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Consumer Perceptions of AI-Generated Content and Disclaimer in Terms of Authenticity, Deception, and Content Attribute

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Consumer Perceptions of AI-Generated Content and Disclaimer in Terms of Authenticity, Deception, and Content Attribute

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Keywords: Generative AI, AI Generated Content, AI Disclaimer, Authenticity, Deception, Utilitarian, Hedonic

1. Introduction

Artificial Intelligence (AI) is rapidly transforming business and social activities, and its impact is often referred to as the 'AI revolution' (Makridakis, 2017). The industry has begun to embrace AI to enhance data-driven decision-making, operational efficiency, and customer experience. Particularly, Generative AI is gaining attention for its ability to autonomously produce novel and unique content in various formats such as text, images, and audio. One of the primary application areas of Generative AI is the media sector, where it can act as a content creator. For example, tools like GPT-4 perform tasks such as writing news articles, poems, and video scripts based on human instructions. Generative AI not only enhances human creativity but also paves the way for innovation in the media industry, with the market size for Generative AI in the media sector expected to reach $17.436 billion by 2024 (GlobeNewswire, 2023).

However, the emergence of AI-generated content (AIGC) has raised concerns about authenticity. The authenticity issues of AIGC can be discussed from two perspectives. Firstly, authenticity means reality and truth (Kennick, 1985). While Generative AI is a useful tool for summarizing and producing content, it sometimes results in 'hallucinations' that lead to incorrect outcomes different from reality (De Vynck, 2023). Therefore, AIGC is associated with authenticity controversies related to the possibility of being 'not real'. Authenticity also means sincerity and originality (Fine, 2003). People may perceive AIGC as fake because they believe AI can't create genuine content reflecting human creativity. Human creativity is rooted in the complex interactions of experience, emotion, and cultural influence, whereas AI operates within predefined parameters, mimicking human results without understanding or emotion (Bringsjord & Ferrucci, 1999). Hence, AIGC can be perceived as lacking depth, spontaneity, and emotional aspects that come from true human experience and reflection (Edwards, 2024). In this context, AIGC is sometimes considered a counterfeit rather than original content.

Despite concerns about authenticity, the evolution of AI may make it difficult to distinguish between AIGC and human-created content, potentially eroding trust in overall digital content. This challenge indicates the need for ethical guidelines and technologies to differentiate AIGC from human-generated content. Consequently, regulations for transparency in AIGC usage are being established in the consumer services sector. For example, the 'Advisory for AI-Generated Content Act' and the 'AI Labeling Act of 2023' require clear labeling of AI-generated materials. The Federal Trade Commission (FTC) also emphasizes that consumers should be aware of interactions with AI, and companies like Google and TikTok have started labeling AIGC, reflecting this stance. Pursuing transparency to align AI usage with current legal standards and consumer awareness will likely apply to most companies moving forward.

However, despite these new regulations, research on consumer understanding of AIGC and AI Disclaimer (AID) is lacking. Current regulations are established through discussions among regulatory experts but do not necessarily reflect the

attitudes of consumers, who are key stakeholders. Particularly, consumers may feel deceived upon realizing that the content was generated by AI, and perceptions of deception can influence their attitudes toward AI disclaimers. Therefore, this study aims to examine the impact of perceived authenticity on consumer perceptions of AIGC and to explore perceptions of AI disclaimers based on the degree of perceived deception when AID is not implemented. Furthermore, it seeks to understand how these perceptions vary when consumers consume content for utilitarian versus hedonic purposes.

2. Research Background

2.1 Utilitarian and Hedonic AIGC

Consumers evaluate products based on their utilitarian value (reflecting functional performance) and hedonic value (related to pleasure or playfulness) (Batra & Ahtola, 1991). Therefore, consumer research traditionally divides products into utilitarian and hedonic categories and compares these two types of values (Chen et al., 2016; Wertenbroch & Dhar, 2000). For example, utilitarian products like laptops are generally perceived as instrumental, cognitive, and goal-oriented, while hedonic products like luxury watches emphasize sensory appeal, aesthetics, and emotional aspects (Wertenbroch & Dhar, 2000). Similarly, digital content can be classified as utilitarian if it is practical and informational or hedonic if it primarily provides enjoyment and emotional engagement. For instance, online news platforms support informed business decision-making and information dissemination through timely news and analysis, whereas streaming services offering movies and dramas focus on entertainment and emotional engagement.

The application of AI in digital content creation has fundamentally changed the processes of content production, customization, and distribution (Chan-Olmsted, 2019). AI enhances the efficiency of content creation and personalizes user experiences, impacting both utilitarian and hedonic content. In utilitarian contexts, AI is widely used by news agencies to quickly generate articles on topics such as sports results, market summaries, and elections. AI-based platforms analyze user data to provide personalized health advice (Alowais et al., 2023), and the Associated Press (AP) uses AI to analyze quarterly financial data and produce thousands of financial reports, surpassing human capabilities. In the hedonic domain, AI also creates content consumed emotionally. Tools like Amper Music and Jukedeck enable users to compose unique music tracks fitting specific moods or genres without deep musical knowledge. Additionally, personalized storytelling, where AI changes the story's progression based on viewer choices, as seen in Netflix's "Black Mirror: Bandersnatch," exemplifies AI's role in creating hedonic content (Ng, 2019). These examples demonstrate that AI not only increases the efficiency of the content production process but also becomes a content creator itself, meeting consumers' utilitarian and hedonic needs in the digital content realm.

2.2 Perceived Authenticity and AIGC

Following the global reception of the chatbot service ChatGPT, which is based on Generative AI technology (Chintalapati & Pandey, 2022), other tools like the image generators Midjourney and DALL-E 2 have emerged, and recently the application scope has expanded to video content creation (e.g., DeepBrain SORA, etc.) (Fui-Hoon et al., 2023). As such Generative AI-based content creation services emerge, digital media companies are also moving to adopt Generative AI technologies and create and distribute new digital content. In the journalism industry, news production algorithms like Quill and Wordsmith are used (Zheng et al., 2018). These news production algorithms have been evaluated for producing somewhat formulaic news relying on data analysis, but with the development of large-scale natural language processing (LLM) technologies, it has become possible to generate goal-oriented narratives (Fui-Hoon et al., 2023). In the field of image and video, Generative AI is

utilized in advertising images, movie and animation production, etc. For example, the official trailer images and videos for the movie ‘Genesis’ were produced using Midjourney and Runway, and the producer has disclosed this fact (Charlie, 2023).

As the application areas of Generative AI-based content in the content industry expand, research on consumer perception and evaluation has been conducted. Brüns & Meißner (2024) studied how followers perceive brands that use Generative AI on social media platforms. The study found that the adoption of Generative AI by brands negatively affects followers' attitudes and behaviors. Research identifying the acceptance and non-acceptance factors of introducing Generative AI in digital marketing campaigns targeted marketing professionals. The study found that factors such as efficiency, scalability, data-driven insights, and automated optimization had a positive influence on acceptance, while risks, uncertainties, complexity, and creativity limitations acted as significant barriers (Soni, 2023). Literature analysis on Generative AI in digital marketing identified positive impacts of Generative AI-based solutions in fields such as display advertising, video advertising, and content marketing, emphasizing the importance of Generative AI's role in digital advertising production (Gołab-Andrzejak, 2023).

However, there are also controversies over authenticity stemming from the fact that the content creator is not human and the hallucination phenomenon. Generally, authenticity, meaning sincerity and originality, is defined as real, true, and unique (Beverland & Farrelly, 2010; Moulard et al., 2014), and consumers perceive authenticity in various dimensions such as product information, message, materials, etc. (Audrezet et al., 2020; Campagna et al., 2023). Moreover, authenticity can be perceived depending on whether appropriate techniques and processes were used to create the product or service and whether a passionate creator produced the content (Littrell et al., 1993; Moulard et al., 2014). When consumers perceive authenticity, they conduct favorable overall product evaluations (Newman & Dhar, 2014) and show positive consumer responses, including attitudes and purchase intentions toward the producer (Carsana & Jolibert, 2018; Moulard et al., 2014; Napoli et al., 2014). This implies that consumers can perceive authenticity when AI is used in the production of content or products. Therefore, perceptions of AIGC's authenticity can influence consumers' perceptions of AI-generated content. Particularly, the fact that Generative AI is the content creator can affect consumer satisfaction and dissatisfaction, leading to the following research questions:

RQ 1-a. How does perceived authenticity of AIGC influence consumer perceptions of AI as content creator?
RQ 1-b. How does the relationship between perceived authenticity of AIGC and consumer perceptions of AI as content creator vary according to the attributes of AIGC (utilitarian/hedonic)?

2.3 Perceived Deception and AID

With the use of data in generative training violating copyrights and generative AI-created content causing issues such as fake news and false advertising, governments in major countries are moving to regulate generative AI to mitigate these risks. Specifically, policies related to generative AI disclosure fall into two categories: AI labeling and AI watermarking. AI labeling involves providing clear and accurate descriptions of the data used to train AI systems (Desmond et al., 2021), while AI watermarking involves identifying AI-generated content to indicate its source and copyright, and user awareness of AI usage (Amrit & Singh, 2022). There is ongoing discussion on whether AI watermarking should be visibly marked or detectable through specific programs.

In this study, perceived deception refers to the extent to which not disclosing AI-generated content is perceived as deceptive. Deception is a commonly used strategy in advertising communication (Riquelme & Román, 2014; Sivathanu et al., 2023). Particularly, perceived deception is a concept mainly discussed in the

context of e-commerce, advertising, and marketing, referring to the degree of deception perceived by information receivers from messages, even if advertisers or marketers did not intentionally deceive them (Burkle et al., 1988). Deception includes various forms beyond blatant false information, with characteristics such as sufficiency, truthfulness, clarity, relevance, and intent (Roman, 2010). Historically, deception in advertising received attention in personal selling and traditional retail sectors, but as the e-commerce market developed, researchers began focusing on online advertising deception (Riquelme & Roman, 2014). Studies on perceived deception in online advertising explain that consumers can change their decision-making processes when marketers provide relevant ambiguous or inaccurate information about specific products and services (Sivathanu et al., 2023).

This study aims to measure perceived deception based on the degree to which consumers perceive non-disclosure of AI-generated content as deceptive and to examine consumer perceptions of AID related to this perceived deception. Consumers with high perceived deception may be more sensitive to the existence of AID, particularly depending on the value pursued in the content. However, since perceived deception has primarily been studied in the context of advertising and varies based on the truthfulness and amount of information, it is necessary to examine perceived deception in the context of AI disclaimers. Therefore, this study presents the following research questions:

RQ 2-a. How does perceived deception from the absence of AID influence consumer perceptions of AID?
RQ 2-b. How does the relationship between perceived deception from the absence AID and consumer perceptions of AID vary according to the attributes of AIGC (utilitarian/hedonic)?

3. Methodology

3.1 Kano Model

This study applied Kano's (1984) model, which uses a dual perception method for quality, to investigate the research questions. The traditional Kano model has been used to identify quality elements in services such as healthcare, internet, education, and e-commerce (Ilbahar & Çebi, 2017; Yao et al., 2018). This model was adopted in this study to examine consumer satisfaction with the use and disclosure of Generative AI in the context of AIGC and AID, as it can analyze the quality elements of a service and consumer satisfaction with specific attributes.

As shown in Figure 1, consumer satisfaction with specific quality attributes of a product or service can vary based on preference for those quality attributes. Kano's model shows how consumer requirements are perceived in a particular service through a dual measurement of satisfaction and dissatisfaction. In Figure 1, the X-axis represents the level of quality performance, and the Y-axis represents consumer satisfaction, which is divided into five categories (Kano, 1984):
(1) One-dimensional elements (O): These are elements that satisfy customers when fulfilled and cause dissatisfaction when not fulfilled. They are desired elements that result in satisfaction or dissatisfaction depending on fulfillment.
(2) Attractive elements (A): These elements create significant satisfaction when fulfilled but do not cause dissatisfaction when not fulfilled. They can exceed customer expectations or provide unexpected satisfaction.
(3) Must-be elements (M): These are elements that customers consider basic requirements. Fulfillment is expected and does not lead to satisfaction, but failure to fulfill them causes significant dissatisfaction.
(4) Reverse elements (R): These elements cause dissatisfaction when fulfilled or satisfaction when not fulfilled. They show characteristics opposite to the expected results.
(5) Indifferent elements (I): These elements do not affect satisfaction regardless of fulfillment.
The Kano model can be used to assess user satisfaction with service elements from a

multidimensional perspective. In this study, the model was applied in the context of utilitarian/hedonic values and perceived authenticity and AIGC, as well as perceived deception and AID.

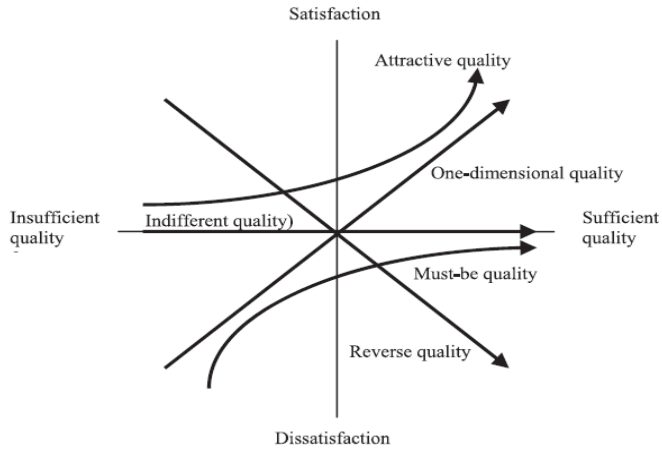

Figure 1. Kano model of customer satisfaction (Kano, 1984)

3.2 Data Collection and Measurement

An online survey was conducted in April 2024, collecting responses from 71 participants. The demographic characteristics of the respondents were relatively balanced, with 45.1% male (32 participants) and 54.9% female (39 participants). The age distribution was primarily in their 20s (74.6%, 53 participants), with 18.3% in their 30s (13 participants), and 7% over 40 (5 participants). A total of 57.7% (41 participants) were college and graduate students, while 26.8% (19 participants) were working professionals.

To classify the five elements of the Kano model according to the research questions, this study categorized content based on value. To measure the dual perception of function and dysfunction of content based on value (utilitarian – news, hedonic – movies and dramas), positive and negative questions were arranged, and these were applied to both AIGC and AID. Additional questions were included to validate the practical and hedonic values of news and movies/dramas. The content format for AIGC and AID was video. Perceived authenticity and deception were measured using a 7-point Likert scale with three items each (Moulard et al., 2014; Riquelme & Román, 2014; Roman, 2010; Sivathanu Pillai & Metri, 2023).

The five elements of the Kano model are classified based on responses to functional and dysfunctional questions about how customers perceive the attribute when appropriate and when not appropriate. Respondents chose from five responses: 'I like it (Like)', 'I expect it that way (Expect)', 'I am neutral (Neutral)', 'I can accept it to be that way (Accept)', and 'I dislike it that way (Dislike)', for both positive and negative questions. Each response to the questions was assigned one of the six quality attributes, with the most frequent result determining the representative attribute. The Q element indicates skepticism, meaning the respondent did not understand the survey or the question was unclear. However, this method ignores proportional differences in each item, so the customer satisfaction coefficient (CSC) was additionally used to complement the model's limitations (Berger et al., 1993).

Attribute		Dysfunc				
		Like(1)	Must-be(2)	Don't care(3)	Don't like but live with(4)	Dislike(5)
Func	Like(1)	Q	A	A	A	O
	Must-be(2)	R	I	I	I	M
	Don't care(3)	R	I	I	I	M
	Don't like but live with(4)	R	I	I	I	M
	Dislike(5)	R	R	R	R	Q

Table 1. Kano Survey Evaluation Results

The customer satisfaction coefficient measures the impact of satisfaction and dissatisfaction through the quality attributes identified in the Kano survey, distinguishing the results into four parts. This coefficient uses two indicators: the Satisfaction Index (S) and the Dissatisfaction Index (D), to calculate the average for each quality attribute. To calculate the satisfaction coefficient, the sum of attractive quality (A) and one-dimensional quality (O) is normalized by dividing it by the sum of all quality types. Conversely, the dissatisfaction coefficient is calculated by summing the must-be quality (M) and one-dimensional quality (O), normalizing it

similarly, and converting this value to negative. The satisfaction coefficient ranges from 0 to +1, while the dissatisfaction coefficient ranges from 0 to -1, indicating the degree of satisfaction and dissatisfaction when customer requirements are met or unmet.

Coefficient	Calculation Formula	Range
Satisfaction Coefficient(S)	$\frac{A+O}{A+O+M+I}$	0~+1
Dissatisfaction Coefficient(D)	$\left(\frac{M+O}{A+O+M+I}\right)*(-1)$	-1~0

Table 2. Customer Satisfaction Coefficient Formula

4. Results

4.1. Perceived Authenticity and Utilitarian/ Hedonic AIGC

To examine the relationship between perceived authenticity and utilitarian/hedonic AIGC presented in Research Question 1, the sample was divided into two groups based on perceived authenticity values. The average perceived authenticity score was 3.60, with a median of 3.67, indicating a small difference. Considering the sample size, the groups were classified using the median value. Consequently, the low-perceived authenticity group consisted of 39 participants, and the high-perceived authenticity group included 32 participants.

As shown in Table 3 (in Appendix), overall, the reverse elements (R) was reported as the main index for utilitarian AIGC, and the indifferent element (I) was reported as the main index for hedonic AIGC. This indicates that when AI writes utilitarian content, consumers can express dissatisfaction, whereas when AI writes hedonic content, consumers show indifference. Additionally, examining the detailed items, attractive element (A) and one-dimensional element (O), which are elements that can provide satisfaction to consumers based on usage, appeared more frequently in the hedonic context.

When examining the results based on perceived authenticity, for utilitarian AIGC, the group with low authenticity reported 24 responses for the reverse element, indicating that consumers with low perceived authenticity show increased dissatisfaction when AI generates utilitarian content. On the other hand, the high authenticity group responded with an indifferent element for AI-generated utilitarian content. In terms of the customer satisfaction coefficient, the low authenticity group showed a satisfaction coefficient of 0.15, which is relatively high because the reverse element is not included in the satisfaction and dissatisfaction coefficient calculations. Therefore, the coefficient for utilitarian AIGC did not show significant results.

For hedonic AIGC, both groups classified based on perceived authenticity mainly reported indifferent elements, indicating that perceived authenticity does not affect consumer satisfaction with hedonic AIGC. However, both groups also reported some reverse elements. Since the reverse element is excluded from CSC, the high authenticity group showed a higher dissatisfaction coefficient despite similar satisfaction coefficients for both groups. This slight difference is because the high authenticity group reported two responses for the one-dimensional element (O) while the low authenticity group reported one response for the must-be element (M).

4.2 Perceived Deception and Utilitarian/Hedonic AID

For Research Question 2, the sample was divided into two groups based on perceived deception. The average perceived deception score was 5.43, with a median of 5.67, indicating a small difference. Consequently, the low-perceived deception group consisted of 32 participants, and the high-perceived deception group included 39 participants.

As shown in Table 4 (in Appendix), the must-be element (M) was reported as the main index for utilitarian AI Disclaimer, with a dissatisfaction coefficient of -0.73. This indicates that AI disclaimers are perceived as a minimum basic requirement for utilitarian content, causing significant dissatisfaction when not fulfilled. For hedonic content AI disclaimers, similar results

were reported to utilitarian content, but with a relatively lower dissatisfaction coefficient of -0.55. However, the need for AI disclaimers is still recognized as a minimum basic requirement for both types of content.

The results varied based on perceived deception. For utilitarian content in the context of AI disclaimers, the low perceived deception group reported an indifferent element 15 times, making it the main index, while the must-be element was reported 14 times, with a small difference. Conversely, the highly perceived deception group reported the must-be element as the main index, followed by the one-dimensional element. The significant difference in indifferent element and one-dimensional element between the two groups affects their satisfaction and dissatisfaction coefficients. The high-perceived deception group showed a high dissatisfaction coefficient of -0.94 and a satisfaction coefficient of 0.28, while the low-perceived deception group showed a lower dissatisfaction coefficient of -0.50 and a relatively low satisfaction coefficient of 0.09.

For hedonic content, the results were similar to utilitarian content. The low-perceived deception group reported an indifferent element, while the high-perceived deception group reported a must-be element. However, the pursuit value influenced the results, with the low perceived deception group reporting fewer must-be elements for hedonic content compared to utilitarian content (utilitarian: 14, hedonic: 6). Additionally, hedonic content reported overall lower dissatisfaction coefficients compared to utilitarian content.

5. Discussion

The innovation brought by Generative AI in the media market continues to expand its influence on creative activities, which are considered the 'human domain.' Amidst these rapid changes and various concerns, this study investigated people's perceptions of Generative AIGC and AID. The scope of Generative AI's creative capabilities can be applied to various fields, with possibilities in text, photos, videos, and more. This study categorized the broad creative scope of Generative AI into utilitarian and hedonic values, using the highest-level video creation to exploratively analyze people's perceptions of AIGC and AID through the Kano model, and examined how these perceptions vary based on perceived authenticity and deception. To supplement the limitations of the Kano model, customer satisfaction coefficients were derived to detail the results of consumer satisfaction with AIGC and AID. The results of this study provide the following implications.

Firstly, consumer perceptions of AIGC and AID differed. While AIGC was reported as an indifferent or reverse element, AID was reported as a must-be element. This indicates that, unlike the indifference or resistance towards the use of AI in content creation, people perceive the disclosure of AI usage as a minimum basic requirement. Regardless of the value pursued, consumers believe that AI usage disclosure should be mandatory, and failure to meet this requirement can cause significant dissatisfaction. Future AI usage disclosure is likely to be perceived as a basic requirement. The dissatisfaction with AID was particularly significant for utilitarian content, indicating that AID is an important element for consumers in utilitarian contexts where information acquisition or purposeful use is involved. This suggests that procedural justice in disclaiming AI technology usage in content creation is crucial, especially for functional value where higher procedural justice is demanded (Leventhal, 1980). The perception of consumers regarding the pursued value is further highlighted when examining AIGC. For utilitarian content, extensive use of AI caused dissatisfaction, whereas the use of AI for hedonic content was mostly reported as indifferent. The study used news as utilitarian content, highlighting that news aims to avoid bias and deliver objective facts (Young, 1990), and that sufficient trust and perceived authenticity of AI were not ensured. Consumers' concerns about the hallucination phenomenon in Generative AI are also reflected (De Vynck, 2023).

Conversely, the relative indifference towards the use of AI in creating hedonic content suggests that testing AIGC introduction through hedonic content may have a lower likelihood of causing consumer dissatisfaction.

Secondly, perceptions of AIGC differed based on perceived authenticity. Although the overall perceived authenticity of Generative AI was relatively low with an average score of 3.60 on a 7-point scale, differences emerged based on perceived authenticity. This was particularly evident in utilitarian content, where the group with low perceived authenticity reported negative impacts of AI in news video production. This implies that consumers may feel significant dissatisfaction when they perceive low authenticity in AIGC for information creation and analysis. Conversely, high perceived authenticity led to indifferent responses even for utilitarian content, indicating that enhancing consumer perceptions of AIGC authenticity is necessary for businesses to actively use AIGC for efficiency. For hedonic content, perceived authenticity did not significantly affect satisfaction, suggesting that the advancement of AI functionality may lead to hedonic AIGC providing consumer satisfaction.

Thirdly, perceptions of AID significantly varied based on perceived deception. Overall, AID was perceived as a basic requirement, but differences were observed between groups. Consumers with low perceived deception primarily reported indifference, showing consistent results with their low opposition to non-disclosure of AI usage. However, for utilitarian content, even consumers with low perceived deception reported a high dissatisfaction coefficient of -0.50, indicating that even small differences in perceived deception can cause dissatisfaction in utilitarian contexts. This suggests that AI usage disclosure in contexts such as advertisements with informational functions is essential. For hedonic content, the relatively low dissatisfaction coefficient of -0.21 indicates that AI usage disclosure perceptions can vary based on the value pursued.

Finally, the limited appearance of one-dimensional and attractive elements in the context of AI-generated content and its disclosure suggests that Generative AI usage and disclosure are not yet perceived as satisfactory factors by consumers. Considering the influence of one-dimensional elements on satisfaction and dissatisfaction coefficients, the necessity of focusing on dissatisfaction rather than satisfaction when researching the use and disclosure of Generative AI is highlighted. In particular, one-dimensional elements represent factors that cause satisfaction when fulfilled and dissatisfaction when not fulfilled, yet these elements did not appear in all responses. This implies that policies and development directions for the use and disclosure of AI should focus more on dissatisfaction than satisfaction. In the context of AID, the frequent reporting of one-dimensional elements suggests that changes in consumer perceptions of AI could potentially lead to AID being used as a satisfaction element. Additionally, some respondents reported attractive elements, especially in the context of hedonic value, indicating a small group of respondents with an optimistic view of AI usage. This suggests that the perspective on AI usage could expand with further development and additional utilization. Examining the study by Longoni and Cian (2022) on AI preference in functional and hedonic value contexts, where AI was preferred for functional value and humans were preferred for hedonic value, suggests continuous interest in the satisfaction elements of Generative AI use and disclosure based on its development level.

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Appendix.

Table 3. Kano Result for Perceived Authenticity Group and Utilitarian/Hedonic AI Generated Content

Utilitarian AI Generated Content								
	A	O	M	I	R	Index	Sat. Coeff	Dissatis. Coeff
Low Auth. G	2	0	1	10	24	R	0.15	-0.08
High Auth. G	1	1	0	20	8	I	0.09	-0.05
Total	3	1	1	30	32	R	0.11	-0.05
Hedonic AI Generated Content								
	A	O	M	I	R	Index	Sat. Coeff	Dissatis. Coeff
Low Auth. G	5	0	1	18	14	I	0.21	-0.04
High Auth. G	3	2	0	18	8	I	0.22	-0.09
Total	8	2	1	36	22	I	0.18	-0.02

Table 4. Kano Result for Perceived Deception Group and Utilitarian/Hedonic AI Disclaimer

Utilitarian AI Disclaimer								
	A	O	M	I	R	Index	Sat. Coeff	Dissatis. Coeff
Low decep. G	1	2	14	15	0	I	0.09	-0.5
High decep. G	0	10	23	2	1	M	0.28	-0.94
Total	1	12	37	17	1	M	0.19	-0.73
Hedonic AI Disclaimer								
	A	O	M	I	R	Index	Sat. Coeff	Dissatis. Coeff
Low decep. G	3	0	6	20	1	I	0.10	-0.21
High decep. G	2	7	22	4	1	M	0.26	-0.83
Total	5	7	28	24	2	M	0.19	-0.55