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Generative AI in Fashion Product Design: Effects of AI Transparency Level and Consumer Age Group on Perceived Creativity, Authenticity, and Purchase Intention

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Abstract This study investigates how transparency in generative AI fashion design and age jointly shape consumer responses. Drawing on information transparency theory and generational perspectives on digital technology, we examine the effects of different AI transparency level on perceived creativity, perceived authenticity, and purchase intention. A 3 (AI transparency level: no transparency vs. partial transparency vs. full transparency) × 2 (age group: 20s vs. 40s–50s) between-subjects online experiment was conducted with 194 Korean female consumers. Participants were randomly exposed to a handbag design generated through a generative-AI workflow, accompanied by product descriptions manipulated to varying levels oft. Results show that AI transparency level has significant positive main effects on perceived creativity and authenticity; full transparency leads to more favorable evaluations than partial or no transparency. For purchase intention, both the main effect of AI transparency level and its interaction with age group are significant. Among consumers in their 20s, purchase intention increases with higher AI transparency, whereas among those in their 40s–50s, partial transparency lowers purchase intention and only full transparency restores it. These findings highlight that partial transparency may backfire, especially for middle-aged consumers, and suggest that fashion brands should adopt age-tailored AI transparency strategies.

Keywords Generative AI, AI transparency, Perceived authenticity, Perceived creativity, Purchase Intention, Age group

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Introduction

Artificial intelligence (AI) has rapidly diffused across the fashion industry in recent years, creating a turning point in multiple domains including design creation, trend forecasting, and personalized recommendation systems (Bae, 2024). Advances in generative AI have opened new possibilities for producing original designs using text prompts alone, prompting global fashion companies to strengthen strategies that pursue both design efficiency and enhanced creativity (McKinsey & Company, 2023). For example, Tommy Hilfiger experimented with an AI-driven design workflow through the "Reimagine Retail" project in collaboration with IBM and the Fashion Institute of Technology (FIT). In this project, AI analyzed runway images, product photos, and consumer trend data to propose new styles, while designers used these outputs to develop creative ideas more quickly. As a result, the project helped automate early-stage design tasks and reduce repetitive work, improving productivity and enabling a more agile response to rapidly changing consumer demand (Fashion Institute of

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Technology, 2019; FashionNetwork, 2017).

Despite these technological advances and efficiency gains, AI's involvement in creative processes has raised critical concerns. Questions regarding unclear authorship, judgments of creativity and authenticity, and broader social acceptance have emerged. Some global fashion firms have actively adopted generative AI in design while withholding detailed information about operational mechanisms, algorithmic structures, or data sources. A prominent example is the ultra-fast fashion platform Shein, which has been alleged to collect popular images and designs from the internet and social media using AI-based algorithms and to translate these inputs into mass production at extreme speed. Consequently, the degree of human designer involvement and the underlying algorithmic processes have not been clearly disclosed, and copyright lawsuits have been filed alleging that AI-enabled systems were used to replicate online artworks for commercial purposes (Philipp, 2025; The Fashion Law, 2024). Such opaque practices may offer advantages in speed and efficiency, but they can also generate ethical concerns related to diminished authenticity, violations of consumers' right to know, and potential copyright infringement.

Against this backdrop, the concept of AI transparency has gained increasing attention. AI transparency refers to the extent to which a system clearly discloses how it operates, makes decisions, and uses data, enabling users to recognize that they are interacting with AI (European Commission, 2019). Conversely, opaque AI use can generate confusion and distrust among consumers (Eiband et al., 2018), undermining trust in products and brands. Accordingly, the European Union has enacted the AI Act, which mandates explicit labeling of AI-generated content and establishes transparency as a core regulatory principle (The AI Act Explorer, n.d.). South Korea has likewise introduced a comparable AI-related legal framework scheduled to take effect in 2026, signaling an important turning point for fashion and other industries.

AI transparency is therefore considered more than a technical explanation; it is increasingly understood as a key determinant of consumer trust, authenticity judgments, and ultimately purchase decisions. Importantly, consumers' acceptance of and evaluative standards for AI may differ across generations. While younger consumers tend to be more familiar with digital environments and more open to new technologies (Prensky, 2001), older consumers are generally more risk-averse and place greater emphasis on authenticity and trust, making them more sensitive to insufficient transparency (Mata et al., 2011).

Building on the distinction between digital natives and digital immigrants (Prensky, 2001), this research compares consumers in their 20s—who are typically more accustomed to digital technologies—with middle-aged consumers in their 40s and 50s, who often acquire such technologies later in life. This study investigates how different levels of AI fashion design transparency influence perceived creativity, perceived authenticity, and purchase intention, and whether these effects vary by age groups.

Literature Review

Generative AI Technology in the Fashion Business

Generative AI has rapidly expanded its presence across the fashion business, reshaping value creation processes from design ideation to marketing content development and consumer engagement. Unlike earlier AI applications that primarily supported prediction and optimization tasks—such as trend analytics, demand forecasting, and recommendation systems—generative AI enables the creation of new visual and textual outputs, allowing companies to accelerate creative workflows and explore broader aesthetic directions (McKinsey & Company, 2023). This shift suggests that AI is no longer merely an operational tool but is increasingly embedded in the symbolic and expressive dimensions of fashion production.

In practice, generative AI is being deployed across multiple functional areas. First, in product development and design, AI-assisted ideation can support early-stage concept generation and rapid exploration of style variations. Second, in marketing and communication, generative AI enables scalable production of campaign images, product descriptions, and personalized content, helping brands react more quickly to fast-changing consumer tastes (McKinsey & Company, 2023). Third, in digital retail and customer experience, AI-generated styling suggestions and interactive content may enrich engagement and support individualized shopping journeys. Collectively, these applications point to business potential in improving speed and efficiency while expanding the range of creative outputs.

However, the diffusion of generative AI in fashion also raises critical concerns. As AI becomes more involved in creative production, questions emerge regarding authorship, originality, and the perceived "human touch" traditionally associated with fashion design (Anantrasirichai & Bull, 2022). In addition, companies do not always clearly disclose how AI is used or which data sources may underpin AI-generated outcomes, which can amplify concerns about responsibility, consumer trust, and legitimacy. These issues suggest that the business value of generative AI cannot be evaluated solely through efficiency metrics and should be understood alongside consumer interpretations of creativity, authenticity, and trust.

Against this background, transparency has become a strategic issue for fashion brands adopting generative AI. The transparency of AI involvement—how explicitly brands communicate the role of AI, the use of data, and the level of human oversight—may shape consumers' interpretations of AI-generated fashion outputs. This perspective provides a basis for examining how AI transparency influences perceived creativity, perceived authenticity, and purchase intention.

AI Transparency and Consumer Responses to AI-Generated Fashion Design

With the growing prevalence of AI-based recommendation systems and automatically generated content, the transparency of AI-provided information has become a key issue. AI transparency is defined as the extent to which consumers can understand how AI works and which data and algorithms it uses (European Commission, 2019). It is widely considered a crucial factor in building trust between consumers and brands. In the context of AI fashion design, transparency can be categorized into three levels: full transparency, which explicitly reveals the specific role and process of AI; partial transparency, which merely states that AI was involved; and no transparency, which does not mention the use of AI at all.

Information transparency theory generally suggests that higher quantity and quality of information reduce uncertainty and increase trust and satisfaction (Bleier & Eisenbeiss, 2015; Schnackenberg & Tomlinson, 2016). From this perspective, fuller disclosure of AI involvement-fuller transparency-should help consumers interpret AI-generated fashion products more confidently, fostering favorable evaluations. However, prior research indicates that transparency effects may not be purely linear. In intelligent system contexts, incomplete or fragmented explanations can cause confusion and distrust, suggesting that partial transparency may backfire rather than reassure users (Eiband et al., 2018). Thus, transparency in AI fashion design should be understood not simply as whether AI use is disclosed, but whether the transparency provides interpretable information about AI's role, data sources, and human involvement.

Moreover, consumer responses to AI-generated design often reflect ambivalence. While AI is associated with speed, novelty, and scalable creative output, it may simultaneously weaken the perceived symbolic value of the "human touch" traditionally tied to fashion. Previous studies suggest that consumers tend to prefer human-designed apparel over AI-designed alternatives, and that this difference is explained by perceived authenticity and expected quality (Lee & Kim, 2024). In this sense, AI transparency can signal new creative possibilities while also activating skepticism about whether an outcome is "real," meaningful, or trustworthy.

Generational Differences in Interpreting AI Transparency

Generational differences may further shape how consumers interpret and respond to AI transparency cues. The distinction between digital natives and digital immigrants is not limited to variations in technological familiarity; rather, it extends to fundamental differences in information processing styles, evaluative norms, and perceived trustworthiness of technology-mediated outputs (Prensky, 2001). Younger consumers, who have grown up in digital environments, tend to exhibit higher digital literacy and greater confidence in navigating online information, thereby showing lower perceived risk in technology-augmented decision contexts

(Chen & Chan, 2014). By contrast, middle-aged and older adults often rely more heavily on systematic processing, place greater weight on diagnostic informational cues, and require more concrete evidence to form judgments about novel technologies (Yoon et al., 2009).

Prior research in online consumer behavior has consistently shown that older consumers are more cautious in uncertain or ambiguous decision-making environments, demonstrating stronger risk aversion and heightened sensitivity to potential loss (Mata et al., 2011). In digital shopping contexts, they experience higher levels of uncertainty due to limited ability to verify product quality, resulting in stronger reliance on trustworthy signals such as clear product descriptions, provenance cues, or third-party verification (Sun et al., 2019). Additionally, older adults tend to be more negatively affected by incomplete or vague information, as they depend on information sufficiency to reduce cognitive load and uncertainty (Hess et al., 2013).

Applied to AI transparency, these tendencies suggest that incomplete transparency may be more likely to trigger suspicion, perceived deception, or ambiguity among middle-aged consumers. In contrast, younger consumers may interpret the same information as a neutral or even innovative signal, due to greater openness to algorithmic systems and lower reliance on detailed contextual information for judgment formation. Consequently, generational differences are expected not only in baseline evaluations of AI-generated design, but also in the degree to which incomplete transparency produces backfire effects.

Perceived Creativity and Perceived Authenticity

This study conceptualizes consumer responses to AI fashion design in terms of perceived creativity, perceived authenticity, and purchase intention. Creativity is defined as the joint presence of novelty and usefulness and is central to product evaluation in expressive categories such as fashion (Amabile, 1996). In AI-based design contexts, consumers may perceive AI outputs as a distinct form of "computational creativity" rather than as a direct extension of human creative intuition (Colton & Wiggins, 2012). Here, transparency about data, algorithms, and human involvement can function as a credibility signal regarding the novelty and feasibility of the output, thereby legitimizing perceived creativity (Eiband et al., 2018).

Authenticity refers to the extent to which a product or brand is perceived as being true and consistent with its identity and values (Napoli et al., 2014). In fashion, authenticity cues typically involve origin, production context, and craftsmanship. In design contexts involving AI, clearly presenting the roles of AI and humans, data sources, and responsible procedures can alleviate concerns that a design is "fake" and serve as a signal of authenticity. Conversely, partial or ambiguous transparency may be interpreted as deceptive communication, diminishing perceived authenticity (Eiband et al., 2018). Such recovery of authenticity under full transparency may be especially salient among older consumers, who tend to be more risk-averse and sensitive to incomplete information (Hess et al., 2013; Mata et al., 2011).

Theoretical Framework

In online settings, consumers cannot physically examine or directly experience products and thus rely on provided information to evaluate quality and value (Dimoka et al., 2012). When information is insufficient or difficult to trust, consumers experience product uncertainty, which can negatively influence purchase intention. From a signaling perspective, firm-provided information serves as a critical cue for inferring unobservable quality online (Akerlof, 1970; Spence, 1973). The clarity and specificity of such information can strengthen inferences related to quality, authenticity, and trust.

Dimoka et al. (2012) distinguish product uncertainty into description uncertainty, which concerns how clearly product attributes are described, and experience uncertainty, which concerns how difficult it is to anticipate actual usage outcomes. Applied to AI fashion design, transparency cues—such as whether AI was used, the scope of its role, data sources, and levels of human involvement—are expected to reduce description uncertainty. At the same time, because consumers may still find it difficult to predict the real-world quality and usage experience of AI-generated designs, experience uncertainty may remain salient. Thus, transparency in AI fashion products should be considered a core informational cue that enhances interpretability and reduces uncertainty in online decision-making.

These effects can be further interpreted through ambiguity aversion theory. The Ellsberg paradox demonstrates that people tend to avoid choices under ambiguity—where probabilities or causal structures are unclear—relative to choices under defined risk (Ellsberg, 1961). In consumer contexts, incomplete or ambiguous information may be perceived as more aversive than a clearly defined absence of information (Camerer & Weber, 1992). In this sense, merely stating that AI was used without offering meaningful details may expose consumers to ambiguous judgments about responsibility, data legitimacy, or quality. Such partial transparency may therefore generate stronger confusion or suspicion than no transparency, particularly among groups with stronger ambiguity avoidance tendencies.

Hypotheses Development

As generative AI becomes increasingly embedded in the fashion design process, consumers are confronted with products whose creative origins are no longer exclusively human-driven. Prior research suggests that the transparency with which firms disclose AI involvement is a critical informational cue that shapes consumer judgment (Eiband et al., 2018; European Commission, 2019). Transparency can reduce informational ambiguity, enhance comprehensibility, and thereby bolster trust and evaluations—particularly in online environments where consumers cannot physically inspect products and must instead rely on informational signals to infer quality and authenticity (Akerlof, 1970; Dimoka et al., 2012; Spence, 1973). From this perspective, higher levels of AI transparency—such as providing detailed explanations of the role of AI, data sources, and human involvement—are expected to reduce description uncertainty and facilitate more favorable responses than partial or absent transparency.

At the same time, prior studies caution that partial or ambiguous transparency may produce "backfire effects," resulting in confusion, distrust, or algorithm aversion (Eiband et al., 2018). When consumers recognize that information is incomplete, they may interpret such partial transparency as a deceptive act or a signal of inferior quality. According to ambiguity aversion theory (Camerer & Weber, 1992; Ellsberg, 1961), individuals tend to avoid options associated with unclear probabilities or ambiguous information. Applied to AI-generated design, partial transparency—simply stating that "AI was used" without further elaboration—may heighten ambiguity more than full transparency or even no transparency, thus diminishing creativity, authenticity evaluations, and purchase intentions.

Generational differences may further shape how consumers interpret AI transparency cues. Younger consumers, often described as digital natives, tend to be more receptive to AI-generated content and more comfortable interpreting technologically mediated creativity (Prensky, 2001). In contrast, middle-aged consumers exhibit stronger risk aversion, greater sensitivity to incomplete information, and heightened concerns about authenticity and trustworthiness (Hess et al., 2013; Mata et al., 2011). Therefore, the negative effects of partial transparency—stemming from ambiguity and perceived deception—are likely to be stronger among middle-aged consumers than younger consumers.

Perceived creativity and perceived authenticity represent two central evaluative mechanisms through which transparency cues may influence consumer responses to AI fashion design. Transparency can legitimize "computational creativity" by clarifying the novelty and feasibility of the design process (Colton & Wiggins, 2012), thereby enhancing creativity judgments. Similarly, transparent disclosure of AI and human roles can serve as an authenticity signal, alleviating concerns that AI-generated designs lack meaning, intentionality, or craftsmanship (Napoli et al., 2014). Consequently, both creativity and authenticity are expected to mediate the effects of transparency on purchase intention.

Drawing on these theoretical foundations, this study develops the following hypotheses:

H1. Effects of AI Transparency level on perceived creativity, perceived authenticity, and purchase intention

H1a. Full transparency will lead to higher perceived creativity than partial transparency, and partial transparency will lead to higher perceived creativity than no transparency.

H1b. Full transparency will lead to higher perceived authenticity than partial transparency, and partial transparency will lead to higher perceived authenticity than no transparency.

H1c. Full transparency will lead to higher purchase intention than partial transparency, and partial transparency will lead to higher purchase intention than no transparency.

H2. Moderating Role of Age group

H2a. The negative effect of partial transparency (vs. full or no transparency) on perceived creativity will be stronger for middle-aged consumers than for younger consumers.

H2b. The negative effect of partial transparency on perceived authenticity will be stronger for middle-aged consumers than for younger consumers.

H2c. The negative effect of partial transparency on purchase intention will be stronger for middle-aged consumers than for younger consumers.

Research Methods

Research Model

Based on the theoretical backgrounds and hypotheses developed above, this study proposes a conceptual model as illustrated in Figure 1. The model delineates the impact of AI transparency levels (No, Partial, and Full transparency) on perceived creativity, perceived authenticity, and purchase intention. Furthermore, it incorporates consumer age group as a moderating variable to examine generational differences in how these transparency cues are processed.

Research Design

A between-subjects 3 (AI transparency level) × 2 (age group) factorial design was employed. AI transparency level was manipulated at three levels: no transparency, partial transparency, and full transparency. Full transparency refers to detailed disclosure of AI involvement and the design workflow (e.g., tools used, data type, and human involvement. In the no transparency condition, the product page included no information about AI involvement. The age groups were selected to represent digital natives (20s) and digital immigrants (40s–50s), enabling comparison between consumers who differ substantially in digital familiarity and information-processing tendencies (Prensky, 2001).

To ensure sufficient power for ANOVA, a priori power analysis assuming a medium effect size ($f = .25$), $\alpha = .05$, and power = .80 indicated a minimum required sample size of 158. Considering potential inattentive responding, the target sample size was set to approximately 180, with equal allocation across the six experimental conditions. A between-subjects 3 × 2 factorial design was employed:

Stimuli Development

The experimental stimuli consisted of a fashion handbag

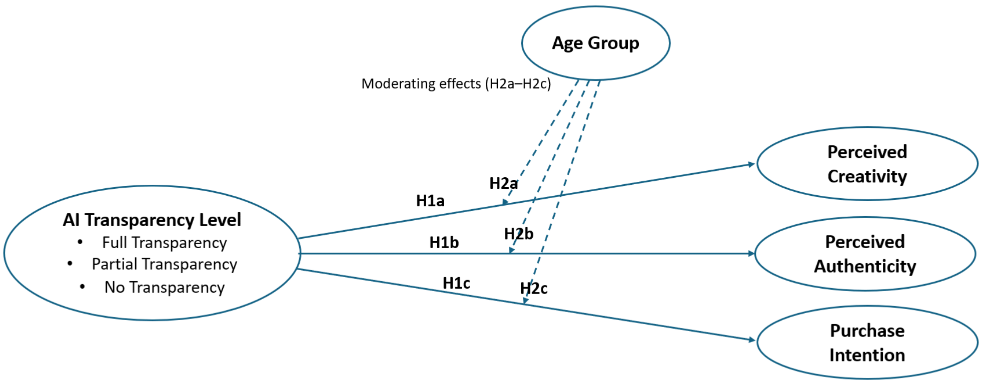

Figure 1. Conceptual Research Model

design generated through a generative-AI workflow: trend analysis with Perplexity, idea generation with Claude, and visual realization using MidJourney. A single design category (handbag) was chosen to minimize category-related variance. The product image used in all conditions was titled “Blue Cream Shoulder Bag.” Only the accompanying text description were manipulated to reflect the three transparency levels (no, partial, full transparency of AI involvement):

Full Transparency Condition: Participants saw a detailed explanation of the AI design process: “This product was designed using artificial intelligence based on a 26SS trend analysis.

(1) Trend Analysis: Using the generative-AI tool Perplexity, trend data were extracted from fashion show reviews, consumer purchase patterns, and social media hashtag rankings from the past five years.

(2) Concept Ideation: Based on these trends, Claude generated creative design ideas incorporating functional and stylistic elements.

(3) Visual Realization: Using Midjourney, 24 design images were produced, and an AI curator selected the final design based on clarity, feasibility, and aesthetic coherence.”

Partial Transparency Condition: A brief statement indicating AI involvement was provided: “This product was designed using artificial intelligence based on a 26SS trend analysis.”

No Transparency Condition: Only the product title and price were shown, with no mention of AI.

Table 1 presents the handbag stimulus used across all conditions.

Table 1. Stimuli Used to Manipulate AI Transparency Level

Full Transparency	Partial Transparency	No Transparency
[26SS] Blue Cream Shoulder Bag ₩189,000	[26SS] Blue Cream Shoulder Bag ₩189,000	[26SS] Blue Cream Shoulder Bag ₩189,000
		
This product was designed using artificial intelligence (AI), based on a trend analysis for the 26SS season conducted through AI-driven processes. **Step 1 Trend Forecasting:** To predict global fashion trends for the 2025 Spring/Summer season, we utilized the generative AI tool Perplexity. Key categories and trend indicators were extracted from a dataset that included: reviews of fashion shows over the past five years, shifts in consumer purchase behavior, and rankings of fashion-related hashtags on social media. **Step 2 Design Ideation:** Based on the derived trends,	This product represents an AI-generated design, developed through a comprehensive AI-driven trend analysis for the 26SS season.	

Full Transparency	Partial Transparency	No Transparency
creative design ideas were generated using the generative AI tool Claude. Prompts included predicted trend keywords, suggestions for design direction, functional considerations such as intended bag usage, and user convenience. **Step 3 Design Visualization:** A total of 24 visual prototypes were created using the AI image generator Midjourney. Among these, designs with clear structure and high feasibility were curated by an AI assistant. The final product image was completed through a refinement process.		

Note. Original Korean descriptions translated into English by the authors.

Participants and Procedure

The survey was conducted online in May 2025 with female consumers who had prior online shopping experience in Korea. Participants were randomly assigned to one of the three AI transparency level conditions during the data collection period, and quotas were monitored to maintain balance across age groups and conditions.

A total of 205 respondents participated. After excluding nine inattentive responses, 194 valid cases were used for analysis (20s: 93; 40s–50s: 101). Table 2 displays the distribution of participants by age group and AI transparency level. Data was analyzed using SPSS 28.0. Descriptive statistics, factor analysis and reliability tests were conducted. Two-way ANOVA was used to examine the main and interaction effects of AI transparency level and age group on perceived creativity, perceived authenticity, and purchase intention.

Measures

All constructs were assessed using items adapted from validated scales and measured on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). Based on previous research (Magni et al., 2024), perceived creativity was measured with four items assessing novelty and originality (e.g., "This product shows a fresh and original style"). Two items were adapted from authenticity literature (Napoli et al., 2014) to fit the fashion design context (e.g., "This product feels trustworthy and natural."). Purchase intention was measured with three commonly used items (e.g., "I would consider purchasing this product if the price is appropriate.").

Results

Participants Characteristics

The participants showed a relatively balanced age distribution between younger and older adults, with respondents in their 20s accounting for 47.9% (n=93), and those in their 40s and 50s combined making up 52.0% (n =101). As shown in Table 3, in terms of educational background, the majority (79.9%,

Table 2. Number of Participants by Age Group and AI Transparency Level

Age Group	Level of AI Transparency		
	No AI transparency	Partial AI transparency	Full AI transparency
20s	30	33	30
40s~50s	41	30	30

Table 3. Demographic Characteristics of Respondents (*N*=194)

Category	Subcategory	Frequency (n)	Percentage (%)
Age	19–29 years old	93	47.9
	40–49 years old	42	21.6
	50–59 years old	59	30.4
Final Educational Attainment	High school graduate	25	12.9
	Enrolled in or graduated from a 4-year university	155	79.9
	Graduate school (Master's degree or higher)	14	7.2
Occupation	Office worker	42	21.6
	Self-employed	11	5.7
	Professional	13	6.7
	Homemaker	34	17.5
	Student	78	40.2
	Other	16	8.2
Monthly Fashion Expenditure	Less than 50,000 KRW	6	3.1
	50,000–100,000 KRW	51	26.3
	100,000–300,000 KRW	91	46.9
	300,000–500,000 KRW	26	13.4
	More than 500,000 KRW	20	10.4
Important Factors When Purchasing Fashion Products	Price	40	20.6
	Product description	39	20.1
	Reviews	78	40.2
	Photos & design	33	17.0
	Other	4	2.1

n=155) had attained or were pursuing a university degree. Regarding occupation, students were the largest group, representing 40.2% (*n* =78).

For monthly fashion expenditure, the largest segment of respondents (46.9%, *n*=91) reported spending between 100,000 and 300,000 KRW (less than 300,000 KRW). When purchasing fashion items, 'reviews' were identified as the most crucial factor (40.2%, *n* =78), followed by price (20.6%, N=40) and product description (20.1%, *n* =39).

Manipulation Check

Before testing the research hypotheses, a manipulation check was conducted using descriptive statistics on the AI transparency level to confirm whether the experimental stimuli were effectively manipulated. The measurement of AI

Table 4. Manipulation Check Results for AI Transparency Level

AI Transparency Level	*n*	Mean	*SD*	*F*	*p*
No Transparency	71	1.50	.918	94.372	<.001
Partial Transparency	63	3.25	1.05		
Full Transparency	60	4.00	1.24		

transparency consisted of two items, assessed using a 5-point Likert scale: "The product image clearly discloses the fact that the product was designed by AI," and "The product image clearly shows how the AI was involved."

The ANOVA was conducted to examine the effect of the three manipulated levels of AI transparency (No transparency, Partial transparency, and Full transparency) on the participants' perceived level of AI transparency. ANOVA results revealed a statistically significant main effect of the manipulated levels on perceived transparency, ($F(2, 191) = 94.372$, $p<.001$). Post-hoc comparisons showed that perceived transparency scores increased significantly as the disclosure level progressed from no transparency ($M=1.50$) to partial transparency ($M = 3.25$) and full transparency ($M = 4.00$), confirming successful manipulation (Table 4).

Factor Analysis

To assess the measurement validity and reliability, exploratory factor analysis and reliability tests were conducted. The results demonstrated strong convergent validity, with all item loadings substantially exceeding 0.5. The factor structure was clearly established, as evidenced by all extracted factors having an Eigenvalue greater than 1.0. Moreover, high Cronbach's α values (0.700 to 0.895) confirmed the internal consistency of all scales. The mean scores of the factors were used for subsequent analyses.

Effects of AI Transparency on Perceived Creativity

To examine the effects of AI transparency level and age group on perceived creativity, a two-way ANOVA was conducted (See Table 6). The results indicated a statistically significant main effect of AI transparency level on perceived creativity, $F(2,188)=8.885$, $p<.001$. However, the main effect of age group ($F(1, 188)=0.523$, $p=0.471$) and the interaction effect between AI transparency level and age group ($F(2, 188)=1.382$, $p=0.254$) were both found to be statistically non-significant.

Subsequently, Bonferroni post-hoc tests were performed to compare mean differences across the AI transparency level conditions. The results showed that perceived creativity was significantly higher in the full transparency condition ($M = 2.98$) compared to both the partial transparency ($M=2.33$) and

Table 5. Results of Exploratory Factor Analysis and Reliability Analysis

Dimension	Items	Factor Loading	Eigen Value	Variance (%)	Cronbach's α
Perceived Creativity	This product displays a novel style that I have not seen before. This product has a fresh and original design. The creative elements stand out in this product's design.	.873 .771 .738	2.357	16.837	.895
Perceived Authenticity	This product has a trustworthy image. This product gives a natural feeling and does not look artificial.	.856 .521	1.317	9.404	.700
Purchase Intention	I am willing to purchase this product if the price is reasonable. I have the intention to buy this product. I would recommend this product to people around me.	.798 .790 .714	2.177	15.550	.893

Table 6. Two-way ANOVA Results for Perceived Creativity

Source	*SS*	*df*	*MS*	*F*	*p*
AI Transparency Level	13.773	2	6.887	8.885***	< .001
Age Group	0.405	1	0.405	0.523	0.471
AI Transparency Level × Age Group	2.142	2	1.071	1.382	0.254
Error	1474.813	188	7.844		
Total	1491.133	193			

*p<.05, **p<.01, ***p<.001

Table 7. Two-way ANOVA for Perceived Authenticity

Source	*SS*	*df*	*MS*	*F*	*p*
AI Transparency Level	8.128	2	4.064	4.968**	0.008
Age Group	1.518	1	1.518	1.856	0.175
AI Transparency Level × Age Group	3.809	2	1.905	2.328	0.100
Error	153.794	188	.818		
Total	167.249	193			

*p<.05, **p<.01, ***p<.001

no transparency (M=2.50) conditions.

Effects of AI Transparency Level on Perceived Authenticity

The two-way ANOVA results for perceived authenticity showed a statistically significant main effect of AI transparency level, F (2,188)=4.968, p<.01 (See Table 7). The main effect of age (F (1, 188)=1.856, p=0.175) and the interaction effect between AI transparency level and age group F (2, 188)= 2.328, p=0.100) were both found to be non-significant. Subsequent Bonferroni post-hoc comparisons revealed that perceived authenticity was significantly higher in the full AI transparency level condition (M=3.41) compared to the partial transparency (M=2.92) and no transparency (M=3.02) conditions.

Effects of AI Transparency Level and Age Group on Purchase Intention

Regarding purchase intention, the Two-way ANOVA results indicated a statistically significant main effect of AI transparency level, F (2,188)=4.428, p<.05, and a significant interaction effect between AI transparency level and age group, F (2,188)=3.315, p<.05. Overall, post-hoc comparisons indicated that purchase intention was highest in the full transparency condition (M=2.67) than in the partial transparency (M=2.18) and no transparency (M=2.17) conditions (See Table 8).

However, the significant interaction effect (as shown in Figure 2) indicates that this pattern differed substantially by age group. As shown in Table 9, among consumers in their 20s, purchase intention increased gradually as AI transparency rose from no transparency (M=1.844) to full transparency (M=2.556). In contrast, for consumers in their 40s–50s, the

Table 8. Two-Way ANOVA: Effects of AI Transparency Level and Age Group on Purchase Intention

Source	*SS*	*df*	*MS*	*F*	*p*
AI Transparency Level	9.928	2	4.964	4.428*	0.013
Age Group	1.864	1	1.864	1.662	0.199
AI Transparency Level × Age Group	7.431	2	3.716	3.315*	0.038
Error	210.746	188	1.121		
Total	229.969	193			

$^{*}p<.05$, $^{**}p<.01$, $^{***}p<.001$

Table 9. Comparison of Estimated Means of Purchase Intention According to AI Transparency Level and Age Group (*N*=194)

Dependent Variable	Age Group	AI Transparency Level	N	M	SD
Purchase Intention	20s	No Transparency	30	1.844^{a}	.193
		Partial Transparency	33	2.323^{ab}	.184
		Full Transparency	30	2.556^{b}	.193
	40s-50s	No Transparency	41	2.504^{ab}	.165
		Partial Transparency	30	2.033^{a}	.193
		Full Transparency	30	2.778^{b}	.193

* Lowercase superscripts denote significant differences based on post-hoc comparisons. Means followed by different letters are significantly different from each other.

relationship exhibited a U-shaped pattern: purchase intention was initially high in the no transparency condition (*M*= 2.504), dropped significantly in the partial transparency condition (*M*=2.033), and then recovered under full transparency (*M*=2.778). The purchase intention under the no transparency condition is higher than under the partial transparency condition. This suggests that the 40s and 50s age group may evaluate receiving ambiguous or incomplete information (partial transparency, 2.033) more negatively than receiving no information at all (no transparency, 2.504). The partial transparency state, being an intermediate or vague state, could potentially lead to a loss of trust. They might perceive partial information as withholding or misleading, which results in a significant drop in their willingness to purchase.

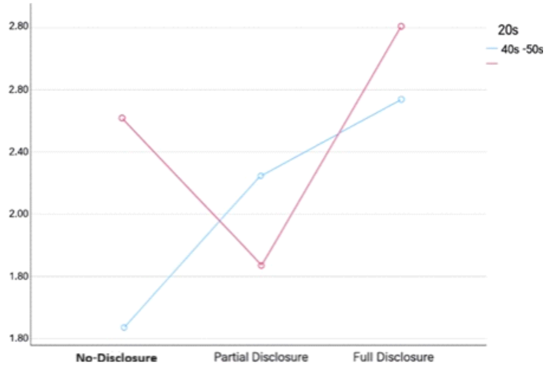

Figure 2. Adjusted Mean Purchase Interaction by AI Transparency Level and Age Group

Hypothesis Testing Summary

The main effects of AI transparency level (H1a, H1b, H1c) and the interaction effect with age (H2c) were tested using a 3X2 two-way ANOVA.

H1: Main Effects of AI Transparency Level

The results supported the hypothesized main effects of AI transparency level on consumer perceptions and intention:

H1a (Perceived Creativity): The main effect of AI transparency level on perceived creativity was significant. Post-hoc comparisons indicated that the full transparency condition (M=2.98) led to significantly higher perceived creativity compared to both partial transparency (M=2.33) and no transparency (M=2.50).

H1b (Perceived Authenticity): The main effect of AI transparency level on perceived authenticity was also significant. Full transparency (M=3.41) resulted in significantly higher perceived authenticity compared to partial transparency (M=2.92) and no transparency (M=3.02).

H1c (Purchase Intention): The main effect of AI transparency level on purchase intention was significant (F (2,188)= 4.428, p=0.013). Full transparency generally elicited a higher purchase intention (M=2.67) than partial transparency (M= 2.18) or no transparency (M=2.17).

H2: Moderating Effects of Age Group

H2a & H2b (Creativity and Authenticity Interaction): The interaction between AI transparency level and age group on perceived creativity and perceived authenticity was not statistically significant (Creativity p=0.254, Authenticity p =0.100 in the full results, implying that AI transparency level's effect on these perceptions is largely similar across age groups).

H2c (Purchase Intention Interaction): The hypothesized interaction effect between AI transparency level and age group on purchase intention was statistically significant (F (2,188) = 3.315, p = 0.038), fully supporting H2c.

- 20s Group: For consumers in their 20s, purchase intention followed a linear increasing pattern as AI transparency level increased (No transparency: M=1.844 →Partial transparency: M=2.323 → Full transparency: M =2.556).
- 40s-50s Group: This group exhibited a U-shaped, non-linear pattern. Purchase intention dropped sharply from no transparency (M=2.504) to partial transparency (M=2.033) and was then highest at full transparency (M =2.778). This pattern indicates a strong backfire effect of partial transparency in the older age group.

Discussion and Conclusion

Discussion

The findings of this study provide meaningful theoretical advancements to the literature on AI transparency and consumer response. Consistent with Information transparency Theory (Schnackenberg & Tomlinson, 2016), the findings demonstrate that higher transparency—particularly full transparency—enhances perceived creativity, authenticity, and purchase intention. This reinforces the assertion that detailed, high-quality information reduces uncertainty and strengthens trust in digital environments where product examination is limited. However, the results also challenge the assumption of a linear positive effect of AI transparency level, demonstrating that partial transparency can lead to unfavorable evaluations. This non-linear pattern highlights a theoretical boundary condition: AI transparency is beneficial only when it is sufficiently complete and interpretable, particularly when AI systems are involved.

Building on Dimoka et al.'s (2012) framework of descriptive and experiential uncertainty, the results show that partial transparency - simply stating that AI was used - fails to reduce descriptive uncertainty because it omits key explanatory details regarding data sources, algorithmic processes, or human involvement. For middle-aged consumers, this ambiguity led to lower authenticity and purchase intention ratings compared to the no transparency condition. Thus, partial transparency may inadvertently function as an uncertainty-increasing signal, contradicting traditional assumptions that any level of AI transparency is inherently beneficial.

The significant AI transparency level × age group interaction further advances research on generational differences in technology perception. The U-shaped response pattern among consumers in their 40s–50s aligns with ambiguity aversion theory (Ellsberg, 1961), suggesting that incomplete information is perceived as riskier than no information at all. This sensitivity reflects characteristics of “digital immigrants” (Prensky, 2001), who tend to rely on clear, structured cues and exhibit heightened risk aversion in decision-making contexts (Mata et al., 2011; Hess et al., 2013). In contrast, younger “digital natives” demonstrated greater tolerance for partial information, indicating reduced ambiguity sensitivity and higher baseline trust in AI-assisted creative processes.

Additionally, the results contribute to the broader discourse on AI-generated design. Previous studies indicate that AI design may weaken perceptions of authenticity and artistic legitimacy (e.g., Lee & Kim, 2024), yet the current findings reveal that full transparency can help restore those perceptions. AI transparency regarding data use and human–AI collaboration appears to function as a credibility and legitimacy cue, reinforcing both creativity and authenticity evaluations consistent with notions of computational creativity (Colton & Wiggins, 2012). The study thus positions AI transparency as a foundational mechanism for building trust in AI-generated fashion products.

Conclusion

The findings of this study show that higher levels of AI transparency in AI fashion design generally enhance perceived creativity, perceived authenticity, and purchase intention. This aligns with the well-established “Information Transparency Theory”, which posits that more and better information reduces uncertainty and increases trust (Schnackenberg & Tomlinson, 2016). Specifically, full transparency consistently yielded the most favorable evaluations for creativity and authenticity across all conditions.

At the same time, the significant interaction between AI transparency level and age group in purchase intention (H2c Supported, p=0.038) is the most critical finding, revealing that partial transparency can have a backfire effect, especially among middle-aged consumers in their 40s–50s. For this group, incomplete explanations appear to be interpreted as ambiguity or potential deception, leading to reduced trust and significantly lower purchase intention (partial transparency M=2.033) than under the no transparency condition (M =2.504). Full transparency was the only strategy that effectively helped restore these evaluations and maximized purchase intention (M=2.778). Overall, clearly and sufficiently disclosing the use of AI tends to strengthen positive perceptions and purchase intention. However, partial transparency strategies may be counterproductive, particularly for middle-aged consumers.

According to Dimoka et al. (2012), because online consumers cannot directly experience the product, they perceive product uncertainty as being divided into 'descriptive uncertainty' and 'experiential uncertainty.' Specifically, when product information lacks clarity and specificity, descriptive uncertainty can increase, potentially weakening purchase responses. From this perspective, partial transparency in AI fashion design, which only presents the fact that 'AI was used,' does not reduce descriptive uncertainty; rather, it amplifies additional questions about the data source and the level of human intervention. Consequently, this can lead to lower purchase intention and authenticity evaluations even compared to the no transparency condition.

The study provides several theoretical contributions to the literature on AI transparency and consumer psychology. First, the findings challenge the simplistic linear assumption of the Information Transparency Theory by demonstrating that the effect of transparency is non-linear and contingent on consumer characteristics. The observed backfire effect of partial transparency establishes a boundary condition for the theory in the context of advanced AI systems. Second, the U-shaped response in the 40s-50s age group supports the ambiguity aversion theory. Partial transparency—an intermediate and vague state—introduced uncertainty about the AI's role, triggering a strong negative response from consumers who are generally more sensitive to incomplete or confusing information. Third, this research empirically clarifies the distinction between how Digital Natives (20s) and Digital Immigrants (40s-50s) process AI-related product information. The differential response to partial transparency suggests that younger consumers are more accepting of gradual AI transparency, while older consumers demand complete information for trust and commitment.

This study also provides several practical implications.

First, firms should design differentiated AI transparency and message strategies that take generational differences in information processing and sensitivity to incomplete information into account. Fashion brands targeting the 40s-50s demographic must avoid vague or incomplete AI transparency strategies as they are actively detrimental to purchase intention. Second, since full transparency maximizes purchase intention across both age groups, it serves as the most effective and safest strategic standard for building consumer trust and driving sales of AI-designed fashion products.

Limitations and Future Research

Although this study provides significant theoretical and practical implications by exploring the effect of AI transparency and age in fashion design, it has certain limitations that should be addressed by future research. First, the sample of this study was limited to Korean female consumers, which may restrict the generalizability of the findings. Future research should expand the sample to include other cultural contexts or male consumers to explore whether cultural differences or gender disparities in technology acceptance and risk perception influence the effects observed in this study. Second, the stimuli used in this research was confined to handbag designs, suggesting caution is needed when generalizing the results to other types of fashion products (e.g., apparel, jewelry) or industries beyond fashion (e.g., furniture, media content). Subsequent studies should utilize diverse product types and services to confirm the generalizability of the AI transparency level effect. Third, a key finding of this study—that partial transparency evokes a backfire effect among middle-aged consumers—suggests the need for further in-depth investigation. While partial transparency triggers consumer ambiguity aversion, the precise source of this ambiguity was difficult to ascertain through this study's quantitative design.

Therefore, future research should specifically explore the origin of the ambiguity and distrust evoked by partial transparency, considering 1) technological uncertainty: investigating whether consumers feel uncertain about the scope of AI involvement (e.g., whether AI provided only the design concept vs. whether AI replaced the human designer) and 2) ethical uncertainty: exploring whether concerns stem from ethical issues related to the opacity of the AI's data collection and learning processes (e.g., the potential for misappropriation of copyrighted designs). Future research could also explore the effects of varying the format of AI transparency (e.g., visual evidence vs. textual description) or manipulating the degree of AI-human collaboration to provide a richer understanding of consumer responses. In addition, AI transparency cues could be further refined—such as specifying AI's role, data sources and licensing, human involvement, and verification or performance information—to identify which elements primarily drive consumer responses.

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