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Analyzing AI-Generated Packaging's Impact on Consumer Satisfaction With Three Types of Datasets

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ABSTRACT

The study quantitatively examines how AI-generated cosmetic packaging design impact consumer satisfaction, offering strategies for database-driven development and design based on this evaluation. A comprehensive evaluation system consisting of 18 indicators in five dimensions was constructed by combining literature review and user interviews with expert opinions. On this basis, a questionnaire survey on AI-generated packaging design was conducted based on three types of datasets. In addition, importance-performance analysis was used to analyze the satisfaction of AI-generated packaging design indicators. The study found that while consumers are highly satisfied with the information transmission and creative attraction of AI-generated packaging design, the design's functional availability and user experience still have to be improved. It is suggested that the public model be combined into the data warehouse to build an AI packaging service platform. Focusing on the interpretability and controllability of the design process will also help increase consumer satisfaction and trust.

KEYWORDS

AI-Generated Design, Consumer Satisfaction, Data Warehouse, Importance-Performance Analysis, Packaging Design

INTRODUCTION

Packaging design plays a vital role in attracting consumer attention, conveying brand identity, and enhancing the attractiveness of products (Alhamdi, 2020; Azzi et al., 2012). The traditional packaging design process requires a large amount of manpower, time, and resources, resulting in high design costs and insufficient levels of innovation for small and medium-sized enterprises (Yueyi et al., 2019). However, thanks to the rapid development of artificial intelligence (AI), AI-generated packaging design presents a new solution where AI uses algorithms and data-driven methods to

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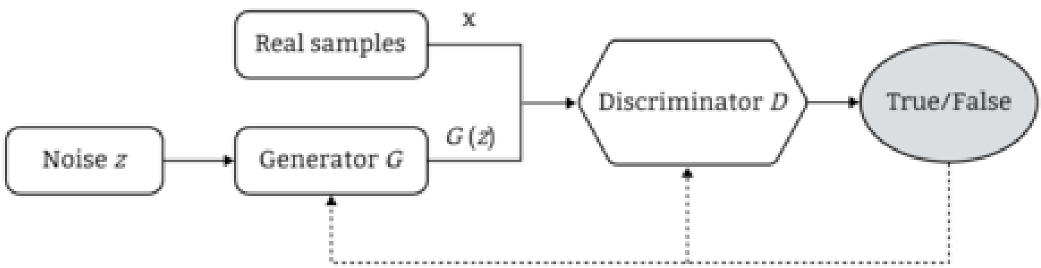
provide customized packaging designs and other related evaluation solutions (Liu, 2022; Shi, 2022). Currently, by understanding consumer preferences and market trends through deep learning and big data analysis, AI-generated models can provide a variety of packaging design solutions according to consumer demands. For example, Japan's Package Design AI (PLUG AI) can complete 1,000 groups of packaging designs within one hour according to image materials, while the VIZIT platform in the United States can automatically predict the market acceptance of packaging designs based on an intelligent database. AI-generated design has some advantages, such as improving efficiency and cost effectiveness and providing highly personalized packaging designs (Zong, 2021). However, it also faces some problems and disputes in terms of the usability of its design functions, the adaptability of creative design to user demands, the balance between diversified and sustainable design, and copyright and ethical issues (Khisamova & Begishev, 2019; Zhu & Yu, 2021). Currently there is relatively little research literature pertaining to the use of AI to generate the design of cosmetic packaging, and there is also not enough research regarding the evaluation of its actual design effectiveness and consumer satisfaction. Therefore, this paper, which is based on the Interpretive Phenomenological Analysis (IPA) method, seeks to study the packaging design generated by training AI from three types of datasets, analyze the key factors that affect consumer satisfaction, and give suggestions for improvement based on the results of the analysis. This research aims to explore users' attitudes and preferences towards AI-generated design by analyzing the effectiveness evaluation and consumer satisfaction of AI-generated packaging design, clarifying the deficiencies of existing data processing and providing design strategies, and providing research reference value for data mining and business intelligence applications in the field of packaging design.

AI-GENERATED PACKAGING DESIGN TECHNOLOGY

Early computer-aided design integrated product style design, colors, graphics, fonts, and other elements to complete packaging designs, representing some progress in terms of improving design efficiency. However, due to limitations in the hardware and software, there were no significant breakthroughs in terms of creativity. However, in recent years with the emergence of AI and the rise of deep learning, there has been a rapid development in the generation of creative content through AI. AI has been used to create and generate text, images, audio and video, design, and other content (Dadman, 2023; Li et al., 2023; Malsattar et al., 2019; Tang et al., 2019), and it has been applied in fields like poetry, painting, music composition, posters, clothing, and architecture. Compared with purely human-based design, AI-generated design does a better job of reducing labor costs and improving production efficiency (Verganti et al., 2020; Zhang, 2022). In the field of cosmetic packaging, in particular, due to the huge demand for packaging design and the rapid frequency with which design styles are updated, using AI-generated packaging design technology properly can help reduce packaging development costs.

In terms of its development history, the core technology of AI has shifted from a traditional classification and regression algorithms base to a more deep learning algorithms base, a change which is represented by things like convolutional neural networks (CNN) (Li et al., 2021) and generative adversarial networks (GAN) (Goodfellow et al., 2020). This generation method emphasizes that machine learning algorithms are algorithms and techniques that generate new data, images, text, or other types of content based on their understanding of training data (Deng, 2018). Since it is a new framework of the generative model, GAN can achieve more realistic generative effects. In the creative content generation process, the intelligent content generation methods that GANs use include text-to-image synthesis (Xu et al., 2018; Yang et al., 2021), image-to-image translation (Isola et al., 2017; Nie et al., 2021), image enhancement, and style conversion (Yang et al., 2019). In general, GANs consist of two separate networks. One of these networks is the generator G, which receives a random noise vector z as input and then outputs the generated data G (z). The other network is the discriminator D, which takes real data x or generated data G (z) as input and then attempts to determine whether things are true or false (see Figure 1) (Wang et al., 2017).

Figure 1. Computation procedure and structure of GAN



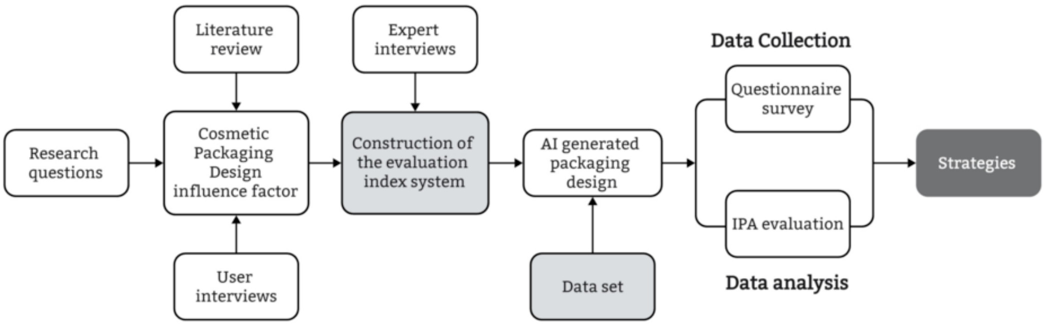
AI-generated design is a design combination of multiple cross-domain elements that are based on GANs. It generates creative design schemes through big data mining technology, semantic thinking networks, visual concept models, design result generation, and feedback-based learning (Chen et al., 2019). Other related AI packaging design technology platforms include PLUG AI, VIZIT, and Dragonfly AI, from outside China, as well as China's Xiaofang AI Packaging Design and Baoxiaohe. These are represented by mass and automated design platforms whose technical logic is to use deep learning algorithms to enable machines to understand designs, do data labeling of packaging design elements, transform the design process into data-driven innovative idea generation and optimal scheme selection, and, ultimately, generate and design packaging or services intelligently according to design principles (Varshney et al., 2019). To explore the actual impact of AI-generated packaging design on consumers, this paper evaluates the factor indicators in AI-generated packaging design by conducting design experiments and related quantitative analysis, as well as by analyzing the relationship between AI-generated packaging design and consumer satisfaction.

RESEARCH METHODS

Research Structure and Methods

The research structure of this paper is as follows (see Figure 2). After clarifying the research questions, literature research and user interviews are conducted to explore the influencing factors of cosmetic packaging designs, and an evaluation index system is constructed based on expert opinions. Then, based on three types of datasets, packaging designs are generated by AI and data about satisfaction toward the generated packaging is collected via questionnaire surveys, after which this data is analyzed using the IPA method. Finally, a design strategy is proposed according to the results of the analysis. The IPA method, proposed in 1977, was initially applied to evaluating the effectiveness of marketing projects (Martilla & James, 1977). The IPA method analyzes the difference between expectations and actual perceptions by comparing the importance and satisfaction of measurement factors so as to determine what the focus of product service improvements should be. IPA is divided into four quadrants according to satisfaction and importance. The first quadrant (H, H) indicates high satisfaction and high importance; it suggests such satisfaction and importance be maintained if possible. The second quadrant (L, H) indicates low importance and high satisfaction; it suggests things in this quadrant should not be pursued deliberately, instead letting nature take its course. The third quadrant (L, L) indicates low satisfaction and low importance; it suggests things in this quadrant be included as a low priority. The fourth quadrant (H, L) indicates high importance and low satisfaction, suggesting things in this quadrant can be improved upon and are, thus, the main focus of improvement.

Figure 2. Research Structure and Method Steps



Construction of the Evaluation Index System

Based on literature review, the design factors of consumers' perceptions of packaging are identified, including packaging materials, visual attraction, functional technology, and brand attitude (Kuo et al., 2021; Lavuri et al., 2022; Orth & Malkewitz, 2008; Ritnamkam & Sahachaisaeree, 2012; Van Ooijen et al., 2017). In addition, the semantic evaluation of the cosmetic packaging design from 53 respondents was collected through user interviews to obtain the key factors of universal perception. The evaluation sample was selected based on the cosmetics packaging the respondents bought and liked using on a daily basis. Subsequently, these collected semantic evaluations were analyzed and all repetitive and meaningless evaluations were eliminated. Finally, a total of 121 valid evaluations was obtained, and the Delphi method was used to classify these evaluations according to expert suggestions. After identifying the factors affecting the evaluation of consumer satisfaction, the design factors extracted from literature research were then used to determine the final evaluation index system for measuring satisfaction toward cosmetic packaging designs. This system includes a total of 18 evaluation indicators in five dimensions (see Table 1).

The five dimensions of this evaluation index system are information transmission, brand recognition, functional availability, creative attraction, and user experience. Of these, Information Transmission B1 means the packaging design should convey information clearly and accurately so consumers can easily understand the efficacy and characteristics of the cosmetics. Brand Recognition B2 means the packaging design should accurately express the brand image and concept so consumers can quickly identify the brand. Functional Availability B3 means the packaging design should be practical. Furthermore, in addition to protecting the product and facilitating its transportation and storage, the packaging should also be done in a way that is convenient for consumers to use. Creative

Table 1. Satisfaction evaluation index system for cosmetic packaging design

Target (*A*)	Dimension (*B*)	Item indicator mark (*C*)
Satisfaction Evaluation for Cosmetic Packaging Design *A*	Information Transmission B_1	Clarity of Information Display C_1; Ease of Comprehension C_2; Information Accuracy and Effectiveness C_3
	Brand Recognition B_2	Consistent Brand Image C_4; Brand Values C_5; Brand Suitability C_6
	Functional Availability B_3	Product Protection C_7; Ease of Use C_8; Ease of Storage C_9
	Creative Attraction B_4	Style Design C_{10}; Color C_{11}; Graphics C_{12}; Font C_{13}; Material C_{14}
	User Experience B_5	Emotional Resonance C_{15}; Aesthetic Preferences C_{16}; Environmental Friendliness C_{17}; Personalization C_{18}

Attraction B4 means consumers should feel a strong visual attraction toward the packaging design so they will be interested in the product. User Experience B5 means the packaging design should be compatible with the demands and preferences of the target consumer group and in line with what appeals to them aesthetically and emotionally.

AI-Generated Design Experiment

The selection of experimental samples is based on the following aspects: the cosmetic packaging mentioned most in the early user interviews; cosmetic packaging that ranks first in terms of the sales volume on e-commerce platforms; and well-known cosmetics packaging with high levels of market recognition. Based on these aspects, eight different types of packaging and public models, were selected as reference samples for AI-generated design (Table 2).

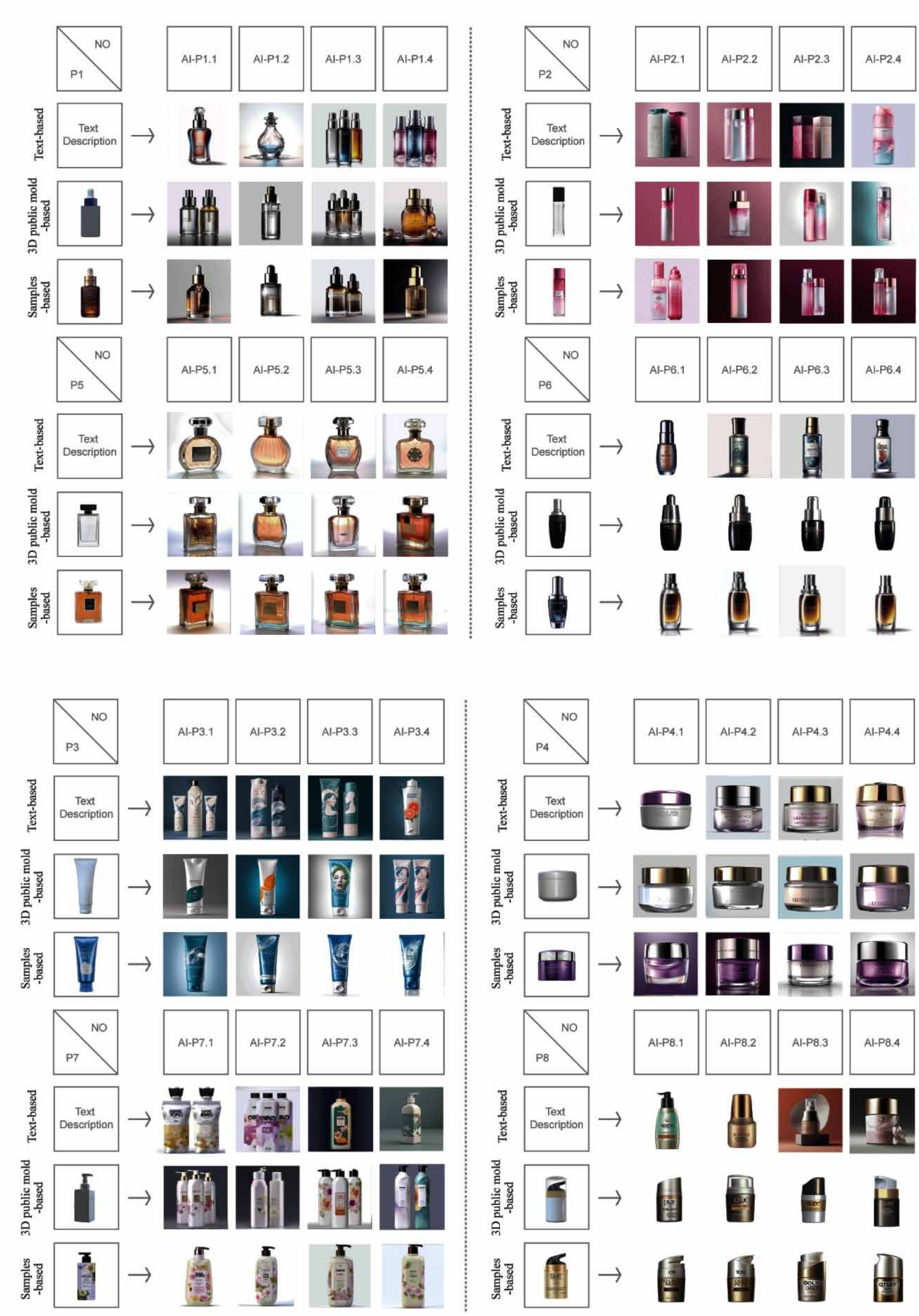
This AI-generated packaging design experiment uses the text, 3D public models, and product samples to compare different generated design effects. Midjourney and PLUG AI, design generation models based on AI technology, were also used in the experiment. Through a combination of algorithmic techniques involving CNNs and GANs, these models generate new design schemes by doing deep learning of a large amount of packaging design data based on design rules and constraints. Prior to the experiment, training was used to validate the model and ensure the generated design met the study's quality requirements.

First, data preprocessing, which included image resolution adjustment and background removal, was performed on the collected product samples to ensure the quality and consistency of the data input into the AI-generated models. Second, the pre-processed data was input into the AI generation model for training. During training, the AI model learned the features and styles of packaging designs and gradually learned how to improve the design quality. To compare the effectiveness of packaging designs generated based on product samples, experiments were also conducted on AI-generated design based on text and 3D public models, respectively. After the training of the model was complete, the AI model was used to generate a new design scheme (see Figure 3). The results of the AI generation reveal the abstract characteristics of the text make the generated packaging both more innovative and more expandable. The packaging generated based on 3D public models also meets relevant design specifications. After training the AI with existing packaging samples in the market, the packaging design result is more mature and has a design language similar to the original brand packaging design. This then makes it possible to generate the product family design.

Table 2. Public models and experimental samples for cosmetic packaging design

No.	3D public model	Product attribute	Product sample	No.	3D public model	Product attribute	Product sample
P1		Serum		P5		Perfume	
P2		Skin toner		P6		Serum	
P3		Facial cleanser		P7		Body lotion	
P4		Foundation cream		P8		Lotion	

Figure 3. Packaging design based on AI model generation after training



PLUG AI was also used to make intelligent predictions in terms of favorability regarding the generated packaging design, and the design with the largest favorability value in each group of cosmetic packaging was selected as the representative of the AI-generated packaging (see Figure 4), which was then used to evaluate consumer satisfaction in the follow-up questionnaire.

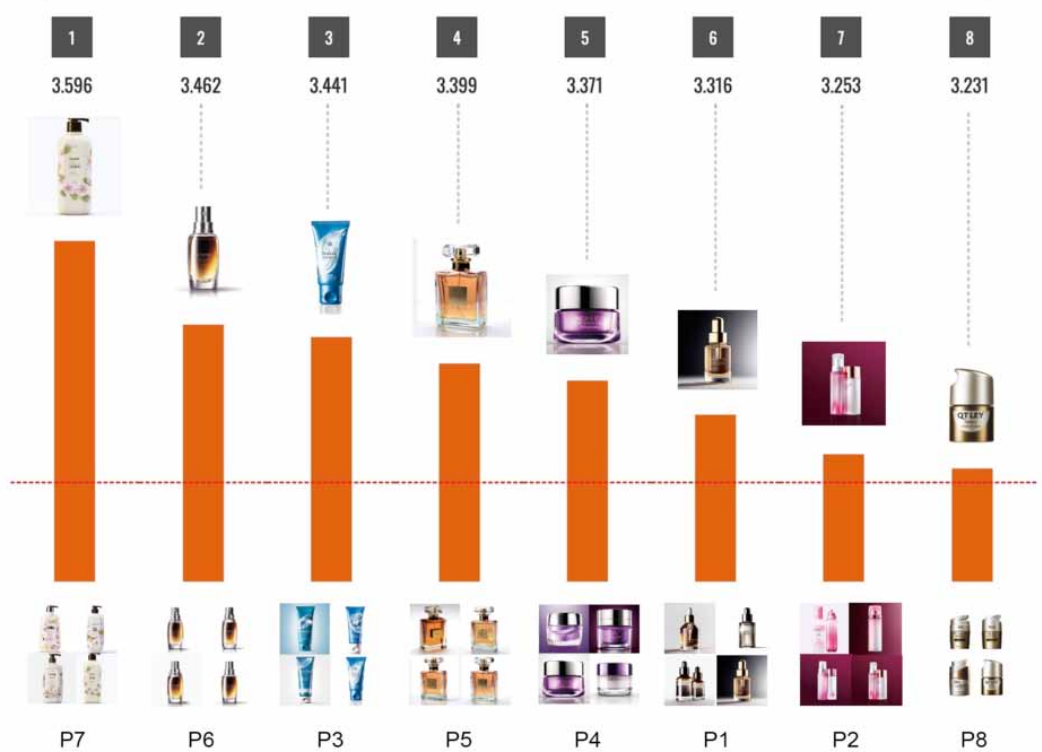
STUDY FINDINGS

Data Collection

Consumer satisfaction data was collected through a questionnaire survey. The questionnaire was based on the item indicators in the evaluation index system and consisted of two parts: (a) a survey of the respondents' demographic characteristics, such as gender, age, and education level and, second, (b), an evaluation by the respondents based on the satisfaction evaluation system with regards to the importance of and satisfaction with AI-generated packaging designs. A five-level Likert scale was used for the evaluation. To obtain authentic data, the study team conducted this questionnaire survey from June 5 to June 20, 2023, using both online and in-person methods. The subjects of the survey included white-collar professionals, university students, and community residents, among others. A total of 330 questionnaires were distributed and 301 valid questionnaires were collected for an effective response rate of 91%. According to a statistical analysis of the demographic statistics of the

Figure 4. Using AI to predict favorability of packaging (by PLUG AI)

Item	Maximum	Minimum	Mean	Standard deviation
Total	3.596	3.231	3.384	0.112



questionnaire (see Table 3), the gender ratio was nearly 2:3, which aligns well with the typical gender characteristics of cosmetics users. In terms of age, the 26-30 age group accounted for the highest proportion of respondents at 22.5%. Over half of the respondents had received a higher education.

Reliability and Validity Analysis

- **Reliability Test:** The reliability of the valid questionnaires was tested using Cronbach's α coefficient and calculated as follows:

$$\alpha = \frac{q}{q-1}\left(1 - \frac{\sum pi^2}{pt^2}\right) \tag{1}$$

In these equations, q represents the total number of questionnaires distributed, pi^2 represents the variance within items for the ith item, and pt^2 represents the total score variance for all questionnaires. The value of Cronbach's α coefficient ranges from 0 to 1. If the α coefficient is higher than 0.6, it is generally considered to have internal consistency, and if the α coefficient is between 0.8 and 0.9, it indicates a high degree of scale reliability. After conducting reliability tests on the scale questions in the questionnaire, the result was 0.952, which was greater than 0.6, and thus, indicated the results of the questionnaire were highly reliable.

- **Validity Test:** Factor analysis was used to examine the structural validity of the questionnaire. Prior to conducting factor analysis, it was necessary to conduct the Kaiser-Meyer-Olkin (KMO) test, for sample adequacy, and the Bartlett's sphericity test, with KMO values ranging from 0 to 1. Analyzing the KMO value, if it is above 0.8, it indicates a high degree of validity; if the KMO value falls between 0.7 and 0.8, it suggests good validity; if it ranges from 0.6 to 0.7, it implies

Table 3. Statistical analysis of demographics

Variable	Value	Frequency	Number of subjects as % of total
Sex	Male	120	39.8%
	Female	181	60.2%
Age	Under 18	36	11.9%
	18-25	39	12.9%
	26-30	68	22.5%
	31-40	64	21.2%
	41-50	46	15.2%
	51-60	26	8.6%
	61 or above	22	7.3%
Educational background	Junior secondary school or below	37	12.2%
	Senior secondary or technical secondary school	91	30.2%
	Associate degree	79	26.2%
	Bachelor's degree	51	16.9%
	Master's degree or above	43	14.2%

acceptable validity, and if it is less than 0.6, it indicates poor validity. The validity test results for the scale questions in the questionnaire yielded a KMO value of 0.913, which was greater than 0.6, and thus, indicated a relatively high level of validity (table 4).

Importance-Performance Analysis (IPA) Model Analysis

- **Importance-Performance Analysis:** Mean and standard deviation analyses were conducted separately on the satisfaction and importance scales using SPSS 26.0 software; the results of the IPA analysis are presented in Table 5. Higher means indicate a higher level of agreement among the test subjects regarding this indicator, while the standard deviation reflects the degree of variation in this indicator among the respondents. Notably, the importance scores for Clarity of Information Display C1 and Information Accuracy and Effectiveness C3 are relatively high, indicating respondents place significant importance on these aspects. On the other hand, Brand Values C5 and Brand Suitability C6 in packaging received lower importance scores, suggesting these aspects are not as highly valued by respondents. In terms of satisfaction, Style Design C10, Color C11, and Graphics C12 received higher scores, indicating respondents feel the greatest amount of satisfaction with these aspects of AI-generated packaging design. However, Personalization C18 and Environmental Friendliness C17 both received lower satisfaction scores, suggesting there is some room for improvement in AI-generated packaging in these areas. Furthermore, most standard deviations are within 1.3, indicating variations among respondents' ratings are relatively small and demonstrating a certain level of stability.

The IPA index was used to objectively quantify the differences between the importance and satisfaction of each indicator. The formula for calculating the IPA index is:

$$IPA = I - P \,/\, I \times 100 \tag{2}$$

The lower the IPA index value, the higher the levels of satisfaction. The IPA index values were divided into five categories: ≤5.00, 5.01–10.00, 10.01–20.00, 20.01–30.00, and ≥30.01, with these categories representing Very Satisfied, Somewhat Satisfied, Neutral, Somewhat Dissatisfied, and Very Dissatisfied, respectively. Based on the analysis of the mean differences between I-P and the IPA index values, the satisfaction levels for each of the 18 indicators can be categorized into three levels: (1) The 10 indicators where users are very satisfied: Consistent Brand Image C4, Brand Values C5, Brand Suitability C6, Product Protection C7, Ease of Storage C9, Style Design C10, Color C11, Graphics C12, Font C13, Material C14, and others; (2) The indicator where users are somewhat satisfied: Aesthetic Preferences C16; (3) The seven indicators where users indicate neutral levels of satisfaction: Clarity of Information Display C1, Ease of Comprehension C2, Information Accuracy

Table 4. Validity test

KMO and the Bartlett's test		
KMO sampling adequacy statistic		0.913
Bartlett's sphericity test	Approximate chi-square	17899.079
	df	630
	p-value	0.000

and Effectiveness C3, Ease of Use C8, Emotional Resonance C15, Environmental Friendliness C17, Personalization C18, and others.

- **Overall IPA Matrix Analysis:** Based on the above analysis, an IPA quadrant matrix was constructed (Figure 5) to provide an overall analysis of the evaluation factors at the indicator level. Using the mean values of importance (x=2.90) and satisfaction (y=2.97) as the intersection point, with importance on the X-axis and satisfaction on the Y-axis, an overall IPA matrix was established and the mean values of the 18 indicators were placed within it for analysis as follows:
  - **Quadrant I (H, H) - Dominant Area:** This area includes seven indicators: Clarity of Information Display C1, Ease of Comprehension C2, Information Accuracy and Effectiveness C3, Consistent Brand Image C4, Style Design C10, Color C11, and Material C14. These are high-importance, high-satisfaction indicators that must be maintained and continuously improved. Of these, Clarity of Information Display C1 is considered the most important, with room for significant improvement in the AI-generated design in this aspect. Additionally, AI-generated packaging design is highly appreciated for its Style Design C10 and Color C11.
  - **Quadrant II (L, H) - Maintain Area:** This quadrant consists of low-importance, high-satisfaction indicators that should be maintained at their current level. The indicators in this area include Graphics C12 and Font C13. For these indicators, AI-generated packaging maintains its existing strengths in Graphics and Font.
  - **Quadrant III (L, H) - Opportunity Area:** This quadrant includes indicators such as Brand Values C5, Brand Suitability C6, Product Protection C7, and Ease of Storage C9. These

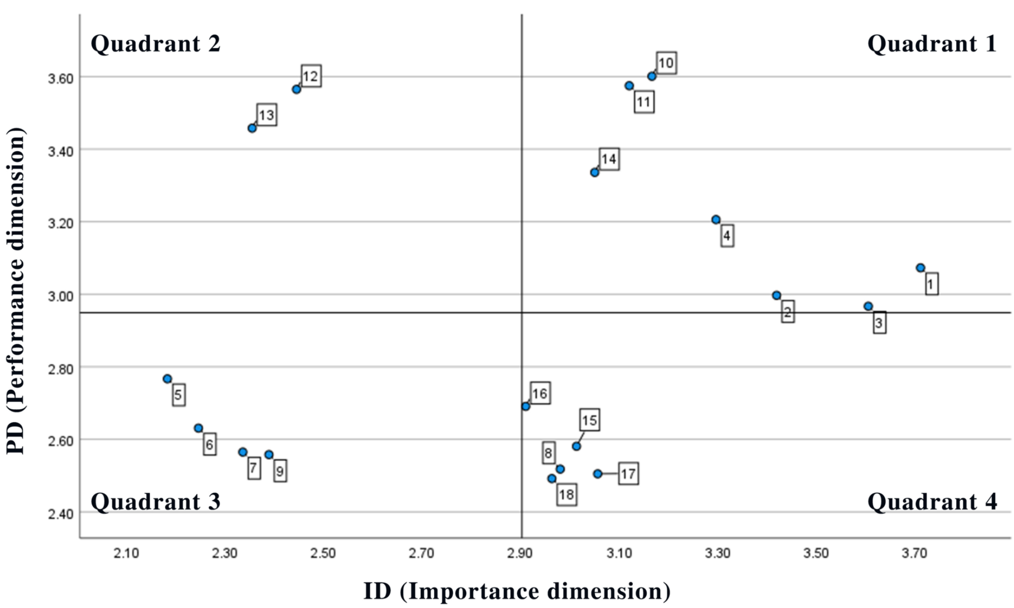
Table 5. IPA statistical analysis

Indicator	Importance			Satisfaction			I-P Mean difference	IPA index	Satisfaction
	Average	Standard deviation	Ranking	Average	Standard deviation	Ranking			
Clarity of Information Display C_1	3.711	1.169	1	3.073	1.309	7	0.638	17.189	Neutral
Ease of Comprehension C_2	3.419	1.356	3	2.997	1.310	8	0.422	12.342	Neutral
Information Accuracy and Effectiveness C_3	3.605	1.283	2	2.967	1.311	9	0.638	17.696	Neutral
Consistent Brand Image C_4	3.296	1.386	4	3.206	1.316	6	0.090	2.722	Very satisfied
Brand Values C_5	2.183	1.159	18	2.767	1.272	10	-0.585	-26.788	Very satisfied
Brand Suitability C_6	2.246	1.186	17	2.631	1.241	12	-0.385	-17.160	Very satisfied
Product Protection C_7	2.336	1.207	16	2.565	1.206	14	-0.229	-9.815	Very satisfied
Ease of Use C_8	2.980	1.311	10	2.518	1.232	16	0.462	15.496	Neutral
Ease of Storage C_9	2.389	1.216	14	2.558	1.236	15	-0.169	-7.093	Very satisfied
Style Design C_{10}	3.166	1.194	5	3.601	1.217	1	-0.435	-13.746	Very satisfied
Color C_{11}	3.120	1.291	6	3.575	1.262	2	-0.455	-14.590	Very satisfied
Graphics C_{12}	2.445	1.220	13	3.565	1.265	3	-1.120	-45.788	Very satisfied
Font C_{13}	2.355	1.196	15	3.458	1.315	4	-1.103	-46.827	Very satisfied
Material C_{14}	3.050	1.322	8	3.336	1.331	5	-0.286	-9.368	Very satisfied
Emotional Resonance C_{15}	3.013	1.299	9	2.581	1.207	13	0.432	14.333	Neutral
Aesthetic Preferences C_{16}	2.910	1.281	12	2.691	1.260	11	0.219	7.534	Somewhat satisfied
Environmental Friendliness C_{17}	3.056	1.306	7	2.505	1.202	17	0.551	18.043	Neutral
Personalization C_{18}	2.963	1.289	11	2.492	1.229	18	0.471	15.919	Neutral

are indicators with low importance but also low satisfaction levels, signaling a potential opportunity for future improvement in AI-generated packaging design. Projections from this quadrant reveal that Brand Values C5, which is closely tied to AI-generated design's ability to convey a consistent brand image, exhibits relatively high levels of satisfaction compared to other indicators. Currently, AI-generated packaging design faces challenges in terms of directly conveying Product Protection C7 and Ease of Storage C9 to respondents. However, as digital technologies like AR/MR become more advanced, it is expected this will help deliver a better user experience (Cascini et al., 2020).

◦ **Quadrant IV (H, L) - Improvement Area:** This quadrant comprises indicators such as Ease of Use C8, Emotional Resonance C15, Aesthetic Preferences C16, Environmental Friendliness C17, and Personalization C18. These are indicators to which respondents attach high importance but also exhibit low levels of satisfaction, indicating a substantial gap between importance and effectiveness. These aspects are very important to respondents but are currently underperforming, resulting in comparatively lower satisfaction levels. Therefore, these aspects should be prioritized for future improvement efforts. Respondents place significant value on the alignment of cosmetic packaging with their emotions, aesthetic preferences, and personalization. Packaging increasingly serves as a projection of users' emotional and psychological states, making it essential that AI-generated packaging design enhance user satisfaction in these areas. As environmental awareness continues to grow, Environmental Friendliness C17 is a focal point for respondents in this quadrant, yet levels of satisfaction remain inadequate, which indicates AI-generated packaging must contribute more significantly to green, sustainable design.

Figure 5. Consumer satisfaction IPA matrix for AI generated packaging design



Strategies and Recommendations

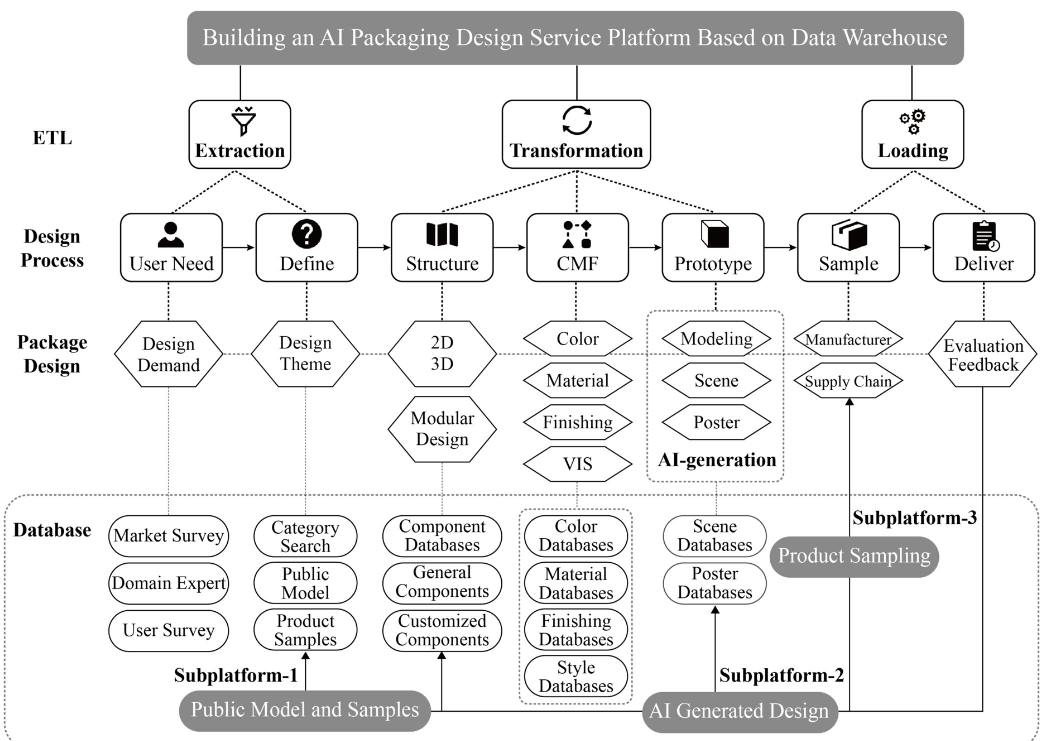
Based on the survey and analysis of AI-generated packaging design satisfaction, it is evident that respondents express high levels of approval and satisfaction with the Information Transmission B1 and Creative Attraction B4 aspects of packaging. However, in general, people also tend to be relatively dissatisfied with the Functional Availability B3 and User Experience B5 aspects. Therefore, it is crucial to enhance the practicability, brand value, and user experience of AI-generated packaging. Based on the IPA data analysis, the following strategies for improving AI-generated packaging design have been proposed.

- **Incorporate Public Models in AI-generated Packaging Design:** Packaging design goes beyond aesthetics; it also includes functionality and availability. AI algorithms do not always fully grasp the practical aspects of packaging, such as usability, ergonomic considerations, or the physical constraints of the manufacturing process. These factors require a richer experience and more specialized knowledge. Public packaging design models widely used in the industry have been tested in the market and demonstrate excellent usability and compatibility with production processes. One strategy for ensuring the availability of packaging is exploring AI-generated model training based on public models. This would ensure AI-generated packaging designs are not only visually appealing, but also practical and user-friendly.
- **Enhance Multi-modal Learning to Enrich Datasets:** AI algorithms rely on extensive data to generate designs, but they can sometimes lack the ability to fully understand contextual factors influencing packaging design, including cultural differences, regional preferences, and market trends. Additionally, packaging design is often intended to evoke specific emotions and establish brand recognition, and so the lack of this emotional connection with users is a real challenge for AI-generated packaging design. To address this, multi-modal learning can be combined with diverse images and textual information from social media and other sources to ensure the datasets used for training AI models are sufficiently comprehensive. This will enhance these models' performance and accuracy in areas such as semantic understanding and emotional quantification methods (Al-Sheikh & Hasanat, 2020; Xu et al., 2021). This can also help models learn more design styles, trends, and user preferences, which will ultimately improve the alignment of AI-generated packaging with target market expectations and emotional appeal for users.
- **Enhance the Explainability and Controllability of the Design Process:** AI uses complex algorithms to generate packaging designs without providing explicit explanations for its decision-making process. This lack of transparency can make it challenging for people to understand and evaluate the fundamental principles behind specific design choices, and this potentially hinders trust and acceptance of AI-generated packaging designs. Donald Norman emphasizes in *The Design of Everyday Things*, a product's design must reflect its workings, operability, and operational status (Norman, 1995). In other words, in a design. the system appearance should be clear and accurate, and the design process should be transparent and perceptible to users. This will then help them accept the design and build the correct mental models. Therefore, it is essential to improve the explainability of AI-generated results because that is what enables users to understand the rationale and reasoning behind model-generated designs. Additionally, providing certain control parameters allows users to intervene and adjust the generation process to meet personalized demands.
- **Build an AI Packaging Design Service Platform Based on Data Warehouse:** Incorporating the three aforementioned recommendations, AI-generated packaging design can leverage data warehouse to create a design service platform that covers the entire lifecycle from product concept to packaging production (see Figure 6). Once a comprehensive data warehouse has been established, it can facilitate the visualization of the packaging design and service management processes. A data warehouse provides robust analyzing and querying functions, enabling

design teams to easily track project progress, allocate resources, and control quality (Aufaure et al., 2013; Farnum et al., 2019). Additionally, data analysis tools can be used to analyze user preferences, packaging functionality, packaging design, and production processes. By gaining deeper insights into consumer demands and market trends, design teams can better meet customer expectations and enhance packaging design quality. The construction of a data warehouse for packaging design not only involves essential aspects like data extraction, transformation, and loading (Oliveira et al., 2021; Schneider, 2008; Vassiliadis, 2009) but also the development of service platforms and data models. It is recommended that a service platform consist of three major sub-platforms: The public model and sample sub-platform, the AI-generated design sub-platform, and the product sampling sub-platform. A data model is a complementary data resource repository that includes structural models, component databases, material databases, color databases, and scene databases. Data extraction can involve gathering demand data from sources like supply chain information, market research data, and user surveys. During the data transformation stage, an enterprise's public model data, product samples, and market demands must be integrated into a consistent data warehouse for packaging design analysis. Data loading involves importing processed packaging design data into a data warehouse and presenting it visually, thus facilitating the analysis of packaging design decisions for enterprises and more effectively meeting personalized consumer demands.

In summary, the intelligence of packaging design goes beyond appearance design; it also encompasses whole-process management based on data analysis. By establishing a comprehensive data warehouse and utilizing data analysis tools, it can improve efficiency and packaging design quality, more effectively meet consumer demands, and enhance adaptability to market changes.

Figure 6. AI packaging design service platform framework



This is a continually evolving, innovative field that will deliver more opportunities and competitive advantages to its enterprises.

CONCLUSION

Utilizing AI in packaging design can enhance the efficiency and innovativeness of packaging development with the evaluation of packaging design largely relying on consumer satisfaction. This paper, which is based on the IPA method, studies and analyzes the key factors with AI-generated cosmetic packaging design that has the greatest on influence consumer satisfaction. The study results show that while most consumers are satisfied with the packaging's visual design and innovativeness, they generally express dissatisfaction with the packaging's functional availability and user experience. For this purpose, we propose a comprehensive approach that incorporates public models, multi-modal training, explainability, and controllability to build an AI packaging design service platform based on data warehouse. This paper conducted preliminary tests of the actual effectiveness of AI-generated cosmetic packaging design and studied the factors influencing consumer satisfaction. However, the human-computer interaction service platform for intelligent packaging design based on users' diversified needs has not yet been developed. The next stage of this study will focus on constructing a data warehouse and service platform for AI packaging design, which will enable enterprises to better understand and utilize data, make better design decisions, and save time and costs in design development. This will ultimately empower innovation and development for small and medium-sized enterprises.

CONFLICT OF INTEREST

The authors of this publication declare there are no competing interests.

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