with TAM-based structural comparisons that often reveal segment-sensitive ease-to-utility translations (Bonn et al., 2016; Deng et al., 2005).

For satisfaction, PU strongly influenced SF across cohorts, with the effect significantly stronger in Generation Z than in Millennials and Generation X, which is consistent with younger cohorts' utilitarian orientation toward technology features that deliver clear functional value in retail interfaces (Kim & Forsythe, 2008; Kim et al., 2021). In contrast, the effect of PEU on SF was significant for Millennials and Generation X and significantly weaker in Generation Z, suggesting that usability serves as a primary evaluation driver among older cohorts who weight experiential fluency and effort reduction more heavily during adoption (Kim & Forsythe, 2008; Mičík et al., 2025).

For behavioral intention, the PEU → BI path was significant only for Millennials and stronger than for Gen Z and Gen X, indicating that for this cohort, reductions in friction translate more directly into adoption intentions in consumer digital services (Lin et al., 2007; Rauniar et al., 2014). In contrast, neither PU → BI nor SF → BI exhibited significant pairwise differences, diverging from pooled results but indicating that, once heterogeneity in belief and evaluation formation is accounted for, downstream intention mechanisms operate in a statistically equivalent pattern across cohorts—an outcome that aligns with evidence of limited, context-contingent cohort differences and with reports of structural robustness in TAM across groups (Deng et al., 2005; Ravid et al., 2024).

Taken together, these findings situate generational heterogeneity primarily in the upstream formation of usefulness and satisfaction (fit- and ease-based routes), while

intention pathways from usefulness and satisfaction show cross-cohort convergence; this pattern underscores the role of contextual and experiential factors in shaping adoption routes in intelligent retail environments, even as core intention drivers remain broadly stable (Gao & Liu, 2022; Huang & Rust, 2020).

Conclusions

This study extends the integrated Task–Technology Fit and Technology Acceptance Model framework to explain adoption of AI-enabled fashion curation by specifying how generational cohorts—Generation Z, Millennials, and Generation X—translate perceived fit and ease into usefulness, satisfaction, and intention. Our multi-group SEM with explicit pairwise constrained-model tests was conducted conditional on measurement invariance, which we established at least at the metric level with acceptable partial scalar properties, thereby allowing substantive structural comparisons in line with recommended practice (Byrne et al., 1989; Vandenberg & Lance, 2000; Yuan & Chan, 2016).

The evidence reveals cohort-sensitive pathways that align with theorized socialization patterns and prior adoption research, while also indicating areas of cross-generational convergence. At the belief-formation stage, task–technology fit most strongly informs perceived usefulness among Gen Z, consistent with their digital nativity and rapid mapping of feature–task alignment to performance expectations, whereas Gen X relies more on ease-of-use cues to build usefulness, reflecting greater sensitivity to usability and cognitive effort during adoption (Kim et al., 2021; Morris & Venkatesh, 2000). Millennials display an intermediate pattern in belief formation but show a distinct ease-to-intention linkage, underscoring the instrumental role of frictionless interaction for this cohort (Kim et al., 2021). At the evaluative stage, usefulness more strongly drives satisfaction for Gen Z, while ease of use exerts a comparatively larger influence on satisfaction for Millennials and Gen X, implying that experiential fluency stabilizes affective responses among older cohorts as interfaces become simpler and more predictable (Morris & Venkatesh, 2000; Shen et al., 2021). By contrast, once usefulness and satisfaction are established, their links to behavioral intention are statistically comparable across cohorts in our model, a result that resonates with mixed meta-analytic conclusions about the magnitude of generational differences and cautions against overgeneralizing cohort stereotypes when final adoption drivers are already in place (Ravid et al., 2024).

These differentiated-yet-convergent patterns refine the integrated TTF–TAM view in three ways. First, they specify where cohort asymmetries reside—namely, in how fit and ease are converted into usefulness and satisfaction—thereby positioning generation as a theoretically meaningful moderator rather than a mere control (Mičik et al., 2025; Shen et al., 2021). Second, they show that the usefulness– and satisfaction–intention links operate robustly across cohorts once core beliefs are formed, suggesting downstream convergence despite upstream heterogeneity (Ravid et al., 2024). Third, by grounding cross-group structural comparisons in established invariance procedures, the study models a transparent pathway from measurement to theory testing in multi-group contexts (Luong & Flake, 2021; Vandenberg & Lance, 2000; Yuan & Chan, 2016).

Implications

By embedding generational cohorts as a structural moderator within an integrated TTF–TAM framework, this study advances theorizing from treating age/cohort as a descriptive control to a mechanism-level account of when and where moderation occurs—namely, during belief and evaluation formation rather than at the final intention stage, as verified through pairwise multi-group SEM conducted only after establishing measurement invariance in line with best practice (metric and acceptable partial scalar) as recommended for substantive cross-group comparisons by organizational methods scholars (Byrne et al., 1989; Cheung & Rensvold, 2002; Vandenberg & Lance, 2000). The selective nature of moderation aligns with evidence that many generational effects are modest or context-bound, cautioning against overgeneralization while encouraging precise theorizing about cognitive routes of adoption (Ravid et al., 2024).

Positioning Gen Z's stronger fit-to-usefulness translation alongside Millennials' and Gen X's greater reliance on ease-based evaluations refines acceptance theory by linking micro-appraisal pathways to sociotechnical socialization patterns observed in adjacent retail technology contexts where cohort-linked differences in technology efficacy, trust, and interaction style emerge (Kim et al., 2021; Mičák et al., 2025). The downstream convergence we observe—statistically comparable usefulness– and satisfaction–intention links—resonates with prior TAM extensions showing robust intention mechanisms across consumer settings even as upstream beliefs are shaped by segment-specific antecedents, thus complementing models that integrate readiness, affect, or technology-specific attributes into TAM (Deng et al., 2005; Kulviwat et al., 2007; Lin et al., 2007).

Methodologically, our invariance-first, pairwise constrained-model workflow operationalizes transparent multi-group theory testing—acknowledging limitations of chi-square-difference procedures and motivating equivalence-oriented or alignment/MNLFA alternatives in future work to balance error control and scalability (Kolbe et al., 2024; Luong & Flake, 2021; Yuan & Chan, 2016)—and it underscores careful handling of partial invariance and parceling choices to avoid spurious conclusions (Byrne et al., 1989; Meade & Kroustalis, 2006).

The cohort-sensitive pathways translate into segmentable levers for AI-enabled fashion curation without fragmenting the core value proposition: for Generation Z, emphasize “fit-to-value” design and messaging that make task–feature alignment, personalization, and discovery gains salient so that perceived usefulness lifts satisfaction efficiently, a pattern consistent with younger users' comfort with contactless, technology-forward interactions and efficacy-driven preferences in retail settings (Kim & Forsythe, 2008; Kim et al., 2021). For Millennials, prioritize “ease-to-intention” pathways by eliminating friction through intuitive navigation, transparent recommendation logic, and seamless onboarding, thereby converting perceived ease directly into intention in line with consumer-TAM evidence that usability signals convert quickly to adoption in digital services (Lin et al., 2007; Rauniar et al., 2014).

For Generation X, foreground simplicity, reliability, and trust-building—clear labels, predictable flows, and control affordances—so that ease-based appraisals effectively bolster usefulness and satisfaction, cohering with findings that older cohorts weight trust and clarity more heavily in digital commerce journeys (Mičák et al., 2025). Because the usefulness– and satisfaction–intention links are robust and statistically equivalent

across cohorts in our model, managers should standardize downstream value and satisfaction cues (e.g., benefit framing, service recovery, and post-use reinforcement) while tailoring upstream belief formation by cohort, a segmentation logic that mirrors how functional and experiential features jointly shape attitudes and use of retail technologies across modalities (Kim & Forsythe, 2008) and how social/value cues channel usefulness in online purchasing (Bonn et al., 2016). Operationally, this implies a two-tier strategy: cohort-specific UX levers for belief and evaluation formation, paired with scalable, consistent value and satisfaction frameworks for intention conversion, thereby balancing personalization efficiency with cross-cohort reach in AI-enabled consumer technology services (Deng et al., 2005).

Limitation and future research

While the study provides clear insights into generational differences in AI acceptance, it is important to acknowledge its limitations. The primary limitation relates to the limited sample, focused largely on specific generational cohorts, which may not be fully representative of all demographics. Additionally, the reliance on self-reported data can introduce biases that affect the accuracy of results (Ruis-Viñals et al., 2024). Thus, ongoing research must refine these models further and investigate broader applications across different cultural and demographic contexts, ensuring that AI-driven fashion solutions remain inclusive and widely accepted (Choung et al., 2022; Ismatullaev & Kim, 2022).

Finally, as fashion increasingly embraces AI, aligning innovation with consumer needs is vital. Leveraging AI's predictive and personalization capabilities can strengthen consumer relationships, advance SF, and secure competitive advantage (Goti et al., 2023; Kang & Choi, 2023; Sohn et al., 2020). Therefore, future research should refine the model and broaden its scope, incorporating cultural and ethical considerations to ensure inclusivity and wide adoption. For this, it should extend demographic and cultural coverage, adopt longitudinal designs, and examine moderating factors such as technological proficiency and cultural influences. Such extensions would enrich the integrated framework and deepen understanding of consumer behavior in the evolving digital fashion landscape.

Author contributions

DJ contributed to the methodology, software development, data curation, formal analysis, investigation, and the writing of the original draft. YK contributed to the conceptualization, validation, and resources, and was responsible for the review and editing of the manuscript as well as overall supervision of the research process. Both authors read and approved the final manuscript.

Funding

This work was supported by the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea (NRF-2023S1A5A8080096).

Availability of data and materials

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate

This research was conducted under the approval and supervision of Chung-Ang University Institutional Review Board (IRB Approval No: 1041078-20250403-HR-106) regarding ethical issues including consent to participate.

Competing interests

The authors declare that they have no competing interests.

Received: 24 June 2025 Accepted: 2 December 2025

Published online: 15 December 2025

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