Doctoral Dissertation

Study of Emotional Craft Design by Exploring Design Features and Emotional Responses within Top-selling Ceramic Teapots in a Chinese E-commerce Platform

Li, Xianghui

Supervisor: Yuizono Takaya

Graduate School of Advanced Science and Technology

Japan Advanced Institute of Science and Technology

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Abstract

With the increasing emphasis on emotional design in product development, understanding how design features elicit specific emotional responses has become important for designers to create products that are popular among consumers. This dissertation focuses on the research on the emotional design of craft products. Taking the ceramic teapot in a Chinese e-commerce platform, a typical representative of craft products, as an example, it explores the relationship between the design features of craft products and emotional responses. To achieve this aim, the dissertation sets the following main research question (MRQ): How is emotional craft design produced based on the relationship between design features and emotional responses of ceramic teapots? For MRQ, the dissertation sets three sub-research questions: SRQ1: Which design features of ceramic teapots are associated with users' perceived impressions? SRQ2: How is the emotional quality of ceramic teapots evaluated? SRQ3: Based on images and online reviews, how do design features of ceramic teapots influence consumers' emotional responses?

The dissertation first addresses SRQ1 by decomposing teapot forms into morphological elements (body, lid, handle, spout) and encoding them as analyzable variables using morphological analysis. Perceived adjectives collected via surveys were reduced through factor analysis, revealing three higher-order impression factors—elegance, fashion, and practicality—that explain over 70% of the variance in consumer evaluations. Multiple regression with dummy variables then maps specific contour types and component configurations to these perceived factors, identifying positive and negative design elements for each emotional orientation.

To answer SRQ2, the dissertation constructs emotion quality classification models using facial emotion recognition data (Face Reader 9.1) and Self-Assessment Manikin (SAM) valence ratings collected from 60 participants viewing teapot images. After data preprocessing, four classifiers—logistic regression (LR), C5.0 decision tree (DT C5.0), random forest (RF), and neural network (NN)—are trained for binary, ternary, and quinary valence classification. The random forest model achieves the best performance (up to 91.0% accuracy in binary and 81.3% in ternary classification) and is selected as the core evaluation tool. The model is externally validated with a new experiment on three newly designed teapots (elegant, fashionable, and practical) whose forms are derived from the earlier feature–emotion mapping. Results show a marked increase in positive valence compared with the original samples, supporting the generalizability of the proposed workflow.

Addressing SRQ3, the dissertation further extends the research from the laboratory to the e-commerce scenario, conducting text mining (such as word frequency and clustering) on 1,316 valid pieces of online reviews of the same batch of teapots, and using generalized linear mixed models (GLMM) and generalized estimating equations (GEE) to analyze and compares review-based emotional responses with emotional questionnaires-based emotional responses, thereby identifying the design features most likely to elicit emotional responses and assessing which features influence emotions both two contexts. Through analysis, specific design features of ceramic teapots, such as form, decoration, and usability-related attributes, have been identified as contributing to emotional satisfaction or dissatisfaction in the e-commerce environment. This analysis highlights design risk points where differences in emotional responses in online reviews-based and emotional questionnaires-based emotional responses, and translates them into specific design decisions.

The dissertation provides an empirical mapping relationship between the design feature of craft products and multi-level emotional responses, enriching the fields of emotional design and knowledge science. Furthermore, a replicable data-driven evaluation process is proposed that integrates semantic evaluation, morphological encoding, facial emotion recognition, machine learning, and text analysis to answer the main research question (MRQ) of this study. At a practical level, this study provides operational design guidance and evaluation tools for the design of ceramic teapots and other craft products. It provides a decision-making basis for designers to create craft products with market sales potential, thereby promoting the development of craft product design.

keywords: Emotional craft design, Design features of ceramic teapot, Emotional response, Facial emotion recognition, Text analysis

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Chapter 1

Introduction

1.1 Research background

With the increasing emphasis on emotional design in product development, understanding how design features elicit specific emotional responses has become crucial for designers. (Vaidya, G. et al., 2021; Alonso-García, M. et al., 2023; van Remmen, J. et al., 2025; Alonso-García, M. et al., 2023; Ng, Y. Y. N. et al., 2025; Zhou, F. et al., 2021) Emotional design can connect products with users, enhance user experience and product value. (Gu, J. and Lee, S., 2025) It emphasizes the emotional responses triggered by products in terms of visual, tactile, and user experience, and emphasizes that the aesthetic and interactive characteristics of products can build emotional connections with users, which are important factors affecting user satisfaction. (Lun, L. et al., 2024; Wang, Z. et al.,2023)

In traditional design, product usability and functionality are the core, and "functionality first" leads to cold and unappealing products that cannot meet the deep psychological needs of users. (Gagnon-King, D.2023). Designers are also primarily responsible for addressing functional issues such as usability and efficiency. (Issa, T. et al., 2022; Rahman, M. A. et al., 2022; Lewis, J. R. et al., 2021). With the advancement of cognitive and affective science, Donald Norman systematically proposed in "Emotional Design" that human cognition is divided into three levels - instinctive level, behavioral level, and reflective level, and emotions affect decision-making and experience at each level. (Roth, M. et al., 2022; Tian, Z. B. et al., 2022, April). Neuroscience and psychological research have also confirmed that emotions are the core driving force behind human decision-making, memory, and interaction. Levine, D. S. (2022). In the context of globalization and consumer upgrading, design is no longer solely focused on optimizing functionality and form, but is gradually shifting towards meeting users' psychological needs and emotional experiences. (Peters, D. 2023).

As emotions become an important decision-making dimension, design decisions are no longer solely based on rational dimensions such as usability testing and ergonomic data. (Buker, T. et al.,2023; Zhou, F. et al., 2021) Designers must proactively consider how to stimulate target emotions through sensory (instinctive layer), interactive (behavioral layer), and meaningful (reflective layer) design. (Edmonds, E. et al., 2024;

Bizmark, N.2025). Every color, material, animation, and interactive process may carry emotional goals (Zhao, L.2022). Therefore, emotional design has profound and transformative significance for designers (Sabyrkyzy, S. A. 2025, May; Dybvik, J. H.2022). Designers need to consider how products can make users feel happy, at ease, confident, or generate a sense of belonging (Patrick, V. M. et al., 2021). The core basis of designers' design decisions has also shifted from logic to a shift from purely logic-based design to logic- and emotion-based design. The purpose of design is to make products attractive and build emotional bonds with users (Yang, J. et al., 2022).

In emotional design, it is crucial to study the relationship between design features and consumer emotional responses. (Vaidya, G. et al., 2021). It is the core bridge that elevates design from "meeting functional needs" to "creating emotional value". Firstly, Donald Norman proposed the "three levels of emotional design" (instinct, behavior, and reflection), providing a theoretical framework for how design features trigger different levels of emotional responses and stimulating empirical research needs (Wu, S. 2024; Sepahpour, G.2022). The application of affective cognitive theory (such as arousal and valence dimensions) and neuroscience tools (such as fMRI and EEG) have transformed "emotion" from a subjective description into a measurable and modeled variable, providing a methodological basis for quantifying the emotional effects of design features in research. (Zhu, Z. et al., 2025; Li, X. et al.,2025).

The development of Kansei engineering and the deepening of research on human-computer interaction (HCI) and user experience (UX) have expanded design from "usability" to "emotional experience", shifting the focus of research to how detailed features such as interface dynamics, micro interactions, and voice tone affect user emotions and long-term stickiness (Alkhomsan, M. N. et al., 2025).

Furthermore, the transformation from traditional design to contemporary design paradigms is also an important reason for its development. (Ugah, U. U. K. et al., 2024; Verganti, R. et al., 2021). Traditional design relies on designer intuition, while emotional response research emphasizes using user psychological data as a basis to promote the transformation of the design process towards scientific and evidence-based approaches. (Fischer, M. et al., 2021; Quiñones-Gómez, J. C. et al., 2025).

In addition, from the trend of interdisciplinary integration, the research field on design features and consumer emotional responses integrates design studies, psychology, cognitive science, computer science, and marketing, forming crossdisciplinary directions such as "neuromarketing" and "emotional computing" to jointly explore the emotional transmission mechanism of design features. (Gkintoni, E. et al., 2025; Samal, P. et al.,2024). Research tools such as eye tracking, facial expression recognition, and biosensing can capture users' subconscious emotional responses to design features in real time, (Rubin, D. 2024; Kaklauskas, A. et al., 2022). thereby shifting research from retrospective interviews to process-based precise measurements. (Kelly, B. C. et al.,2025).

Emotional craft design is a product of the deep integration of emotional design theory and craft design practice (Nimkulrat, N. 2022). It not only responds to the practical question of "how to design enjoyable products", but also marks the formal entry of design into a new stage of "emotional quantification and experiential design”. (Kim, J. et al., 2022; Yang, X. et al., 2023). Ceramic tea sets, as craft products, have both practical functions and aesthetic value, while also reflecting profound cultural connotations. It is an ideal carrier for exploring emotional design features. With the increasing and diversified demand for tea sets from consumers, innovative ceramic tea set designs have attracted considerable attention (Zhao, Y. X. et al., 2024). Therefore, exploring the relationship between the features of ceramic teapots and consumer emotional responses, systematically studying how emotions are implanted, transmitted, and perceived through design, can help designers create more marketable works and promote the development of the entire craft industry. (Kofler, I. et al., 2024; Zeng, M. et al., 2024; Anooja, J. et al., 2025).

1.2 Research objectives

This dissertation aims to provide practical knowledge about the emotional design of craft products. Taking the ceramic teapot, a typical representative of craft products in a Chinese e-commerce platform, as an example, it explores the relationship between the design features of craft products and emotional responses.

To achieve this aim, the dissertation pursues the main objective and three sub-objectives:

MRO: To study emotional craft design by exploring the design features and emotional responses of top-selling ceramic teapots in a Chinese e-commerce platform.

SRO1: To identify morphological design features associated with the perceived impressions of ceramic teapots;

SRO2: To develop an emotional quality model to evaluate the emotional quality of ceramic teapots and its application in new emotional craft product design.

SRO3: To explore the design features of craft products by comparing online reviews-based emotional responses with emotional questionnaires-based emotional responses.

Accordingly, the main research question (MRQ) and three SRQs are as follows:

MRQ: How is emotional craft design produced based on the relationship between design features and emotional responses of ceramic teapots?

SRQ1: Which design features of ceramic teapots are associated with users' perceived impressions?

SRQ2: How is the emotional quality of ceramic teapots evaluated?

SRQ3: What are the differences in ceramic teapot design features based on emotional responses elicited by online reviews versus those derived from emotional questionnaires?

In summary, this study focuses on emotional craft products design, taking top-selling Chinese and Japanese ceramic teapots as examples, to explore the relationship between their design features and emotional responses, and thus construct a strategic framework of "design features-emotional responses-design decisions" for craft products, providing data-driven support for designers to create craft products that meet consumer preferences.

1.3 Research contribution

This dissertation systematically explores the relationship between the design features of top-selling Chinese and Japanese ceramic teapots and the emotional responses of consumers by integrating morphological analysis, perceived factor analysis, facial emotion recognition modeling, and text mining. Compared with previous studies, the innovation of this research mainly lies in the following aspects.

1) Unlike prior studies that typically focused on a single craft category (Ho & Siu, 2012; Yan et al., 2011) or a single cultural lineage (Kim et al., 2020; Wang et al., 2024; Ding et al., 2024; Chitturi, 2009; Xue et al., 2022; Setchi & Asikhia, 2019; Zhou et al., 2021; Li & Zhang, 2024) this research concurrently selected two types of top-selling ceramic teapots from China and Japan as samples, covering a wider range of forms and decorative elements. This “cross-style juxtaposition” of objects enables the model to learn a more transferable and design-guiding “form–emotion” mapping. The results

indicate that incorporating categories not only increases the complexity of model construction but also yields emotional design features with greater generalizability.

2) This study developed an emotional quality model to evaluate the emotional quality of ceramic teapots. Departing from research paradigms that primarily rely on text sentiment, generic image aesthetics, or single questionnaire-based regression (Chitturi, 2009; Xue et al., 2022; Yan et al., 2011; Zhou et al., 2021; Li & Zhang, 2024), this study systematically compared four classifiers—LR, DT C5.0, NN, and RF—under binary, ternary, and quinary classification. The results show that RF consistently maintained superior performance in multi-class settings (Macro-F1: 87.3% for binary, 81.5% for ternary, 62.4% for quinary), clearly outperforming NN and LR. This difference highlights the advantages of ensemble learning when handling complex emotion-design data—especially when product form features are highly similar and emotional response differences are subtle—by better capturing nuance in consumer affect. To develop an emotional quality model to evaluate the emotional quality of ceramic teapots and its application in new emotional craft product design;

3) Compared with existing approaches that only perform cross-validation on the original samples or merely contrast subjective satisfaction (Zhao et al., 2024), (Chitturi, 2009), (Bo, 2020), this dissertation went beyond mixed-sample training and testing by additionally designing three new teapots and conducting an external experiment to verify model stability. The external validation shows that the new designs achieved 91.1% accuracy in binary classification and 64.5% in ternary classification—both significantly higher than the original samples (37.4% and 28.9%). This finding demonstrates that the model not only accounts for emotional preferences in existing samples but can also predict and guide new product design, helping to build an effective "data-to-design" closed loop. To further illustrate the practical applicability of our approach, this study proposes a replicable evaluation workflow that translates research findings into actionable design guidance.

4) In e-commerce contexts, there remains limited research that integrates emotional responses across the emotional questionnaires-based evaluation and the online reviews-based evaluation (Liu, C., & Xu, Y. 2021; Yang, X. et al., 2023; Semuel, H. et al.,2017), In addition, there is a lack of transforming empirical evidence into actionable design decisions. (Dai, J., Wang, T., & Wang, S. 2020; van Kuijk, J. et al.,2017; Hong, W. et al.,2019). To address these gaps, this dissertation analyzes 1,791 online reviews of the

same set of ceramic teapots using text mining, word-frequency analysis, and clustering/topic modeling. In addition, generalized regression models—specifically a generalized linear mixed model (GLMM) and generalized estimating equations (GEE) — are applied to compare emotional responses between the emotional questionnaires-based evaluation and the online reviews-based. This analysis identifies design feature risk points for consumers at different stages of their experience and transforms them into data-driven design decisions.

In short, by filling the aforementioned research gaps, this study not only deepens our understanding of process in craft product design but also provides designers with data-driven design decision. It offers a scientific methodology and empirical foundation for the field of emotional design in craft products, thereby promoting the development of craft product design.

1.4 Dissertation structure

This dissertation is organized into seven chapters (see Figure 1.1). Chapter 1 introduces the research background, research objectives, and research questions (MRQ and SRQs), and summarizes the main contributions of the study. Chapter 2 reviews related literature on emotional design, consumer emotional responses and design features, and existing emotional evaluation approaches, and then clarifies the research gaps addressed by this dissertation. Chapter 3 describes the overall methodology, including data collection procedures and analysis methods.

Chapters 4-6 correspond to the three sub-research questions (SRQs). Chapter 4 (SRQ1) investigates which design features of ceramic teapots are associated with consumers' perceived impressions. It extracts and encodes teapot morphological features through morphological analysis, derives perceived impression factors from a semantic differential (SD) questionnaire via factor analysis, and builds feature–impression mappings using dummy-variable multiple regression. Chapter 5 (SRQ2) focuses on how to effectively evaluate the emotional quality of top-selling ceramic teapots. It integrates facial emotion recognition with the Self-Assessment Manikin (SAM) scale and constructs emotion-quality classification models through machine learning, followed by model evaluation and external validation. Chapter 6 (SRQ3) compares emotional responses based on images and online reviews to derive design feature risk points in ceramic teapot design, supporting designers' design decisions.

Finally, Chapter 7 summarizes the findings of Chapters 4-6, discusses theoretical and practical implications, and outlines limitations and future research directions.

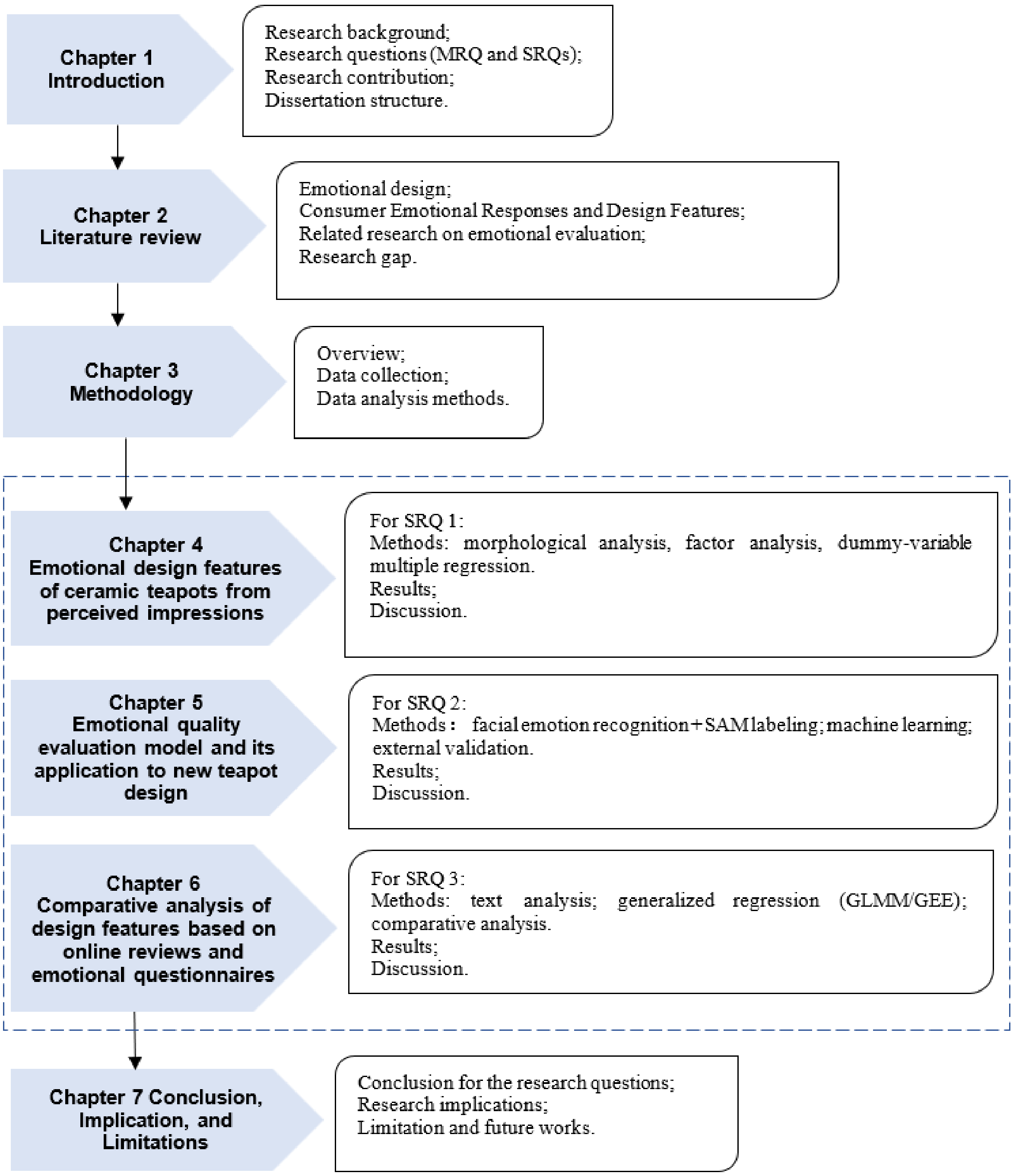


Figure 1.1 Content structure diagram of the dissertation.

Chapter 2

Literature Review

2.1 Emotional design

Emotional design originated from the first "International Conference on Design and Emotion," held at Delft University of Technology in the Netherlands in 1999, where the International Society for Design and Emotion was established, and research on emotional design was pursued (Overbeeke & Hekkert, 1999). The concept of emotional design was first promoted in the global design research community by Norman, Green, and Jordan, as well as the International Conference on Design and Emotion (Bouchard, 2009). Before this, American researchers Norman and Draper initially outlined the prototype of emotional design, proposing the design slogan of "user-centered" and "The Three Level Theory of Emotional Design" (as shown in Figure 2.1) (Fishwick, 2004), (Ho & Siu, 2012).

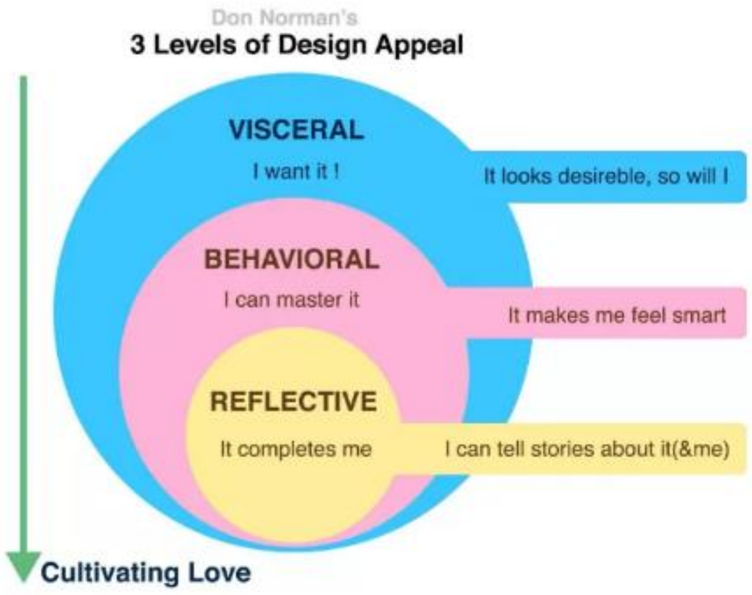


Figure 2.1 Three Level Theory of Emotional Design (Image source: https: //www.toptal.com/designers/product-design/design-for-emotion-to-increase-user-engagement)

Emotional design plays a significant role in various fields of product research. Norman conducted a detailed and comprehensive study of emotional design, emphasizing the role of emotional factors in product design (Bagnara & Crampton-Smith, 2020). Numerous studies have explored how design elements, such as product color, shape, and texture, influence users' emotional experiences (Hidayatulloh, T., & Astuti, K. S., 2022; Bagnara & Crampton-Smith, 2020; Kim et al., 2020). Researchers have employed methods such as semantic differential scales, factor analysis, and fuzzy comprehensive evaluation to quantify and analyze consumers' emotional responses to different design schemes (Bagnara & Crampton-Smith, 2020; Wang et al., 2024). Additionally, some studies have focused on integrating user emotions into the design of intelligent product-service systems, proposing emotion design generation models based on knowledge graphs and machine learning (Ding et al., 2024). Consumers' emotional perception of products significantly affects their design decisions. In sum, Researchers have investigated the influence of emotions on design from various perspectives, including product appearance (Homburg et al., 2015), functionality (Chitturi, 2009), and marketing strategies (Alvarez, 2019; Brusch & Rappel, 2020; Qu, 2022).

Emotional craft design focuses on user-centered emotional insights, and some scholars use methods such as in-depth interviews, cultural probes, and experiential prototypes to explore users' emotional needs, usage scenarios, and potential desires. These qualitative studies are the cornerstone of defining design directions. Moreover, emotional craft design has begun to pay more attention to the emotional needs of specific groups (such as the elderly, children with autism, etc.), providing them with emotional comfort and social support through customized crafts and materials. Research on young consumers' emotional responses to products primarily focuses on traditional handicraft fashion (Xue et al., 2022) and sustainable products (Meeprom et al., 2023), (Trentinaglia et al., 2024), (Islam et al., 2024). Regarding traditional handicraft fashion, Xue et al. focused on young consumers in Mainland China and found that emotional, social, intellectual, and nostalgic values significantly influence their purchase impressions (Xue et al., 2022). Although studies on consumers' demand for ceramic tea sets are limited, emotions generally play a crucial role in shaping their meaning (Borghi & Mariani, 2022).

2.2 Consumer emotional responses and design features

2.2.1 Consumer emotion

The in-depth study of human emotions was conducted as early as the late 19th century. As human emotions are difficult to observe directly, facial expressions provide an effective proxy for emotion recognition (Munezero et al., 2014). The study of facial expressions dates back to the 19th century. In 1872, Darwin elucidated the connections and distinctions between human and animal facial expressions. In 1971, Ekman and Friesen advanced modern facial expression recognition by identifying six basic human emotions: happiness, sadness, surprise, fear, anger, and disgust. They detailed the facial changes associated with each emotion and built a comprehensive database of facial expression images (Tian et al., 2011). In 1978, Suwa et al. pioneered facial expression recognition in video animations and proposed an automated analysis of facial expressions in image sequences (Clark, 2020). Russell et al. proposed a two-dimensional emotion model in 1979 and introduced two emotion indicators: valence and arousal (1979). The valence describes the degree of positive and negative emotions; the arousal level reflects the intensity of emotions. Figure 2.2 shows the circular emotion model proposed by Posner, Russell and Peterson.

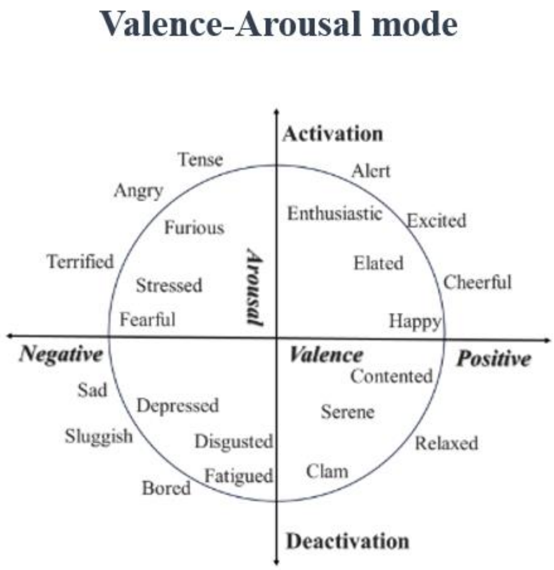


Figure 2.2 Russell's two-dimensional emotional model (Posner, Russell and Peterson, 2005)

In 1997, American computer science expert Picard explained the concept of affective computing in his book Emotional Computing and pointed out a high correlation between emotions and affective computing (Guo et al., 2018). Emotion computing is a highly integrated field of technology. So far, research has made some progress in facial expressions, posture analysis, emotion recognition, and expression in speech. With the increasing research on affective computing (Ho et al., 2021), its ethical issues have also attracted attention (Kumar et al., 2023). The research field of affective computing is constantly expanding. For example, affective computing is used to design emotional response interfaces to enhance user experience (Prasetya et al., 2025), and affective computing frameworks are used to explore the impact of interventions on students in e-learning and classroom environments (Ashwin & Guddeti, 2020). The focus of emotional computing research is to obtain physiological and behavioral characteristic signals caused by human emotions through various sensors, build an "emotional model", and create a personal computing system that can perceive, recognize, and understand human emotions, and can make intelligent, sensitive, and friendly responses to users' emotions, shorten the distance between humans and machines, and create a truly harmonious human-machine environment. At present, research on the correlation between emotional design and emotional computing is becoming increasingly common (Lan et al., 2023; Draheim et al., 2025).

2.2.2 Consumer emotional responses and design features of craft products

Research on the emotional response of consumers to the design features of craft products. Some scholars argue that consumers' emotional reactions to product appearance can guide the design of product features such as the choice of color, shape, and material (Homburg et al., 2015). Others suggest that consumers' emotional responses may vary across different product types (Chitturi, 2009; Malik & Hussain, 2017) and that these reactions can be leveraged to optimize product usability and practicality, such as button placement and operational design (Chitturi, 2009). Understanding these emotional responses enables designers to create products that better meet consumer and enterprise needs (Alvarez, 2019; Brusch & Rappel, 2020; Qu, 2022). Emotional design can evoke positive emotions, such as pleasure, comfort, and safety, through elements such as form, materials, and color (Kim et al., 2020). For example, a teapot that elicits positive emotions is more likely to appeal to consumers and succeed.

In ceramic designs, the significance of consumers' emotional responses is evident. Scholars have employed methods, such as questionnaires and interviews, to collect semantic evaluation data on user perceptions of ceramic product texture, form, and other attributes, followed by quantitative analysis (Ye, 2024). Research findings demonstrate that user-perceived semantic evaluations effectively guide ceramic product design and enhance the user experience (He et al., 2024). Because the appearance of craft products plays a pivotal role in attracting consumer attention and fostering emotional connections, the shape of a teapot can evoke diverse emotional reactions (Agyei et al., 2021). Elements, such as size, proportion, and lines, are instrumental in conveying emotions. Additionally, color choices influence emotional responses: warm tones often evoke passion and vitality, whereas cool tones suggest tranquility and elegance (Yang et al., 2019). Decorative patterns, whether traditional or modern, must align with the aesthetic preferences of the target user group (Lin & Liu, 2019) (Table 2.1).

2.2.3 Consumer emotional responses to e-commerce products

The research on emotional responses to e-commerce products mainly focuses on User Generated Content Sentiment Analysis (Liu, C., & Xu, Y., 2021) (Table 2.2). These studies focus on the analysis of user review data on e-commerce platforms, analyzing users' attitudes and emotions towards specific aspects of products or services. Scholars have conducted research on cloud service platforms for e-commerce product design based on consumer willingness in the context of blockchain, exploring the relationship between consumer product intimacy, psychological distance, and social distance (Peng, X. Q., & Hu, F., 2019, July). Analyze user narratives to understand interactive product experiences and compare the differences between positive and negative experiences in

Table 2.1 Related research on consumers' emotional response to craft products.

Ref	Research object	Method	Dataset	Participants	Research Results/Findings
Timothy J. Scrase, 2005	Asian handicrafts	Analyze text and visual images	Three websites	N/A	'National brand' is an important marketing feature. Marketing materials often use terms such as "traditional," "natural," and "authentic.
Carsten Baumgarth et al. 2020	Graffiti/Street Art	T-test ANOVA Structural Equation Modeling (SEM)	Study 1: 7 images. Study 2: Processed product packaging images.	Study 1: 22 respondents. Study 2: 255 respondents.	Confirming the 'urban art injection effect': street art products are significantly better evaluated than non-art versions; Graffiti is significantly better only in the beer category. The perception of luxury and lifestyle are important driving factors for the injection effect of art. The fit between art and product has a significant impact on product evaluation.
Yang, 2022	Cultural and creative product design	Perception Engineering Methods, Eye Tracking	Questionnaire data	Online comment text data	The perceived design method combines human and artificial intelligence, improving psychological acceptance and competitiveness. More than 80% of consumers highly value the novelty and cultural significance of cultural and creative products.
Li WT, et al.2019	traditional handicrafts	Expert questionnaires, factor analysis, Experimental method	Expert questionnaires (45). Six ceramic product prototypes.	30 students; 60 experts	24 "indicators of sustainable value of handicraft design" and four value dimensions built. Proposed five dynamic thinking methods and five design strategies. Evaluation of Prototypes: Handicraft and cultural value had the highest scores (7.38 average), while material and innovative value had the lowest (6.51).
Cahyadi D, et al.2024	Indonesian rattan handmade crafts	SLR	Searched three databases;	N/A	Aesthetic factors are the main requirements for Indonesian wooden/rattan handicrafts. In the development of wicker packaging products, six aesthetic factors are applied: material, pattern, ethnicity/culture, shape, style, and color. The final decision of the buyer is often subjective, influenced by personal fashion preferences and actual needs.
Çetinkaya F,2019	Ceramic Painting	RCTs	n=15.	15	The increase in the average life satisfaction scale score was not statistically significant. Improved cognitive abilities and increased life satisfaction.
Liu W, et al.2024	Ceramic teapot design	Orthogonal experimental method, Eye tracking, questionnaire	9 samples	60	The subjects had the highest satisfaction with sample 8 (4.12 points) and the lowest satisfaction with sample 7 (2.57 points). The semantic evaluation of sample 8 tends to be warm, comfortable, and relaxed; Sample 7 tends to be hard, personalized, and difficult.
LEI QIAO, 2024	International Exchange of Tea Culture and Brand Design	questionnaire survey interview method	90	90	Interview records and case study analysis help to understand communication methods. The design process produced visual elements, illustrations based on the Kungfu tea ceremony, a brand logo incorporating bamboo elements ("Tea Life"), and a Teatime Management App.
Yang SC, et al.2021	Tea cup design	Questionnaire, fsQCA	Five different tea cups (A-E)	N/A	Tea cup design can affect users' taste perception, generating pleasure and happiness. The fsQCA analysis yielded a model of the relationship between explanatory variables.

(SEM: Structural Equation Modeling; NLP: Neuro-Linguistic Programming; SLR: Systematic Literature Review; RCTs: Randomized controlled trials; fsQCA: Fuzzy Set Qualitative Comparative Analysis)

terms of content, narrative structure, needs satisfaction, emotions, and product quality (Tuch, A. N. et al., 2013, April; Wang, Q. et al., 2023) (Figure2.3). Construct a product review usefulness prediction model to explore the impact of discrete positive and negative emotions in review content on the usefulness rating of reviews (Malik, M. S. I., & Hussain, A., 2017). Liu Wei and others aim to extract user needs for bamboo furniture through text mining. (Liu, W. et al., 2025).

Those previous related studies mainly focused on the following three aspects:

① Analyzed User-Generated Content (UGC) via sentiment analysis (e.g., ABSA)

② Focused on functional aspects (logistics/service) in many studies.

③ Used ML for classification/prediction on product-related texts.

Table 2.2 Research on the Relationship between E-commerce Products and Consumer Emotional Response

Ref	Research object	Method	Dataset	Participants	Research Results/Findings
Liu, C., & Xu, Y. (2021)	Products or services and emotions	ABSA method	7.72 million NLP clause records	N/A	A user-generated content sentiment analysis (ABSA) method was proposed and implemented. Seven main categories have been identified for sentiment analysis: product, logistics, price, brand, packaging, service, and event.
Yang, X. et al., 2023	Experiential products	Experimental study	Collected multi-channel physiological instrument data	38	Regardless of whether the background color is warm or cool, participants had more positive emotions towards product images in the model group compared to the non-model group. Regardless of the presence of models, participants prefer product images with warm toned backgrounds. Compared to modeling factors, warm tones have a more significant effect in stimulating positive emotions.
Semuel, H. et al.,2017	Internet user consumer group	Online questionnaires and fFGDs.	214 valid questionnaires	214 netizens and 35 business owners	User background does not affect purchase impression. Cultural background and website quality have a positive impact on purchase impression, with cultural experience having a stronger influence than website quality. The willingness to purchase has a positive impact on the call to action. The ability of the model to predict action calls is 51.58%.
Dai, J., Wang, T., & Wang, S. 2020	E-commerce products	machine learning methods	4000 sample titles, 35 product categories	N/A	The classification accuracy of gcForest reaches 92.38%, which is superior to RBF kernel SVM (86.88%), linear kernel SVM (89.73%), and CNN (86.86%). GCForest shows significant advantages in multi classification problems when dealing with multiple categories and small data volumes. The accuracy of major category classification is 99.79%, medium category 95.33%, and minor category 92.38%.
van Kuijk, J. et al.,2017	Consumer Electronics	Online comments and semi-structured interviews	Online consumer reviews; 35 availability issues	19 respondents	The framework identifies three main "driving factors" for usability: priority, user-centered design (UCD) capability, and design freedom. Usability issues often stem from a lack of design freedom. Early, less reliable knowledge is more valuable than later, highly deterministic knowledge.
Hong, W. et al.,2019	Consumer satisfaction	CNN；text analysis	15,000 online comments	N/A	Five identified logistics service elements: Responsiveness, integrity, reliability, convenience, and communication. Proportion of factors in comments: Reliability (38%), Communication (18%), Convenience (17%), Integrity (17%), Responsiveness (10%). Impact on Customer Satisfaction: Convenience, communication, reliability, and responsiveness had a significant positive impact on customer satisfaction.

(ABSA: Aspect-based sentiment analysis; NLP: Neuro-Linguistic Programming; FGDs: focus group discussions; RBF kernel: Radial Basis Function Kernel; SVM: Support Vector Machine; CNN: Convolutional Neural Network; GCForest: Multi-Grained Cascade Forest; UCD: user-centered design)

In summary, exploring the influencing factors of emotional tendencies in product reviews, analyzing product reviews and extracting keywords, summarizing the impact of emotional reviews, and subdividing positive and negative emotional factors are designed to help companies improve their review systems and win consumer trust. (Bharadwaj, L., 2023). There are limitations of product design feature research in E-commerce environment, and without comparing emotion-based design features.

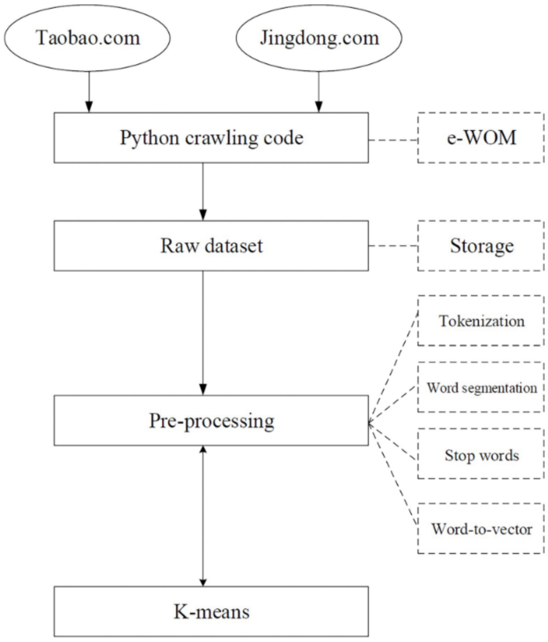


Figure 2.3 Research techniques used in this study (Wang, Q. et al., 2023).

2.3 Related research on emotional evaluation

2.3.1 Emotion evaluation

Emotional evaluation is the process of assessing an individual's emotional state, commonly used in fields such as psychology and product usability testing (Rodrigues, A. A., et al., 2025). The theoretical basis of emotional evaluation is the theory of emotional cognitive evaluation. Cognitive evaluation theory of emotion is a cognitive science term, also known as “cognitive evaluation theory” or “emotion evaluation excitement”. This theory suggests that emotions are generated by varying degrees of activation or arousal states, with strong emotions triggered by high arousal and mild emotions triggered by low arousal (Kılıç, B., & Aydın, S., 2022).

Emotional evaluation is a specific technical step in affective computing. Since 1997, when American computer science expert Picard introduced the concept of affective computing, it has been applied in various fields (Pei, G. et al.,2024). Pei, G., It mainly uses data such as facial expressions, speech intonation, physiological signals, etc., and uses machine learning or deep learning models to classify and evaluate emotional states (such as happiness, depression, etc.) (Chaudhari, A. et al., 2023).

In the PAD model, emotions are composed of three dimensions, including pleasure, arousal, and dominance (Xu, W. et al.,2025). Generally, physiological measurements (such as skin conductance response and heart rate) and psychological measurements (such as questionnaires) are used to measure emotions. Product usability testing can evaluate users' emotional responses while using the product through physiological and psychological measurements, optimizing the user experience (Wang, X., & Hu, B., 2024).

2.3.2 Emotional evaluation in product design

In the field of emotional design for craft products, an increasing number of scholars are investigating methods for quantifying and identifying consumers' emotional reactions during product purchase and use. Some scholars have investigated user perceptions, emotions, and behavioral responses to various craft products and services (Zhang et al., 2024; Kuo et al., 2020). Researchers have employed methods such as questionnaire surveys, experimental studies, eye tracking, and physiological signal measurements to collect and analyze user experience data (Kim et al., 2020; Malik & Hussain, 2017; Zhang et al., 2024), (Wang et al., 2024), (Li & Yuizono, 2022), Adilova, A., & Shamoi, P. (2024). and Kansei theory has been applied to analyze consumers' psychological needs and personal tastes in accepting art products (Yan et al., 2012), (Yan et al., 2011), (Huynh et al., 2010). Additionally, researchers explored consumers' emotional responses in virtual shopping environments (Maican et al., 2020). However, emotion state recognition relies primarily on probabilistic statistics and machine learning methods that involve labeled data for training and testing classifiers (Tian et al., 2018; Wu, J.et al., 2025). Regarding research on ceramic tea sets, some scholars constructed a hierarchical model of tea set product evaluation indicators, calculated the weight of each indicator, designed three tea set solutions, and selected and optimized the best solution (Zhao et al., 2024) (Figure 2.5). Although many studies have explored consumer emotions and preferences in product design, research on craft products and ceramic tea sets are still limited (Table 2.3).

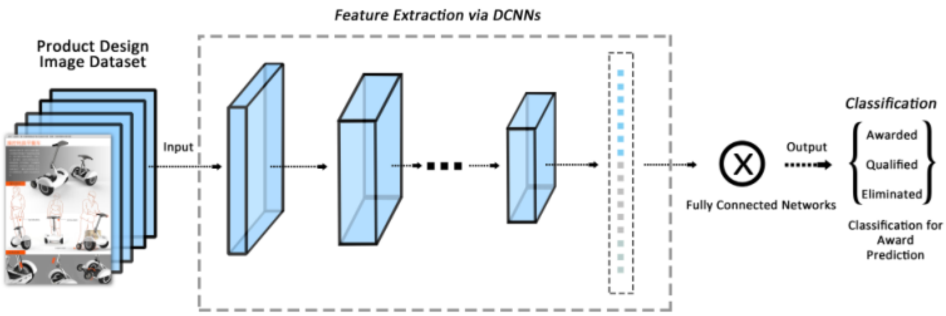


Figure 2.4 Illustration of design award prediction modeling procedure using deep neural networks architecture (Wu, J.et al., 2025)

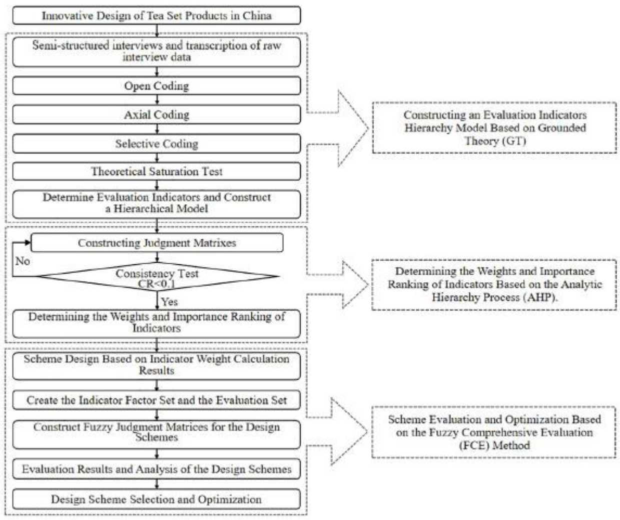


Figure 2.5 The design and comprehensive evaluation process of tea sets (Zhao et al., 2024).

Table 2.3 Relevant literature on emotional design features in the evaluation of products.

Ref.	Research Object	Method	Participants	Dataset	Research Results
Chu, C. H.et al., 2013	Product appearance design	Questionnaire	N/A	3D face scanning data	Design features of eyeglass frames can influence the user's perceived level of confidence, friendliness, and attractiveness.
Xiaohong, M. et al., 2023	Consumer emotions	Macro computing micro analysis stacking	2350	Physiological signal data	A predictor that can predict the MeanHR of physiological signals was built and trained on 1888 samples and tested on 472 samples to evaluate model performance.
Joosten, J. et al.,2024	GAI products	Likert scale, eye-tracking, facial coding analysis	1 Expert	ChatGPT-generated product ideas	ChatGPT outperformed the human product in terms of novelty and customer benefit, but there was no significant difference in feasibility.
Okamoto, S. et al., 2023	Images of different materials	Hierarchical structure model, structure equation modeling	29	FMD	The research provides computational methods for understanding the sensory and emotional experience of different materials, which can be used in product design and material selection.
Setchi, R. et al., 2019	Product form aesthetics	Semantic approach, DSO, TAP, direct observation	8	Product manual and description	This study provides a method for analyzing the quality of interactions and specific design features and develops a domain-specific image schema ontology.
Mai, S. et al.,2020	Multimodal emotional computing	LMFN, specific-modality, and cross-modality interaction modeling	N/A	CMU-MOSI、POM、IEMOCAP	A local restricted modality fusion network with a global perspective is proposed, and its effectiveness is verified on multiple datasets.

Table 2.3 Relevant literature on emotional design features in the evaluation of products (continued table).

Ref.	Research Object	Method	Participants	Dataset	Research Results
Moon, S. E. et al., 2021	Automotive design	EEG, eye-tracking, Likert scale, bimodal regression model	12	Car pictures	Physiological signals and eye-tracking data can be used to predict user perception of product design and provide new methods for automotive design evaluation.
Wang, Y., et al. (2024)	Product aesthetic quality	Correlation analysis, multivariate logistic regression model	110	70 product images (mugs and bookmarks)	A product aesthetic quality evaluation model was constructed and the feasibility of fNIRS data for product aesthetic quality evaluation was demonstrated.
Wu, J., et al. (2020)	Product design award prediction modeling	Image preprocessing; feature extraction, aesthetic quality classification, model evaluation	Training set: 75% of images; test set: 25% of images	10,003 product design images	The best classification accuracy achieved using the SEFL-ResNet method is 70.79%.
Li, X. et al.,2020	Image aesthetic quality computing	Upstream network; downstream network; feature fusion; model evaluation	N/A	AADB dataset AVA dataset	The classification accuracy of the proposed method on the two datasets reached 76.60% and 82.8250%, respectively. During the test phase, the proposed method only takes 0.02 s to test a 224×224 image.
Zhou, A. et al.,2021	Product design evaluation	Model evaluation: ACC, P, R, and F1 score, text analysis, deep CNN	Training set: 6750 Test set: 750	750 front-facing images of cars	The MeiduNet model achieved good performance on the aesthetic evaluation task, with an accuracy of 98.9%.
Zhao et al., 2024	Chinese tea sets	GT, AHP, FCE	10	Semi-structured interview transcripts	Constructed a hierarchical model of tea set product evaluation indicators; calculated the weight of each indicator; designed three tea set solutions, selected the best solution, and optimized it.
Li, Y. et al., 2024	Cultural and creative design trends	Descriptive statistics, LR, DT, and cluster analysis	Training set: 8,000 Test set: 2000	Approximately 10,000 pieces of data	The GAN model showed the highest accuracy (0.85) and recall (0.82) in predicting user aesthetic preferences, with an F1 score of 0.83 and a mean square error (MSE) of 0.04, achieving the best overall performance.
Wang, M. et al.,2021	Styling design of air purifiers	Morphological analysis. SD, FA, partial correlation analysis	89	67 samples, 19 design element categories	This study proposes a design method for a portable desktop air purifier based on emotion engineering.
Huynh, V. N. et al.,2010	Kutani porcelain	Goal-oriented decision analysis, OWA, SD	112	30 patterns of porcelain	A consumer-oriented traditional handicra evaluation model based on perceived da recommends products according to consum needs.
Bo, W. (2020)	Teacup shape	User survey, literature research, design practice	20	Survey data of 20 people	A new teapot design is proposed, which aims to shorten the psychological distance between people and promote emotional communication.
Homburg, C. et al.,2015	Product appearance design	Questionnaire, constructing a satisfaction model, MDS method, HCA	2544 reviews	2544 customer reviews	Companies can conduct multi-dimensional satisfaction surveys based on emotion engineering to make the survey results more accurate and easier to understand and make data mining more meaningful.
Malik & Hussain, 2017	Product reviews	Machine learning algorithms: NB, RDA, SVM, RF, PART, DNN.	32,434 reviews	32,434 reviews, 34 product categories	Positive emotion features are the best predictors when the individual category of features is considered. Furthermore, the hybrid set of features with positive emotion features produces the best predictive performance for the helpfulness of online reviews.
Yan, H.-B. et al.,2012	Kanazawa gold leaf	SD and linguistic variables	211	211	A Kansei evaluation model based on multi-attribute fuzzy target-oriented decision analysis and prioritized aggregation is proposed.

(GAI: Generative Artificial Intelligence; MeanHR: Mean Heart Rate; ChatGPT: Chat Generative Pre-Trained Transformer; FMD: Flickr Materials Database; TAP: Transformer Think Aloud Protocol; DSO: Domain-Specific Ontology; LMFN: locally confined modality fusion network; CMU-MOSI: Carnegie Mellon University Multimodal Opinion Sentiment Intensity; CMU-MOSEI: Carnegie Mellon University Multimodal Opinion Sentiment and Emotion Intensity; IEMOCAP: Interactive Emotional Dyadic Motion Capture Database; EEG: Electroencephalogram; fNIRS: Functional Near-Infrared Spectroscopy; SEFL-ResNet: Squeeze and Excitation – Focal Loss – ResNet; AADB: Aesthetics with attributes database; AVA: Aesthetic visual analysis; ACC: Accuracy; P: Precision; R: recall; CNN: Deep convolutional neural network; GT: Grounded theory; AHP: Analytical Hierarchy Process; FCE: Fuzzy comprehensive evaluation; DS: Descriptive statistics; LR: linear regression; DT: Decision trees; GAN: Generative Adversarial Network; MSE: mean square error; SD: Semantic Differential Method; FA: factor analysis; OWA: Ordered Weighted Averaging; MDS: The multi-dimensional scaling method; HCA: hierarchical cluster analysis; NB: Naïve Bayes; RDA: Regularized discriminant analysis; SVM: Support Vector Machine; RF: Random Forest; PART: Pruned C4.5 Decision trees; DNN: Deep Neural Network)

As shown in the table above, methods for assessing consumer emotions and preferences in product design often include questionnaires, sentiment analysis of online reviews, and multimodal methods, as well as the application of eye tracking and physiological data to measure consumer reactions to product appearance (such as tea sets and craft products). Researchers use tools such as quantitative theory, fuzzy mathematics, and behavioral science models to analyze consumer perceptions of craft product design, and then integrate these insights into craft product innovation and sustainable design, ultimately increasing the acceptance of craft product design.

However, it is worth noting that the application of machine learning in the design of handicrafts and ceramic tea sets still needs further exploration.

2.4 Research gap

From the statements of previous related research mentioned above, we can see that although the importance of emotional design has become a consensus, there are still some obvious deficiencies in the existing research on the emotional design of craft products.

1) The scope of the research is narrow, leading to insufficient universality of the conclusions.

Existing research often focuses on a single category of craftsmanship or a single cultural background, which limits the complexity that the research can cover. Furthermore, there is a lack of research on the differences in emotional responses (such as pleasure, arousal, and dominance) and their emotional mechanisms. Additionally, external validation of design evaluation models is rarely conducted.

2) The mechanism and mapping of "design features and emotional responses" are still unclear.

The correspondence between design features and emotional responses remains ambiguous. In particular, there is currently a lack of a clear "feature–emotion" mapping model to explain how the design features of specific craft products, such as ceramic pots, systematically influence specific emotional dimensions of users. Furthermore, this model requires more comprehensive and systematic empirical data support.

3) The transformation from "evaluation and interpretation" to "actionable design guidance" is insufficient, and external validation is rare.

This study built an emotional quality model, and evaluated new teapots. in additional, the design of craft products is shifting from being experience-driven to data-driven, yet the innovation in ceramic teapot design still heavily relies on designers' experience and intuition. Simultaneously, most empirical studies remain at the level of interpreting and assessing consumer emotions, lacking assessable and reusable workflows that can directly translate research findings into executable design decision-making recommendations.

4) In the e-commerce environment, there is limited exploration of design pathways based on consumers' emotional responses. Specifically, little research has been conducted on which design features of ceramic teapots can better evoke consumers' emotional responses in two-dimensional images versus physical products, and on the relationship between different emotional responses and the design features of emotional crafted products. Furthermore, there is a lack of research on how to build data-driven design decisions.

By addressing the aforementioned research gaps, this study not only deepens our understanding of emotional craft product design but also provides designers with specific recommendations for design decision-making.

Chapter 3
Methodology

3.1 Overview

Although the importance of emotional design has become a consensus, previous research on emotional design of craft products often only focuses on a single craft category or cultural background, weakening the complexity of the research process and the universality of research results. The mapping relationship between design features and emotional responses still has ambiguity. There is currently a lack of a clear "feature emotion" mapping model for how specific design features of ceramic teapots systematically and unpredictably affect users' specific emotional dimensions, which requires strengthening the support of systematic empirical data.

In terms of design practice, craft product design is transitioning from experience-driven to data-driven. At present, the design innovation of ceramic teapots largely relies on the personal experience and intuition of designers, and this model has uncertainty. In addition, most relevant empirical studies are still in the stage of interpreting and evaluating consumer emotional responses, so it is necessary to build an assessable workflow to translate research results into actionable design guidance.

Behind the top-selling lies a common emotional code among the masses. Why can some teapot designs surpass regions and cultures and become popular classics? Interpreting the emotional design features in these top-selling products not only helps designers accurately grasp the pulse of the ceramic teapot market but also promotes the development of emotional design in craft products.

This dissertation takes the top-selling Chinese and Japanese ceramic teapots as the research object, exploring the emotional design of craft products. By analyzing the design features of the top-selling Chinese and Japanese ceramic teapots, this dissertation reveals how they trigger different emotional responses from users. A predictive evaluation model based on empirical data, "Design Features Emotional Response," was constructed and externally validated. This method provides a solid foundation for emotional evaluation of innovative ceramic teapot designs, reducing errors caused by individual differences in consumer preferences and product perception attributes, and improving the accuracy of evaluation results. Upgrading of design practice from "experience driven" to "data and theory driven".

Based on the main research question of this dissertation (MRQ): How is emotional craft design produced based on the relationship between design features and emotional responses of ceramic teapots? This study collected five types of data: SAM scale data, SD questionnaire data of top-selling Chinese-Japanese ceramic teapots, ceramic teapot morphological feature data, facial emotion data, and online reviews data. After obtaining these five types of datasets (Figure 3.1), combined with three sub-research questions, SRQ1: Which design features of ceramic teapots are associated with users' perceived impressions? SRQ2: How is the emotional quality of ceramic teapots evaluated? SRQ3: What are the differences in ceramic teapot design features based on emotional responses elicited by online reviews versus those derived from emotional questionnaires? This study will process and analyze these data through the following three main steps, as shown in Figure 3.2.

Table 3.1. The datasets used in each chapter of the dissertation

Chapter of the dissertation	Physical feature data	SD questionnaire data	SAM scale data	Facial emotion data	Online reviews data
Chapter 4	√	√			
Chapter 5			√	√	
Chapter 6	√	√	√		√

Step 1: Morphological features and perceived impression analysis

Regarding SRQ1, based on the analysis of morphological and semantic differences (SD), build a mapping relationship between consumer perceived imagery and teapot design features. This was achieved through dummy variable multiple regression analysis, which provided information for the design of the new teapot.

Step 2: Model building and evaluation, as well as evaluation of the new ceramic teapots.

Regarding SRQ2, a facial emotion recognition classification model was developed using data from the Self-Assessment Manikin (SAM) questionnaire survey and facial emotion recognition data. Subsequently, the model was evaluated to ensure its accuracy and reliability. Regarding the external validation of the model, facial emotion data was collected from three newly designed teapots as a test set to validate the predictive model. This step ensures the universality and stability of the model. Thus, achieving the evaluation of the emotional quality of newly designed ceramic teapots.

Step 3: The influence of design features of ceramic teapots on emotional responses based on online reviews and emotional questionnaires.

Regarding SRQ3, a mixed method combining morphological analysis, SAM scale, semantic difference (SD) questionnaire, and text analysis was used to explore the key design features of ceramic teapots that affect consumer emotional responses through generalized linear mixed effects model (GLMM) analysis and generalized estimating equations (GEE) analysis. A theoretical model of "design features emotional response design decision-making" was constructed to analyze the impact of design features of ceramic teapots on consumer emotions in the e-commerce environment. And provided actionable guidance for designers in emotional design. The research framework diagram is shown in Figure 3.1.

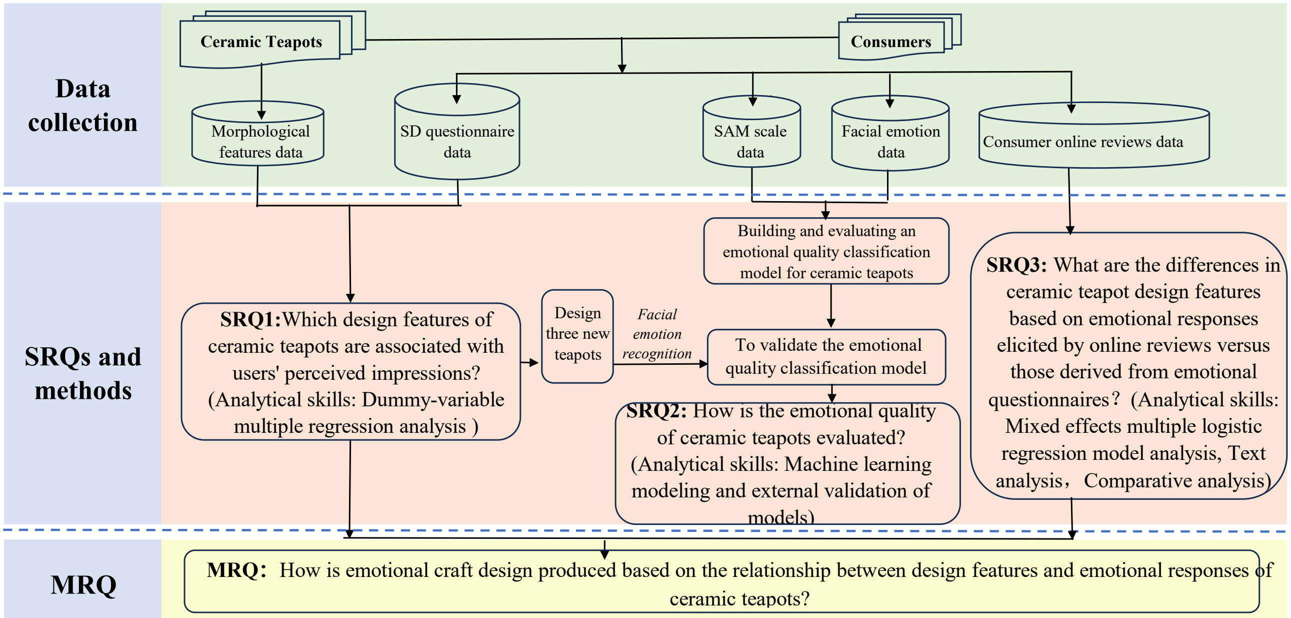


Figure 3.1 The research framework

3.2 Data collection

To ensure compliance with the scientific ethical norms, we sought research approval after developing a research plan. In accordance with the Regulations on the Conduct of Research Involving Human Subjects built by the Japan Advanced Institute of Science and Technology (JAIST), we submitted a human study proposal to the JAIST Research Ethics Committee and obtained approval (Ethics Review Number: 人 06-089; date: December 20, 2023-March 31, 2027). This study was conducted in accordance with the principles of the Declaration of Helsinki. In this study, the participants were only involved in questionnaire completion and facial photo collection. All participants were adults who participated voluntarily. Before the study, the participants were informed of the study objectives, the use of questionnaire survey data, the purpose of facial photo collection, and their rights as participants. All participants provided written informed consent, agreed to participate voluntarily, and pledged not to share the research data. Data were anonymized and stored on secure servers, and participants could withdraw at any time.

3.2.1 Sample selection

This dissertation takes two different categories of ceramic teapot products, Chinese and Japanese ceramic teapots, as research samples. However, my research objects did not include a comparison of the two cultures. Due to the few differences in emotional responses to Chinese and Japanese ceramic teapots, this study targeted the Chinese and Japanese ceramic teapots to increase the diversity of the sample.

Based on sales rankings, on December 30, 2023, we selected the top 10 top-selling Chinese and Japanese ceramic teapots, respectively, from JD.com, a famous online sales platform in China (https://www.jd.com/), resulting in a total of 20 samples. The retrieval keywords used were "JD Rankings - Chinese Ceramic Teapot Hot Sales List" for Chinese ceramic teapots and "JD Rankings - Japanese Ceramic Teapot Hot Sales List" for Japanese ceramic teapots. And then, I selected the top ten ceramic teapots, each with a total of 20 samples (10 Chinese and 10 Japanese) (Appendix A).

The reason why I chose 10 Chinese and 10 Japanese teapots from JD.com is that JD.com (also known as Jingdong) is one of the largest B2C (Business-to-Consumer) e-commerce platforms in China, ranking as the second-largest overall e-commerce company in the country after Alibaba's Tmall. It is widely recognized for its high-quality products and, most notably, its proprietary, fast, and reliable logistics network.

To enhance the accuracy of the experiment, the order in which participants browsed the ceramic teapot samples was randomized, as illustrated in Figure 3.2. About random arrangement: In the experiment, the playback order of the teapots was randomly assigned to control for sequential effects for each participant.

Figure 3.2 Twenty ceramic teapot samples.

During the data collection process, two participant groups were used in this study for different purposes.

In the adjective-screening stage, 30 participants were recruited to determine a set of 72 semantic adjectives for a ceramic teapot (Appendix C and Figure 3.3). This group includes design expert teachers (10 design teachers from the School of Art and Design, DPU) and undergraduate students (20 students from the School of Art and Design, DPU) (Male: female ratio 5:5, average age 21; Major:10 Product design/ 10 Art and design) (Appendix B. Participant information).

In the evaluation of the emotional quality stage, 60 Undergraduate students participated in the evaluation of all 20 teapot samples, including the SD questionnaire survey, SAM scale, and facial emotion recognition (Appendix B. Participant information).

3.2.2 Questionnaire production

To construct the perceived-image vocabulary for ceramic teapots, an initial pool of candidate adjectives was compiled from four sources: prior Kansei and emotional-design studies, and books and magazines related to ceramic and product design (Yan et al., 2012; Yan et al., 2011; Huynh et al., 2010; Zhao et al., 2024; Ho, A. G., & Siu, K.

W. M., 2012; Liu W et al., 2024; Yang SC et al., 2021). Online product descriptions and reviews, and preliminary descriptive terms encountered during pilot observation of ceramic teapot forms. These adjectives were intended to describe perceived impressions of form, decoration, texture, and usability.

After removing synonyms and approximate repeated expressions, 30 respondents evaluated a list of 72 words, including 10 design expert teachers and 20 undergraduate students from the School of Art and Design, DPU. They were asked to choose the word they thought best suited to describe the appearance of a ceramic teapot (Appendix C).

As shown in Table 6, the total score is>10, and each group score is⩾3. Therefore, "more than 10 votes" not only means obtaining approximately one-third of the agreement, but also implies that adjectives cannot only come from one group; they must receive support from different groups.

This study retained 16 adjectives that received 10 or more votes. The most representative adjectives are: Interesting=18; Colorful = 18; Delicate texture = 17; Low-key = 16; Modern = 15; Light = 15; Rich patterns = 14; Rounded = 14; Unbreakable = 14; Expensive = 14; Easy to use = 14; Regular shape = 13; Warm = 13; Concise = 12; Exquisite = 12; Glossy=11. Each retained adjective was then converted into a bipolar SD pair to form the formal 7-point SD questionnaire used in this study (Figure 3.3 and Table 3.2-3.3).

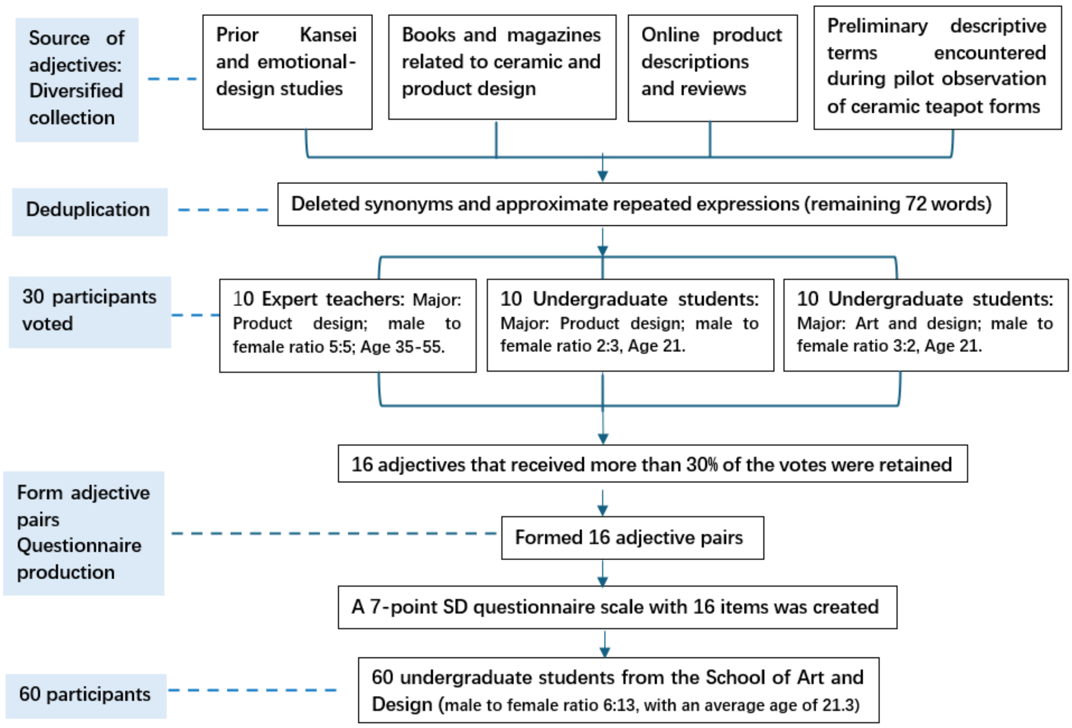


Figure 3.3. Construction of the SD adjective pairs.

Table 3.2. Score for selected adjectives.

Adjectives	Teachers N=10	Students Group1 (n=10)	Students Group2 (n=10)	Total	Adjectives	Teachers	Students Group1 (n=10)	Students Group2 (n=10)	Total
Safe	2	3	2	7	Bright	4	2	2	8
Practical	3	2	2	7	Lightweight	3	3	2	8
Rich patterns	4	6	4	14	Expensive	3	5	6	14
Metallic	2	1	1	4	Clean	4	3	2	9
Durable	2	4	1	7	Refreshing	2	2	2	6
Popular	3	5	1	9	Concise	5	4	3	12
Fashionable	4	2	2	8	Elegant	3	3	3	9
Interesting	7	5	6	18	Regular shape	4	4	5	13
Gorgeous	1	1	3	5	Unique	3	2	3	8
Fantastic	2	1	2	5	Exquisite	5	4	3	12
Graceful	4	3	2	9	Glossy	4	3	4	11
Classical	2	3	2	7	lovely	2	3	3	8
Serene	2	1	2	5	Free	2	1	3	6
Still	1	4	2	7	Friendly	1	2	2	5
Pretty	2	6	1	9	Plain	3	2	4	9
Conventional	2	5	1	8	Lustrous	2	1	2	5
Rounded	7	3	4	14	Soft	3	2	2	7
Streamlined	3	1	2	6	Having quality	2	1	2	5
Pure	2	3	2	7	Advanced	1	1	2	4
Simple	3	3	2	8	Delicate texture	5	5	7	17
Unbreakable	4	5	5	14	Low-key	4	6	6	16
Bright	2	3	2	7	Fresh	2	2	2	6
Rustic	1	1	2	4	Distinctive	3	2	2	7
Transpicuous	1	2	1	4	Cold	3	3	3	9
Neutral	2	3	2	7	Light	5	4	6	15
Colorful	7	6	5	18	Prosaic	2	2	2	6
Artificial	3	4	2	9	Easy to use	4	5	5	14
Monotonous	2	2	2	6	Rhythmic	2	2	2	6
Modern	4	5	6	15	Dynamic	2	2	1	5
Smooth	3	3	2	8	Warm	4	4	5	13
Solemn	1	1	2	4	Flowery	1	1	3	5
Formal	2	2	2	6	Moist	1	2	2	5
Reserved	1	2	2	5	Attractive	2	1	3	6
Luxurious	3	1	4	8	Happy	1	2	3	6
Gentle	2	2	4	8	Novel	3	2	2	7
Cultural	2	2	1	5	Natural	2	1	3	6

Table 3.3. Selected 16 adjectives.

Adjectives	Teachers N=10	Students Group1 (n=10)	Students Group2 (n=10)	Total
Rich patterns	4	6	4	14
Interesting	7	5	6	18
Rounded	7	3	4	14
Unbreakable	4	5	5	14
Colorful	7	6	5	18
Modern	4	5	6	15
Expensive	3	5	6	14
Concise	5	4	3	12
Regular shape	4	4	5	13
Exquisite	5	4	3	12
Glossy	4	3	4	11
Delicate texture	5	5	7	17
Low-key	4	6	6	16
Light	5	4	6	15
Easy to use	4	5	5	14
Warm	4	4	5	13

In the process of using the semantic differential method, the questionnaire was designed based on 16 groups of positive and negative adjective pairs. On this basis, a 7-level evaluation scale was set up, including: completely (-3), very (-2), average (-1), neutral (0), average (1), very (2), and completely (3). (Table 3.4).

Table 3.4 Questionnaire on consumer perception of Chinese and Japanese ceramic teapots.

X_n	Left adj. word	V_n^{+3}	V_n^{+2}	V_n^{+1}	V_n^{0}	V_n^{-1}	V_n^{-2}	V_n^{-3}	Right Adj. word
		完全地（Entirely）	非常地（Very）	相当地（Fairly）	中立地（Neutral）	相当地（Fairly）	非常地（Very）	完全地（Entirely）	
X_1	彩色的（Colorful）	☐	☐	☐	☐	☐	☐	☐	单色的（Monochromatic）
X_2	图案丰富的（Rich patterns）	☐	☐	☐	☐	☐	☐	☐	图案简单的（Simple patterns）
X_3	有光泽的（Glossy）	☐	☐	☐	☐	☐	☐	☐	无光泽的（lackluster）
X_4	质地细腻的（Delicate texture）	☐	☐	☐	☐	☐	☐	☐	质地粗糙的（Rough texture）
X_5	形状规则的（Regular shape）	☐	☐	☐	☐	☐	☐	☐	形状不规则的（Irregular shape）
X_6	现代的（Modern）	☐	☐	☐	☐	☐	☐	☐	传统的（Traditional）
X_7	有趣味的（Interesting）	☐	☐	☐	☐	☐	☐	☐	严肃的（Serious）
X_8	优美的（Graceful）	☐	☐	☐	☐	☐	☐	☐	丑陋的（Ugly）
X_9	低调的（Low-key）	☐	☐	☐	☐	☐	☐	☐	夸张的（Exaggerated）
X_10	轻盈的（Light）	☐	☐	☐	☐	☐	☐	☐	厚重的（Heavy）
X_{11}	简洁的（Concise）	☐	☐	☐	☐	☐	☐	☐	复杂的（Complex）
X_12	温暖的（Warm）	☐	☐	☐	☐	☐	☐	☐	冷淡的（Cold）
X_13	圆润的（Rounded）	☐	☐	☐	☐	☐	☐	☐	坚锐的（Hard）
X_{14}	昂贵的（Expensive）	☐	☐	☐	☐	☐	☐	☐	廉价的（Cheap）
X_15	使用方便的（Easy to use）	☐	☐	☐	☐	☐	☐	☐	使用不方便的（Inconvenient to use）
X_16	不易碎的（Unbreakable）	☐	☐	☐	☐	☐	☐	☐	易碎的（Fragile）

3.2.3 The process of data collection

1) Collect experimental data and questionnaire data.

The experiment involved 60 randomly selected students, with an average age of 21.3 years. The experiment was conducted in a controlled laboratory environment to ensure minimal disturbances. Each participant was seated at a table, and a photograph of a ceramic teapot was displayed on a computer screen every 3 s, with each photograph remaining visible for 5 s. In the middle of the 5 s interval, a high-definition camera (Logitech C930) (Figure 3.4) captured the participant's facial expressions. Participants viewed all 20 teapot photos in this manner and subsequently completed the SAM scale and the SD questionnaire (Table 3.4), based on the order in which the photos were displayed. Through this process (Figure 3.5), we collected 1,200 facial photos (Figure 3.6) and obtained data on participants' emotional valence, arousal, and SD scale responses for each ceramic teapot.

Figure 3.4 A high-definition camera (Logitech C930).

Figure 3.5 Experimental data acquisition.

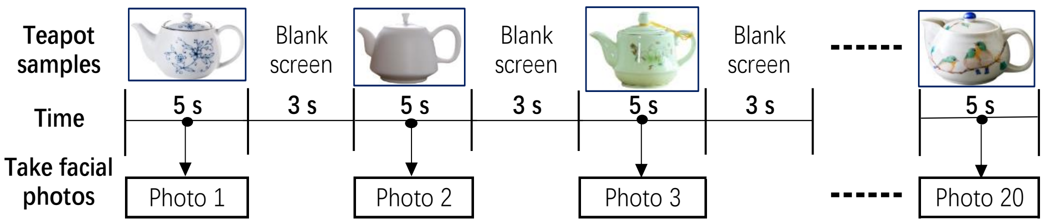


Figure 3.6 Display process of ceramic teapot sample images.

Figure 3.7 Sixty facial photos of participants.

2) Crawl consumer text comments data

The author used the Octoparse collector to crawl consumer online comment data from 20 selected samples of Chinese and Japanese ceramic teapots on the well-known JD.com e-commerce platform in China (refer to Appendix D, E, and F), with a total of 1791 pieces of data.

Figure 3.8 Crawl sample screenshot.

3.3 Data Analysis Methods

3.3.1 Semantic differential method

The semantic differential method is a psychological measurement tool used to evaluate user's attitudes toward specific concepts, brands, products, or services (Wang, J.et al.,2025). It measures participants' feelings in different dimensions through a set of adjective pairs. Each adjective pair represents a dimension, such as "like-dislike", or "good-bad". Participants need to choose a position between these adjective pairs to reflect their attitude. In this dissertation, factor analysis is used to extract common factors, combined with the three-level theory model of emotional design, to provide data support for designing new ceramic teapots.

3.3.2 Morphological analysis

Morphological analysis is a systematic design method developed by Swiss psychologist and educator Franz Zacharias von Ziegler. This method decomposes complex problems into multiple dimensions, defines different variables on each dimension, and then combines these variables to generate multiple possible design solutions (Butt, M.,2025). Application steps: 1) Define the problem: Clarify the goals and constraints of product design; 2) Determine dimensions: Identify various dimensions related to the problem (such as material, shape, color, function, etc.); 3) Define variables: Define possible variable options on each dimension; 4) Building a matrix: Create a matrix where rows represent different dimensions and a list represents variables on each dimension; 5) Combination scheme: Generate multiple design schemes based on the combinations in the matrix; 6) Evaluation plan: Evaluate the generated plan and select the optimal plan. This dissertation uses morphological analysis to extract the main characteristic lines of ceramic teapots, defines variables, and encodes them to provide data support for exploring the mapping relationship between the morphological features of ceramic teapots and perceived impressions.

3.3.3 Facial emotion recognition

Facial emotion recognition is a technology in the fields of computer vision and artificial intelligence, aimed at identifying an individual's emotional state by analyzing facial expressions (Ballesteros, J. A.et al.,2024). It is usually based on machine learning algorithms, which locate and analyze facial feature points to determine the emotional categories of people, such as happiness, sadness, anger, etc. This technology is widely used in fields such as security monitoring, marketing, and mental health assessment (Karizat, N.et al.,2024). In this dissertation, machine learning methods were used to achieve good recognition and prediction performance of the model.

3.3.4 Self-Assessment Manikin (SAM)

The Self-Assessment Manikin Scale (SAM) is a nonverbal tool used to measure an individual's emotional responses, particularly in human-computer interaction, product design, and user experience research. (Wang, J.et al.,2024)

This scale was developed by Dr. John A. Langley and colleagues (Lang, 1980; Bradley & Lang, 1994), using facial and body images to assess the three dimensions of emotion:

1)Pleasure: measures an individual's level of liking for a certain experience.

2)Arousal: measures whether an experience makes an individual feel excited or calm.

3)Dominance: Measuring an individual's sense of control in a specific context (Gonzalez, A., & Matias, J. N.,2025).

The questionnaire used in this dissertation was not the full original three-dimensional SAM. This study used an adapted SAM format including two dimensions: valence and arousal. The dominance dimension was not used because the present experiment focused on participants' immediate emotional assessment of static ceramic teapot images. In this dissertation, the SAM dataset and facial emotion recognition dataset are used to build an emotion quality evaluation model. The following figure shows the Self-Assessment Manikin and discrete emotion questionnaire.

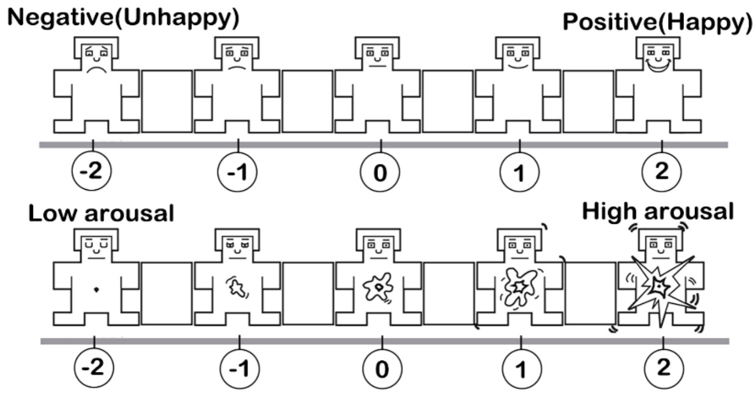


Figure 3.9 Self-Assessment Manikin and discrete emotion questionnaire

(Lang, 1980; Bradley & Lang, 1994)

3.3.5 Text analysis

Text analysis is a widely used research method in the fields of humanities and social sciences (Thanajirawat, Z., & Chuea-nongthon, C., 2022), (Preeti, D., 2024), which systematically and objectively quantifies or qualitatively analyzes text (including written text, images, symbols, audio/video transcription content, etc.) to reveal the underlying meanings, structural patterns, ideologies, or social contexts hidden in the text. Among them, the content analysis method leans towards quantitative analysis. By categorizing text content into meaningful categories and counting their frequency of occurrence, the clear features and trends of the content can be described. (Krippendorff, K. 2018).

This dissertation extracts meaningful information from unstructured text data, analyzes the design features of ceramic teapots that affect consumers through text data preprocessing, feature extraction, modeling, and evaluation, and proposes design strategies for designers' reference.

3.3.6 Generalized regression analysis

1)The generalized estimating equations (GEE)

The Generalized Estimating Equations (GEE) method is a statistical approach for analyzing longitudinal or clustered data where observations within the same group (e.g., repeated measurements from a single subject) may be correlated (Huang, F. L. 2022). Unlike mixed-effects models, GEE focuses on estimating population-averaged effects (marginal models) rather than subject-specific effects. Its main characteristics are as follows: Handles non-normal data: Binary (logit link), count (log link), continuous (identity link).

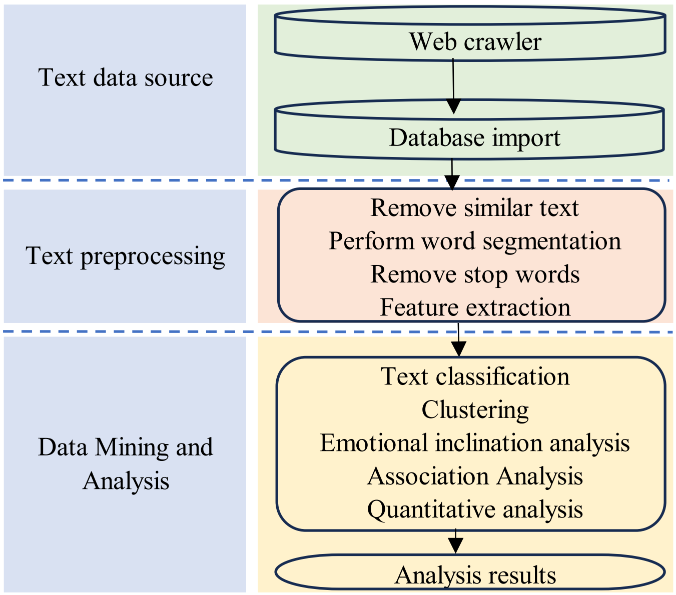


Figure 3.10 General Processing of Text Mining.

Mathematical Formulation:

The GEE model is specified as:

$$g(E[y_{ij}]) = X_{ij}^{T}\beta$$

y_{ij}: Response for the i-th cluster (e.g., patient) at the j-th time point.

g (·): Link function (e.g., logit, log, identity).

X_{ij}: Covariate vector.

β: Fixed-effect coefficients.

Variance–covariance structure:

$$Var(Y_i) = \varphi A_i^{1/2} R(\alpha) A_i^{1/2}$$

A_i: Diagonal matrix with Var(y_{ij}).

R(α): Working correlation matrix (e.g., exchangeable, AR (1)).

φ: Dispersion parameter.

2) The generalized linear mixed effects model (GLMM)

The Generalized Linear Mixed Effects Model (GLMM) is an extension of the Generalized Linear Model (GLM) that incorporates random effects to account for hierarchical or clustered data structures (Stroup, W. W.et al.,2024), (Loan, C. M.2024), (Ragni, A.et al., 2023). It is used when: The response variable is non-normal (e.g., binary, count, ordinal). Observations are correlated within groups (e.g., repeated measures, multilevel data). GLMM combines: Fixed effects: Population-level predictors. Random effects: Group-specific variations.

Mathematical Formulation:

The GLMM is defined as:

$$g(E[y_{ij} \mid b_i]) = X_{ij}^T \beta + Z_{ij}^T b_i$$

y_{ij}: Response for the i-th group (e.g., subject) and j-th observation.

g (·): Link function (e.g., logit for binary data, log for Poisson).

X_{ij}: Fixed-effect design matrix.

β: Fixed-effect coefficients.

Z_{ij}: Random-effect design matrix.

b_i: Random effects (b_i ~ N (0, G)).

G: Covariance matrix of random effects.

This dissertation applies generalized regression analysis to analyze the correlation between the SAM values collected by participants before purchasing ceramic teapots, the emotional values of online consumer reviews after purchasing, and the perception and morphological characteristics of ceramic teapots. Due to the group effect between the independent and dependent variables, where each participant evaluates all teapots and multiple consumers evaluate the same teapot, the results may involve grouping and repeated measurements. Therefore, the generalized linear mixed effects model (GLMM) and generalized estimating equations (GEE) are used for analysis, both of which are suitable for statistical methods for handling non normal distributions and repeated measurement data.

Meanwhile, when the independent variable is the average feature score of each teapot obtained through SD questionnaire data analysis (continuous variable), GLMM analysis is used; When the independent variable is the characteristic code (categorical variable) of each ceramic teapot obtained through morphological analysis, GEE is used for analysis. Through generalized regression analysis, the key design features of ceramic teapots that influence consumer emotional responses were identified.

3.4 Summary

This chapter introduces the research framework, data collection, and research methods of this dissertation. The author selected the top ten Chinese ceramic teapots and the top ten Japanese ceramic teapots from the well-known online shopping center JD.com in China, for a total of 20 ceramic teapots. Five types of datasets were collected, including SAM scale data (questionnaire), perception and evaluation data of Chinese and Japanese ceramic teapots (questionnaire), feature data of ceramic teapots (morphological analysis method), facial emotion recognition data (facial emotion recognition technology), and online user comment data (text analysis method). These data are used to analyze the mapping relationship between the morphological characteristics of ceramic teapots and consumer perceived impressions, construct emotional quality models, and explore the relationship between consumer emotional responses and ceramic teapot design features. In this chapter, we introduced six data processing and analysis techniques to achieve the research objectives mentioned above.

Chapter 4

Emotional design features of ceramic teapots from perceived impressions

4.1 Introduction

In recent years, emotional design has become an important dimension in product aesthetics and user emotional response research. In addition to functional efficiency and material craftsmanship, successful craft product design increasingly relies on the ability to evoke emotions and build emotional connections between objects and consumer. Ceramic teapot is a craft product that combines practical functionality and aesthetic value. As a traditional utensil closely related to daily life and cultural rituals, it carries rich emotional values and cultural symbols, and is an ideal carrier for exploring emotional design features.

This chapter takes the top-selling Chinese and Japanese ceramic teapot as the research object, aiming to answer SRQ1 (refer to Figure 4.1). By analyzing the morphology of the top-selling Chinese and Japanese ceramic teapots, extract the main morphological features that affect teapot cognition. At the same time, factor analysis is used to summarize the design features that affect the cognitive image of ceramic teapots.

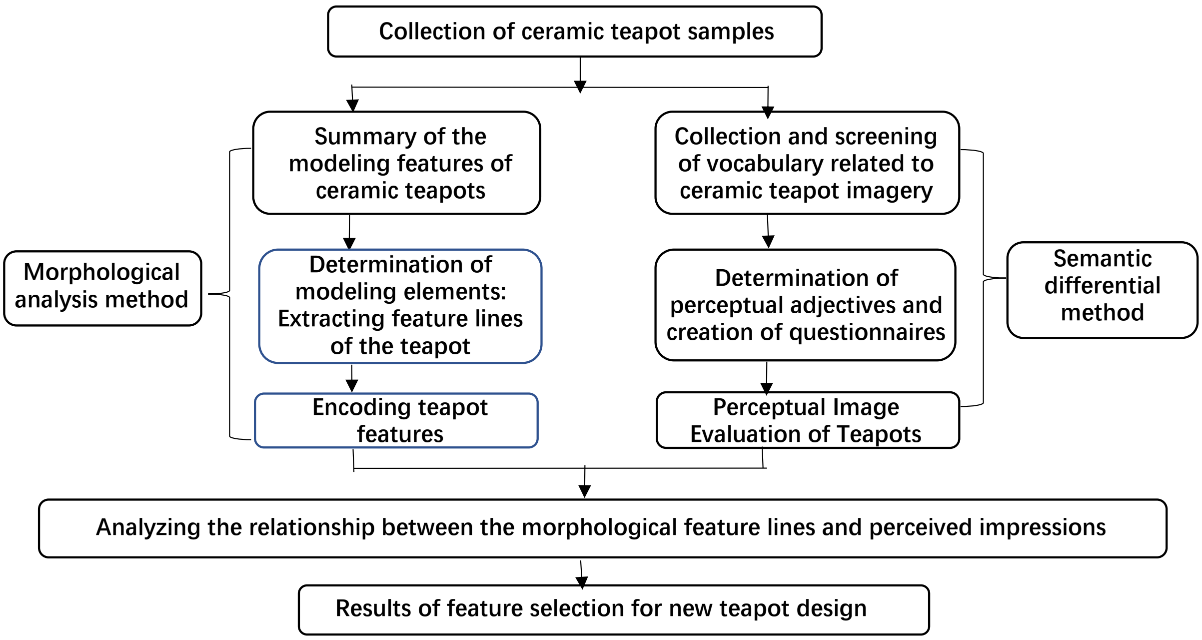


Figure 4.1 Chapter 4 research flowchart

Through dummy variable multiple regression analysis, this chapter explores the mapping relationship between design features and consumer impressions, revealing which design features can most stimulate consumers' positive emotional responses, and how these features affect young consumers' emotional preferences for teapots, providing design basis for the emotional design of new ceramic teapots.

4.2 Methods

4.2.1 Ceramic teapot morphology analysis

4.2.1.1 Induction of emotional design features of ceramic teapots

According to morphological analysis methods and cognitive psychology theory, people's perception of morphological imagery stems primarily from the recognition of morphological features. Therefore, extracting the main morphological features of ceramic teapots can provide valuable insights into the design of new ceramic teapots. Based on morphological analysis, each product is considered an independent entity composed of distinct parts, and this principle applies to ceramic teapots as well (Sunder M, V. et al.,2019). Ceramic teapots are comprised of multiple components, each of which exhibits unique morphological characteristics. Consequently, the overall shape of a teapot can be decomposed into various independent physical features, that is, the teapot shape is an organic combination of numerous independent morphological features. We decomposed ceramic teapots of different shapes into their constituent elements to form a set of teapot elements (Figure 4.2). For instance, Teapot O_1 is divided into morphological features O_1–O_n, and each feature O_1–O_n can be further subdivided into morphological elements F_1–F_n. These elements enable the arrangement and combination of the ceramic teapot shapes, resulting in various teapot designs. Among these, the subdivided elements E_1–E_n represent the smallest morphological units that could not be further divided in this study. Designers can arrange and combine these morphological features based on their experiences and methodologies to create unique and distinctive teapot shapes, thereby conveying different imagery styles to consumers.

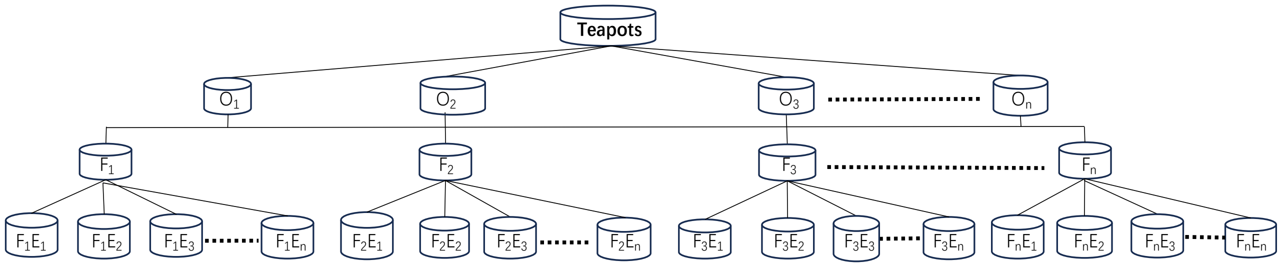


Figure 4.2 Feature element set of ceramic teapots.

Ceramic teapots come in various shapes, and from a formal perspective, they are all composed of the most basic elements such as points, lines, surfaces, bodies, and spaces. From the components of a teapot, it includes the body, handle, spout, lid, and other parts. In the emotional design of ceramic teapots, the front and top view characteristic lines mainly include the contour lines of the spout, body, handle, and lid (as shown in Figure 4.3-4.6). It is very important to understand the composition rules of these constituent elements, which can guide us to better design ceramic teapots.

Because the external components of ceramic teapots mainly consist of a spout, body, lid, handle, etc., these elements determine the overall shape of the teapot. The spout, body, lid, handle, and other components of a ceramic teapot are composed of various contour lines and shapes. The combination of different contour lines and shapes forms different styles of teapots. Therefore, this article mainly extracts the characteristic lines of the ceramic teapot from the front and top views and analyzes the design form elements.

Figure 4.3 Experiment sample O1

Figure 4.4 Composition of ceramic teapot front view.

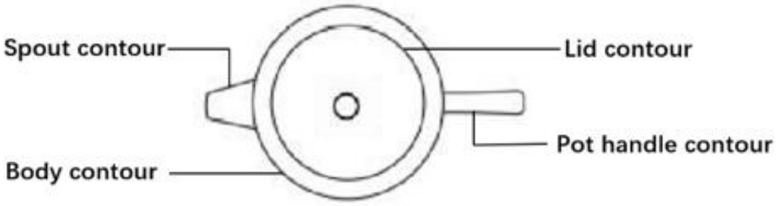
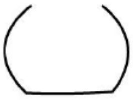
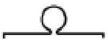
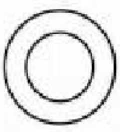
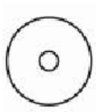
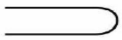


Figure 4.5 Experiment sample O6

Figure 4.6 Composition of ceramic teapot front view

Table 4.1 Front view feature lines and top view feature lines of ceramic teapot sample 6.

Sample front view				
	Teapot body	Teapot lid	Teapot spout	Teapot handle
Front view feature line				
	Curve+straight line	Curve+Line	Curve+straight line	Arc
Sample top view				
	Teapot body	Teapot lid	Teapot spout	Teapot handle
Top view feature line				
	Concentric circle	circular	Curve+straight line	Curve+straight line

As shown in Table 4.1, the top and front view spout contours, top and front view pot body shapes, top and front view pot handle contours, and top and front view pot lid contours are the key feature lines for recognizing the top view and front view of ceramic teapots. For example, by using morphological analysis methods to decompose the top view characteristic lines of ceramic teapots, the decomposed elements can form four different combinations, among which combination two and combination three are closest to the prototype perception of the top of the teapot (as shown in Figure 4.7-4.8). Therefore, it can be seen that the top view spout contour line, top view pot body shape, top view pot handle contour line, and top view pot lid contour line are the most important feature lines affecting the top view of ceramic teapots.

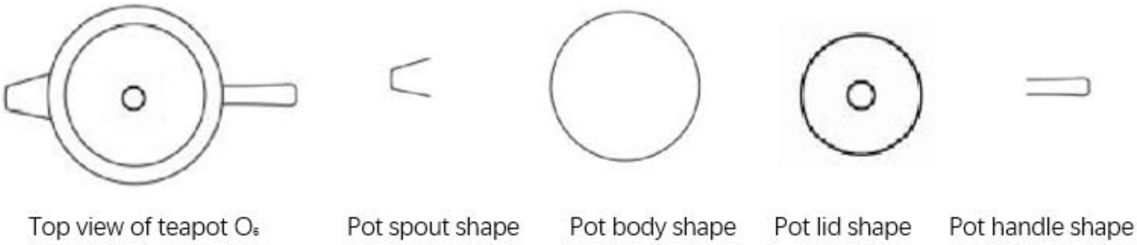


Figure 4.7 Top view feature lines of O_6 ceramic teapot's spout, body, lid, and handle.

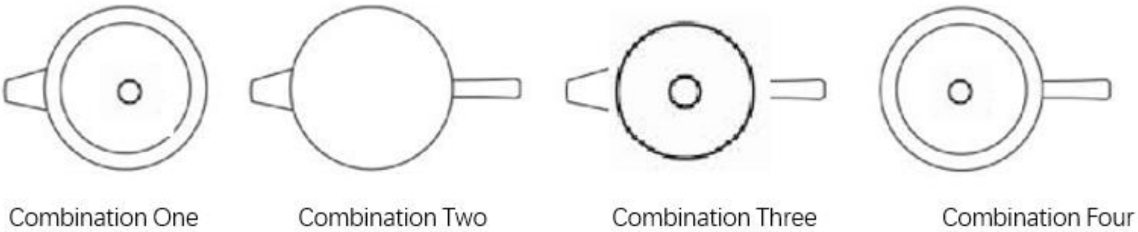


Figure 4.8 Several possible combinations of top view elements.

Extract the characteristic lines of the ceramic teapot from the front and top views as follows. the author extracted the front view and top view features of ceramic teapot samples. The following Tables show the front view and top view feature lines of the ceramic teapot's spout, body, lid, and handle (See Appendix A).

4.2.1.2 Analysis of features of ceramic teapot

By analyzing, refining, and summarizing the morphological elements of ceramic teapots, a table of morphological elements of ceramic teapots is summarized. Based on the representative ceramic teapot samples, combined with the ceramic teapot morphological element features extracted from the above tables (See Appendix A), the morphological elements of 20 representative ceramic teapot samples were coded A~H to form a ceramic teapot feature analysis table (as shown in Table 4.2) to facilitate coding.

The categories under each extracted morphological element feature are represented by numbers 1, 2, 3, and 4. For example, the top view of the pot handle outline is B, and the four types of its subordinate categories are represented by B1(Straight line +curve), B2 (Arc+ Straight line), B3 (Straight line), and B4(no handle).

Table 4.2 Ceramic teapot feature analysis.

	Design feature classification			Extract feature lines
Features of ceramic teapots	**Form (A-H)**	**Top view contour line (A-D)**	Body (A)	1.Circular+Straight line +Curve
				2. Circular
			Handle (B)	1. Straight line +Curve
				2.Arc+Straight line
				3. Straight line
				4.No handle
			Lid (C)	1. Circular
				2.Circular+Curve
				3.Circular+Straight line +Curve
			Spout (D)	1. Straight line +Curve
				2. Curve
		Front view contour line (E-H)	Body (E)	1.Arc+Straight line
				2. Curve
				3. Straight line
				4. Hyperbola +Straight line
			Handle (F)	1.Curve+Straight line
				2. Arc
				3. Curve + Arc
				4. No handle
			Lid (G)	1.Arc+Straight line
				2. Straight line +Curve
				3. Straight line
			Spout (H)	1. Curve
				2.Curve+Straight line
				3. Straight line

4.2.1.3 Quantitative table of morphological design elements for the ceramic teapot

To quantify the morphological design elements of the ceramic teapot samples, a binary encoding system was used: "1" indicates the presence of a category in a teapot, and "0" indicates its absence (Table 4.3). For example, the top-view contour line of the teapot handle for the first sample is B1 (Straight line + Curve) and its quantization encoding is B1=1, B2=0, B3=0, and B4=0. Similarly, the top-view contour line of the teapot body is A2 (Circular), and its quantization encoding is A1=0 and A2=1. The remaining contour lines were quantified using the same method, completing quantitative coding of the morphological elements for all 20 ceramic teapot samples (Table 4.4).

Table 4.3 Encoding table for design features of 20 ceramic teapot samples.

Ceramic Tea Pot Samples	Top view of ceramic teapot feature lines				Front view of ceramic teapot feature lines			
	Body	Handle	Lid	Spout	Body	Handle	Lid	Spout
Number	A	B	C	D	E	F	G	H
1	A2	B1	C1	D2	E1	F2	G1	H2
2	A2	B1	C1	D1	E3	F2	G2	H2
3	A2	B1	C1	D2	E4	F4	G1	H1
4	A2	B2	C1	D2	E1	F3	G1	H2
5	A1	B3	C1	D2	E2	F1	G1	H3
6	A2	B1	C1	D2	E1	F1	G1	H3
7	A2	B1	C2	D1	E4	F3	G1	H2
8	A2	B1	C1	D2	E1	F4	G1	H1
9	A2	B2	C1	D1	E1	F2	G1	H2
10	A1	B4	C2	D1	E2	F3	G2	H1
11	A2	B2	C1	D2	E1	F2	G1	H1
12	A2	B2	C1	D2	E1	F2	G1	H1
13	A2	B1	C1	D2	E1	F2	G1	H1
14	A1	B3	C3	D1	E1	F1	G1	H1
15	A2	B2	C1	D1	E1	F1	G1	H3
16	A2	B1	C1	D2	E1	F1	G1	H2
17	A2	B4	C1	D2	E1	F1	G3	H3
18	A2	B2	C1	D1	E3	F1	G1	H3
19	A2	B1	C1	D1	E1	F3	G1	H1
20	A2	B3	C1	D1	E1	F1	G1	H1

Table 4.4 Quantitative table of the design feature of 20 ceramic teapot samples

Ceramic Tea Pot Samples	Top view of ceramic teapot outline											Front view of ceramic teapot outline													
	Body		Handle				Lid			Spout		Body				Handle				Lid			Spout		
Number	A	A	B	B	B	B	C	C	C	D	D	E	E	E	E	F	F	F	F	G	G	G	H	H	H
	1	2	1	2	3	4	1	2	3	1	2	1	2	3	4	1	2	3	4	1	2	3	1	2	3
1	0	1	1	0	0	0	1	0	0	0	1	1	0	0	0	0	1	0	0	1	0	0	0	1	0
2	0	1	1	0	0	0	1	0	0	1	0	0	0	1	0	0	1	0	0	0	1	0	0	1	0
3	0	1	1	0	0	0	1	0	0	0	1	0	0	0	1	0	0	0	1	1	0	0	1	0	0
4	0	1	0	1	0	0	1	0	0	0	1	1	0	0	0	0	0	1	0	1	0	0	0	1	0
5	1	0	0	0	1	0	1	0	0	0	1	0	1	0	0	1	0	0	0	1	0	0	0	0	1
6	0	1	1	0	0	0	1	0	0	0	1	1	0	0	0	1	0	0	0	1	0	0	0	0	1
7	0	1	1	0	0	0	0	1	0	1	0	0	0	0	1	0	0	1	0	1	0	0	0	1	0
8	0	1	1	0	0	0	1	0	0	0	1	1	0	0	0	0	0	0	1	1	0	0	1	0	0
9	0	1	0	1	0	0	1	0	0	1	0	1	0	0	0	0	1	0	0	1	0	0	0	1	0
10	1	0	0	0	0	1	0	1	0	1	0	0	1	0	0	0	0	1	0	0	1	0	1	0	0
11	0	1	0	1	0	0	1	0	0	0	1	1	0	0	0	0	1	0	0	1	0	0	1	0	0
12	0	1	0	1	0	0	1	0	0	0	1	1	0	0	0	0	1	0	0	1	0	0	1	0	0
13	0	1	1	0	0	0	1	0	0	0	1	1	0	0	0	0	1	0	0	1	0	0	1	0	0
14	1	0	0	0	1	0	0	0	1	1	0	1	0	0	0	1	0	0	0	1	0	0	1	0	0
15	0	1	0	1	0	0	1	0	0	1	0	1	0	0	0	1	0	0	0	1	0	0	0	0	1
16	0	1	1	0	0	0	1	0	0	0	1	1	0	0	0	1	0	0	0	1	0	0	0	1	0
17	0	1	0	0	0	1	1	0	0	0	1	1	0	0	0	1	0	0	0	0	0	1	0	0	1
18	0	1	0	1	0	0	1	0	0	1	0	0	0	1	0	1	0	0	0	1	0	0	0	0	1
19	0	1	1	0	0	0	1	0	0	1	0	1	0	0	0	0	0	1	0	1	0	0	1	0	0
20	0	1	0	0	1	0	1	0	0	1	0	1	0	0	0	1	0	0	0	1	0	0	1	0	0

4.2.2 Factor analysis: SD questionnaire data processing

4.2.3.1 Validity analysis and reliability analysis

We inputted 60 valid questionnaire data into SPSSAU software and conducted a factor analysis on 16 Perceived adjectives. The results obtained through reliability and validity analysis showed that the Reliability Coefficient Value is 0.705 (see Table 4.5), which is greater than 0.7, indicating that the reliability quality of the research data is very good. The KMO value is 0.824 (see Table 4.6), which is greater than 0.6 and meets the requirements of factor analysis. The data can be used for factor analysis research. Bartlett's test (P value=0.000<0.05) indicates that this analysis is effective.

Table 4.5 Cronbach reliability analysis.

Perceived impression adjectives	Correction item-total correlation (CITC)	Items that have been deleted α coefficient	Cronbach α coefficient
Colorful/Monochromatic	-0.022	0.76	0.705
Rich in patterns/Simple patterns	0.019	0.759	
Glossy/Lackluster	0.51	0.67	
Delicate texture/Rough	0.786	0.638	
Regular shape/Irregular shape	0.604	0.66	
Modern/Traditional	0.442	0.681	
Interesting/Serious	0.555	0.67	
graceful/Ugly	0.699	0.654	
Low-key/Exaggerated	0.149	0.707	
Light/Heavy	0.673	0.651	
Concise/Complex	0.035	0.722	
Warm/Cold	0.642	0.669	
Rounded/Hard	0.624	0.659	
Expensive/Cheap	0.288	0.695	
Easy to use/Inconvenient to use	0.381	0.688	
Unbreakable/Fragile	-0.366	0.742	

Standardized Cronbach α coefficient: 0.797

Table 4.6 KMO and Bartlett's test.

KMO and Bartlett's test		
KMO Value		0.824
Bartlett Sphericality test	Approximate card square	1515.614
	Degrees of freedom	120

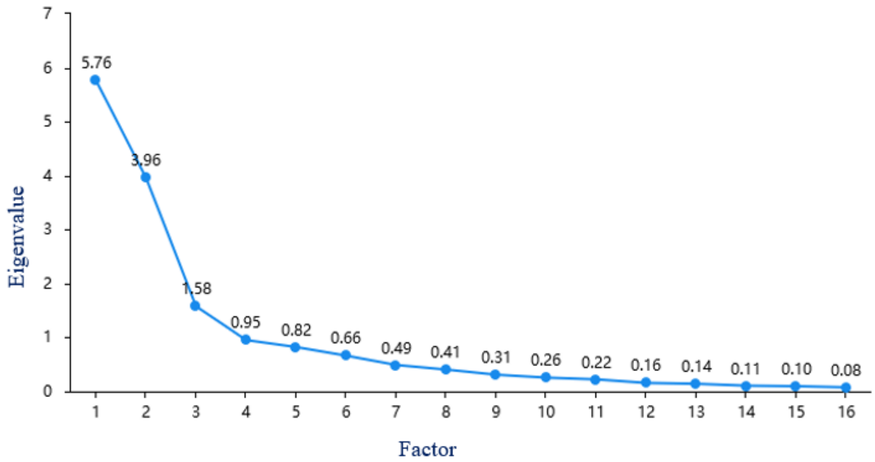


Figure 4.9 Screen plot

From Figure 4.9 and Table 4.7, we can see that the three semantic factors with eigenvalues greater than 1 explain a cumulative variation of 70.624%. The above results are in line with Ealtman and Burger's suggestion: when the value of each factor is greater than 1 and can explain more than 40% of the variables, then the factor analysis result is acceptable. Therefore, we can determine that 16 perceived adjectives can be classified into three semantic factors.

As shown in the rotated component matrix in the table, the perceived imagery adjectives belonging to three types of factors are arranged in order of factor loading. The larger the factor loading value, the greater the correlation with that factor.

From the variance explained by the perceived imagery adjectives factors in the table 4.7, it can be seen that the contribution ratios of the factor axes of factor one, factor

Table 4.7 Variance explanatory rate.

Factor number	Feature root			Interpretation rate of the difference before rotation			Interpretation rate of variance after rotation		
	Feature root	Variance interpretation rate%	Accumulate %	Feature root	Variance interpretation rate%	Accumulate %	Feature root	Variance interpretation rate%	Accumulate %
1	5.762	36.011	36.011	5.762	36.011	36.011	4.071	25.446	25.446
2	3.96	24.752	60.762	3.96	24.752	60.762	3.859	24.121	49.568
3	1.578	9.862	70.624	1.578	9.862	70.624	3.369	21.057	70.624
4	0.952	5.952	76.576	-	-	-	-	-	-
5	0.822	5.138	81.714	-	-	-	-	-	-
6	0.663	4.143	85.857	-	-	-	-	-	-
7	0.49	3.066	88.923	-	-	-	-	-	-
8	0.405	2.533	91.456	-	-	-	-	-	-
9	0.31	1.936	93.392	-	-	-	-	-	-
10	0.256	1.597	94.989	-	-	-	-	-	-
11	0.223	1.395	96.384	-	-	-	-	-	-
12	0.157	0.983	97.367	-	-	-	-	-	-
13	0.141	0.884	98.251	-	-	-	-	-	-
14	0.107	0.667	98.917	-	-	-	-	-	-
15	0.097	0.605	99.522	-	-	-	-	-	-
16	0.076	0.478	100	-	-	-	-	-	-

two, and factor three are 36%, 24.8%, and 9.9%, respectively. The six image vocabulary words, Delicate texture, Interesting, Graceful, Warm, Rounded, and Expensive, have eigenvalues of 5.762 and explainable variables of 36.011%. The most influential factors are Expensive and Delicate texture, with factor loadings of 0.802 and 0.766; Colorful, Rich patterns, Glossy, Low key, Concise, and Unbreakable are six image vocabulary words with eigenvalues of 3.960 and explanatory variables of 24.752%. Among them, Rich patterns and Colorful have the highest influence factors, with factor loadings of 0.919 and 0.916; Four image words, including Regular shape, Modern, Light, and Easy to use, have an eigenvalue of 1.578 and an explanatory variable of 9.862%. Among them, the most influential factors are Regular shape and Easy to use, with factor loadings of 0.895 and 0.787.

From Table 4.8, it can be seen that the corresponding relationship between research items and factors is consistent with psychological expectations, and is divided into three groups of common impression factors.

4.2.2.2 The weight value of each factor

Factor analysis can use load coefficient information to calculate weights. Calculate the weight and normalize the comprehensive score coefficient to obtain the weight value of each indicator (Table 4.9).

Table 4.8 Post-rotation Factor Load Coefficient.

Perceived impression adjectives	**Factor load coefficient**			**Common degree (variance of the common factor)**
	Factor1	**Factor2**	**Factor3**	
Delicate texture/Rough texture	**0.766**	0.183	0.427	0.803
Interesting/Serious	**0.745**	0.423	-0.074	0.74
Graceful/Ugly	**0.754**	-0.075	0.386	0.723
Warm/Cold	**0.681**	0.166	0.263	0.56
Rounded/Hard	**0.693**	-0.311	0.485	0.812
Expensive/Cheap	**0.802**	-0.384	-0.175	0.82
Colorful/Monochromatic	-0.125	**0.916**	0.015	0.855
Rich in patterns/Simple patterns	0.11	**0.919**	-0.127	0.873
Glossy/Lackluster	0.47	**0.586**	0.164	0.591
Low-key/Exaggerated	0.158	-**0.681**	0.543	0.783
Concise/Complex	0.13	-**0.793**	0.497	0.893
Unbreakable/Fragile	-0.207	-**0.431**	-0.294	0.315
Regular shape/Irregular shape	0.2	-0.037	**0.895**	0.843
Modern/Traditional	0.292	0.132	**0.438**	0.295
Light/Heavy	0.562	-0.125	**0.644**	0.746
Easy to use/Inconvenient to use	0.003	-0.167	**0.787**	0.647

Table 4.9 Linear combination coefficient and weight results.

Perceived impression adjectives	**Factor1**	**Factor2**	**Factor3**	**Comprehensive score coefficient**	**Weight**
Feature root (after rotation)	4.071	3.859	3.369		
Variance interpretation rate	25.45%	24.12%	21.06%		
Colorful/Monochromatic	0.0618	0.4664	0.0082	0.184	5.57%
Rich in patterns/Simple patterns	0.0544	0.4679	0.0694	0.2001	6.05%
Glossy/Lackluster	0.2328	0.2984	0.0896	0.2125	6.43%
Delicate texture/Rough	0.3799	0.0932	0.2326	0.238	7.20%
Regular shape/Irregular shape	0.0991	0.0186	0.4877	0.1875	5.67%
Modern/Traditional	0.1447	0.067	0.2388	0.1462	4.42%
Interesting/Serious	0.3693	0.2155	0.0401	0.2186	6.61%
graceful/Ugly	0.3737	0.0383	0.2102	0.2104	6.37%
Low-key/Exaggerated	0.0782	0.3468	0.2956	0.2348	7.10%
Light/Heavy	0.2784	0.0639	0.3507	0.2267	6.86%
Concise/Complex	0.0645	0.4037	0.2707	0.2418	7.32%
Warm/Cold	0.3373	0.0845	0.1431	0.193	5.84%
Rounded/Hard	0.3436	0.1582	0.2641	0.2566	7.76%
Expensive/Cheap	0.3972	0.1954	0.0952	0.2383	7.21%
Easy to use/Inconvenient to use	0.0013	0.085	0.4287	0.1573	4.76%
Unbreakable/ Fragile	0.1025	0.2192	0.1602	0.1596	4.83%

The average of each feature value: the average value obtained by multiplying each feature value by its weight and adding them together (as shown in the table 4.10).

Table 4.10 Average value of the impression factors for ceramic teapots.

Perceived impression adjectives	Average value	Standard deviation
Colorful/Monochromatic	-0.459	1.817
Rich patterns/Simple patterns	-0.373	1.910
Glossy/lackluster	0.744	0.839
Delicate texture/Rough texture	0.938	0.847
Regular shape/Irregular shape	0.646	0.818
Modern/Traditional	0.311	0.553
Interesting/Serious	0.514	0.647
Graceful/Ugly	0.800	0.676
Low-key/Exaggerated	0.427	0.908
Light/Heavy	0.226	0.773
Concise/Complex	0.598	1.039
Warm/Cold	0.496	0.459
Rounded/Hard	0.784	0.799
Expensive/Cheap	0.599	0.481
Easy to use/Inconvenient to use	0.702	0.501
Unbreakable/Fragile	-0.020	0.540

4.3 results

4.3.1 Ceramic teapot perceived impressions analysis Results

From Post-rotation Factor Load Coefficient, it can be observed that these 16 perceived impression adjectives can be divided into three groups of common factors, named elegance factor, fashion factor, and practicality factor.

The most influential factors are Expensive and Delicate texture, with factor loadings of 0.802 and 0.766. It is named: Elegance factor; Rich patterns and Colorful have the highest influence factors. It is named: Fashion factor; The most influential factors are Regular shape and Easy to use, with factor loadings of 0.895 and 0.787. It is named: Practicality factor

Based on the perceived impressions contained in the common factors, it is planned to design three new teapots: elegant teapot, fashionable teapot, and practical teapot. Consequently, we propose the design of three new teapots: an elegant teapot, fashionable teapot, and practical teapot. As can be seen from Table 4.11, the average value of elegant factor is 0.679, indicating that the elegance factor is the most prominent in the overall evaluation. The average value of practical factor is 0.471, indicating that the practical factor plays a strong role in consumer perception. The average value of fashionable factor is only 0.153, indicating that the "fashionable" feature plays a weaker role in the overall image, but it can reflect the surface decorative features. In addition, A high factor load coefficient (>0.7) indicates that the feature is a core constituent element of the factor and can strongly represent or explain the factor. Among them, Expensive, Delicate texture, Graceful, and Interesting are the most important manifestations of the elegance factor. Regular shape and Easy to use are the most important manifestations of the practicality factor, while Rich patterns, Colorful, and Complex are the most important manifestations of the fashion factor. These results provide simplified dimensions for subsequent design and classification.

Table 4.11 Common factors and new teapot design themes.

	New teapots to be design	Perceived impression adjectives	Factor load	Average value
Emotional design	Elegant teapot	Delicate texture/Rough texture	0.766	0.938
		Interesting/Serious	0.745	0.514
		Graceful/Ugly	0.754	0.744
		Warm/Cold	0.681	0.496
		Rounded/Hard	0.693	0.784
		Expensive/Cheap	0.802	0.599
		Average		0.679
	Fashionable teapot	Colorful/Monochromatic	0.916	-0.459
		Rich in patterns/Simple patterns	0.919	-0.373
		Glossy/Lackluster	0.586	0.744
		Low-key/Exaggerated	-0.681	0.427
		Concise/Complex	-0.793	0.598
		Unbreakable/Fragile	-0.431	-0.020
		Average		0.153
	Practical teapot	Regular shape/Irregular shape	0.895	0.646
		Modern/Traditional	0.438	0.311
		Light/Heavy	0.644	0.226
		Easy to use/Inconvenient to use	0.787	0.702
		Average		0.471

4.3.2 Mapping the relationship between ceramic teapot design morphology and perceived impression

A dummy variable multiple regression analysis was conducted to build and quantify the relationship between users' emotional imagery and ceramic teapot design elements. First, we excluded four perceived impression adjectives that were not directly related to formal design elements: delicate texture, colorful, rich in patterns, and glossy (indicated by asterisks in Table 4.12. The remaining 12 impression adjectives were subjected to multiple linear regression analysis.

We employed the average scores of the 12 teapot impression factors as the dependent variable and the quantitative values of the morphological elements of the 20 ceramic teapot samples as the independent variables to conduct a multivariate linear regression analysis. This analysis generated the category scores for each morphological element, as listed in Table 4.12. The bold numbers in the table indicate that the adjusted R-squared values are all below 0.4, suggesting that the reliability of the quantitative analysis results is insufficient for practical application. Consequently, in the subsequent analyses, perceived impression adjectives with low reliability were excluded (see Table 4.13-4.15). The following tables show the regression analysis results for elegant, practical, and fashionable factors.

Table 4.12 Extracting common factors and calculating the R-squared value and adjusted R-squared value for each impressional vocabulary.

Common factor	Impressional characteristic vocabulary	Factor load coefficient	Average value	R	R square	Adjusted R square	Std. error of the estimate	Durbin-Watson
Elegant factor	Delicate texture/Rough texture	0.766	0.938	*	*	*	*	*
	Interesting/Serious	0.745	0.514	.667[a]	0.445	**0.359**	0.043	1.563
	Graceful/Ugly	0.754	0.744	.711[a]	0.505	0.429	0.041	1.584
	Warm/Cold	0.681	0.496	.514[a]	**0.264**	**0.15**	0.036	1.505
	Rounded/Hard	0.693	0.784	.799[a]	0.639	0.583	0.046	1.448
	Expensive/Cheap	0.802	0.599	.633[a]	0.401	**0.308**	0.038	1.652
Fashionable factor	Colorful/Monochromatic	0.916	-0.459	*	*	*	*	*
	Rich in patterns/Simple patterns	0.919	-0.373	*	*	*	*	*
	Glossy/Lackluster	0.586	0.744	*	*	*	*	*
	Low-key/Exaggerated	-0.681	0.427	.873[a]	0.763	0.726	0.038	2.458
	Concise/Complex	-0.793	0.598	.922[a]	0.85	0.827	0.035	1.983
	Unbreakable/Fragile	-0.431	-0.02	.640[a]	0.409	**0.317**	0.030	1.967
Practical factor	Regular shape/Irregular shape	0.895	0.646	.844[a]	0.712	0.668	0.031	2.101
	Modern/Traditional	0.438	0.311	.610[a]	**0.372**	**0.275**	0.029	1.785
	Light/Heavy	0.644	0.226	.759[a]	0.576	0.511	0.046	1.506
	Easy to use/Inconvenient to use	0.787	0.702	.739[a]	0.546	0.475	0.023	2.469

a. Predictors: (Constant), I3, E2, C2, F4, F2, D3, I2, C4, F3, G2, G4, C3, A2, G3, H2, D2, H3.
b. Dependent Variable: The average score of each Impressional factor.
*The adjectives representing perceived impression are not related to design form elements.

Table 4.13 Practical factor multiple regression analysis results.

Regular shape/Irregular shape			Light/Heavy			Easy to use/Inconvenient to use		
Form element code	**Unstandardized Coefficients(b)**	**Sig.**	**Form element code**	**Unstandardized Coefficients(b)**	**Sig.**	**Form element code**	**Unstandardized Coefficients(b)**	**Sig.**
F3	0.054	0.002	F3	0.08	0.003	F3	0.036	**0.249**
H3	0.049	0.013	F4	0.059	**0.056**	G2	0.026	0.008
G2	0.037	**0.129**	B4	0.056	**0.453**	B3	0.026	**0.163**
F2	0.034	0.037	H3	0.053	**0.074**	F2	0.024	**0.135**
B3	0.032	**0.154**	F2	0.05	0.041	H3	0.021	**0.057**
F4	0.032	**0.118**	G2	0.043	**0.236**	D2	0.02	**0.157**
B4	0.021	**0.681**	B3	0.019	**0.567**	F4	0.017	0.007
D2	0.014	**0.153**	C3	0.006	**0.818**	E3	0.012	**0.284**
H2	0.008	**0.39**	D2	0.002	**0.886**	C3	0.007	**0.36**
E4	-0.001	**0.958**	H2	0.001	**0.966**	E4	-0.006	**0.604**
C3	-0.012	**0.496**	E3	-0.035	**0.163**	H2	-0.007	**0.645**
E3	-0.031	**0.064**	E4	-0.043	**0.108**	C2	-0.014	**0.357**
B2	-0.077	0	C2	-0.046	**0.221**	G3	-0.03	**0.481**
C2	-0.082	0.001	G3	-0.094	**0.254**	B2	-0.033	**0.474**
E2	-0.124	0	B2	-0.109	0	B4	-0.035	0
G3	-0.134	0.016	E2	-0.137	0.002	E2	-0.051	**0.361**

Note: This table is arranged in descending order of regression coefficients.

Table 4.14 Elegant factor multiple regression analysis results.

Graceful/Ugly			Rounded/Hard		
Form element code	**Unstandardized Coefficients(b)**	**Sig.**	**Form element code**	**Unstandardized Coefficients(b)**	**Sig.**
B4	0.19	0.005	F4	0.149	0
F4	0.108	0	B4	0.144	**0.056**
F3	0.099	0	F3	0.109	0
F2	0.093	0	H3	0.1	0.001
B3	0.074	0.016	B3	0.098	0.004
H3	0.069	0.009	G2	0.088	0.017
H2	0.018	**0.161**	F2	0.084	0.001
D2	-0.021	**0.104**	H2	0.024	**0.097**
E3	-0.022	**0.318**	D2	0.019	**0.19**
C3	-0.023	**0.337**	C3	0.009	**0.739**
G2	-0.037	**0.262**	B2	-0.066	0
E4	-0.037	**0.12**	C2	-0.082	0.031
C2	-0.061	**0.075**	E3	-0.102	0
B2	-0.08	0	E4	-0.109	0
E2	-0.094	0.019	E2	-0.206	0
G3	-0.2	0.007	G3	-0.207	0.013

Note: This table is arranged in descending order of regression coefficients.

Table 4.15 Fashionable factor multiple regression analysis results.

Low-key/Exaggerated			Concise/Complex		
Form element code	Unstandardized Coefficients(b)	Sig.	Form element code	Unstandardized Coefficients(b)	Sig.
F3	0.253	0	F4	0.234	0
F4	0.232	0	H3	0.217	0
H3	0.23	0	F3	0.214	0
F2	0.201	0	F2	0.175	0
B3	0.163	0	E4	0.173	0
B4	0.147	0.019	B3	0.135	0
E4	0.121	0	G2	0.123	0
G2	0.101	0.001	C3	0.112	0
C3	0.051	0.023	B4	0.096	**0.09**
D2	0.037	0.002	D2	0.071	0
H2	0	**0.99**	C2	0.032	**0.261**
E3	-0.021	**0.301**	E3	0.017	**0.347**
C2	-0.031	**0.317**	H2	0.015	0.012
B2	-0.074	0	B2	-0.059	0
G3	-0.268	0	G3	-0.233	0
E2	-0.311	0	E2	-0.357	0

Note: This table is arranged in descending order of regression coefficients.

Combined with the regression analysis results, the design feature statistical variables for the three new teapots were classified according to the positive and negative values of the regression coefficients (see Table 4.16). We excluded morphological feature codes with P>=0.05 and perceived impression adjectives with low credibility, and then determined the positive and negative design elements of three new types of ceramic teapots through morphological analysis and feature classification (see Table 4.17).

Table 4.16 Characteristic variable statistics of three types of new ceramic teapots (Delete P>=0.05).

Design of new types of teapots	Perceived impression adjectives	Unstandardized coefficients ranking (Positive value) (descending)	Unstandardized coefficients ranking (Negative value) (descending)
Elegant teapot	Graceful/Ugly	B4, F4, F3, F2, B3, H3	B2, E2, G3
	Rounded/Hard	F4, F3, H3, B3, G2, F2	B2, C2, E3, E4, E2, G3
Fashionable teapot	Low-key/Exaggerated	F3, F4, H3, F2, B3, B4, E4, G2, C3, D2	B2, G3, E2
	Concise/Complex	F4, H3, F3, F2, H2, B3, E4, G2, C3, D2	B2, G3, E2
Practical teapot	Regular shape/Irregular shape	F3, H3, F2	B2, C2, E2, G3
	Light/Heavy	F3, F2	B2, E2
	Easy to use/Inconvenient to use	G2, F4	B4

Table 4.17 Positive design elements of three types of new teapots.

	Design of new types of teapots	Classification of morphological features	Encoding of features	Design features
Positive design features	Elegant teapot	Top view contour line(A-D)	B4, B3	Handle(B): 4. No handle 3. Straight line
		Front view contour line(E-H)	F4, F3, H3, G2, F2	Handle(F): 4. No handle 3. Curve + Arc 2. Arc； Spout(H) 3. Straight line; Lid(G): 2. Straight line +Curve
	Fashionable teapot	Top view contour line(A-D)	B3, B4, C3, D2	Handle(B): 3. Straight line, 4. No handle; Lid(C): 3. Circular +Straight line + Curve; Spout(D): 2. Curve
		Front view contour line(E-H)	F3, F4, H2, H3, F2, E4, G2	Handle(F): 3. Curve + Arc, 4. No handle, 2. Arc； Spout(H): 2. Curve + Straight line, 3. Straight line; Body(E): 4. Straight line + Hyperbola; Lid(G): 2. Straight line +Curve
	Practical teapot	Top view contour line(A-D)	*	*
		Front view contour line(E-H)	F3, H3, G2, F2, F4	Handle(F): 3. Curve + Arc 2.Arc； 4. No handle； Spout(H) 3. Straight line; Lid(G): 2. Straight line +Curve
Negative design features	Elegant teapot	Top view contour line(A-D)	B2, C2	Handle(B): 2. Arc + Straight line； Lid(C): 2. Circular + Curve
		Front view contour line(E-H)	E2, E3, E4, G3	Body(E): 2. Curve, 3. Straight line 4. Straight line + Hyperbola; Lid(G): 3. Straight line
	Fashionable teapot	Top view contour line(A-D)	B2	Handle(B): 2. Arc + Straight line
		Front view contour line(E-H)	G3, E2	Lid(G): 3. Straight line; Body(E): 2. Curve;
	Practical teapot	Top view contour line(A-D)	B2, C2, B4	Handle(B): 2. Arc + Straight line, 4. No handle; Lid(C): 2. Circular + Curve
		Front view contour line(E-H)	E2, G3	Body(E): 2. Curve; Lid(G): 3. Straight line

This approach will help design ceramic teapot products that are highly accepted by consumers. According to the results of the dummy variable multiple regression analysis in Table 4.18, when designing elegant, practical, or fashionable new teapots, we should first choose positive design feature elements for the top and front view of the teapot, and avoid using negative design feature elements. If there are no relevant positive feature elements, we can choose alternative element features with relatively small correlation coefficients, which can serve as alternative design bases. As shown in Table 4.18, this provides a design basis for designing new ceramic teapots.

4.4 Discussion

This chapter set out to clarify how the morphological features of top-selling Chinese and Japanese ceramic teapots are related to consumers' perceived impressions, thereby answering SRQ1. By combining morphological analysis, SD–scale factor analysis, and dummy variable multiple regression, the study makes several theoretical and practical contributions to emotional craft design.

4.4.1 Structure of perceived impression: elegance, fashion, and practicality

The factor analysis of 16 SD adjective pairs produced three robust higher–order factors—elegance, fashion, and practicality—that together explained over 70% of the total variance (see Table 4.7). From a theoretical perspective, these three factors align perfectly with Norman's three levels of emotional design. In addition, the factor means (see Table 4.11) show that elegance (mean = 0.679) is the most salient dimension in the

Table 4.18 Emotional design feature lines for the new teapot ("√" is optional, and " X " is not optional).

Design feature classification			Extract feature lines	Elegant teapot			Practical teapot			Fashionable teapot		
				Pos.	Neg.	Alt.	Pos.	Neg.	Alt.	Pos.	Neg.	Alt.
Feature lines of ceramic teapot (A-H)	Top view feature lines (A-D)	Body (A)	1.Circular+Straight line +Curve			√			√			√
			2.Circular			√			√			√
		Handle (B)	1.Straight line +Curve			√			√			√
			2.Arc+Straight line		X			X			X	
			3.Straight line	√						√		
			4.No handle	√				X		√		
		Lid(C)	1.Circular			√			√			√
			2.Circular+Curve		X			X				
			3.Circular+Straight line +Curve							√		
		Spout (D)	1.Straight line +Curve						√			√
			2.Curve			√				√		
	Front view feature lines (E-H)	Body (E)	1.Arc+Straight line			√			√			√
			2.Curve		X			X			X	
			3.Straight line		X							
			4.Hyperbola +Straight line		X					√		
		Handle (F)	1.Curve+Straight line			√			√			√
			2.Arc	√			√			√		
			3.Curve + Arc	√			√			√		
			4.No handle	√			√			√		
		Lid(G)	1.Arc+Straight line			√			√			√
			2.Straight line +Curve	√			√			√		
			3.Straight line		X			X			X	
		Spout (H)	1.Curve			√			√			√
			2.Curve+Straight line							√		
			3.Straight line	√			√			√		

Note: Pos.: Positive; Neg.: Negative; Alt.: Alternative.

overall evaluation, followed by practicality (mean = 0.471), with fashion (mean = 0.153) playing a relatively weaker role. This implies that for top-selling teapots, consumers first look for an "elegant" emotional image and then assess whether the product appears practical; "fashionable" attributes are desirable, but not dominant, and may act as an additional decorative layer rather than a core decision driver. This pattern is consistent with the idea, discussed in the literature review, that for craft products, emotional resonance and usability jointly underpin purchase decisions, while highly trendy or experimental features are often secondary.

4.4.2 Morphological characteristics and emotional responses

One of the core contributions of this chapter is the analysis of the morphological features of ceramic teapots. This method transforms qualitative shape impressions into analyzable variables and allows the mapping of form to emotion to be viewed as a statistical relationship (Figure 4,11) rather than purely intuitive knowledge. Regression analysis using dummy variables indicates that not all visual elements contribute equally to perceived impression.

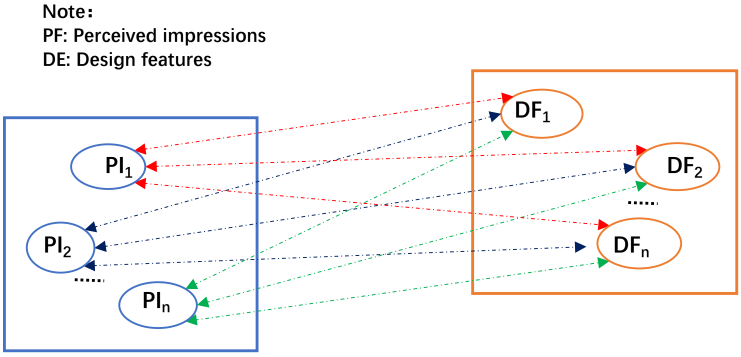


Figure 4.10 Relations between users' perceived impressions and design features.

From the perspective of design decision, these results indicate that for top-selling craft products, designers should first ensure an elegant and practical basic form, and then selectively introduce fashionable features that do not affect usability. Then, priority can be given to one factor over another based on the design objectives.

In summary, from the morphological analysis process to the extraction of important features, and finally to the design of the new ceramic teapots, this process indicate that the emotional imagery of teapots is not just a subjective impression, but is systematically related to recognizable morphological patterns (Figure 4.12). The proposed coding system and regression analysis concretize this relationship and go beyond purely descriptive or case-based design guidance.

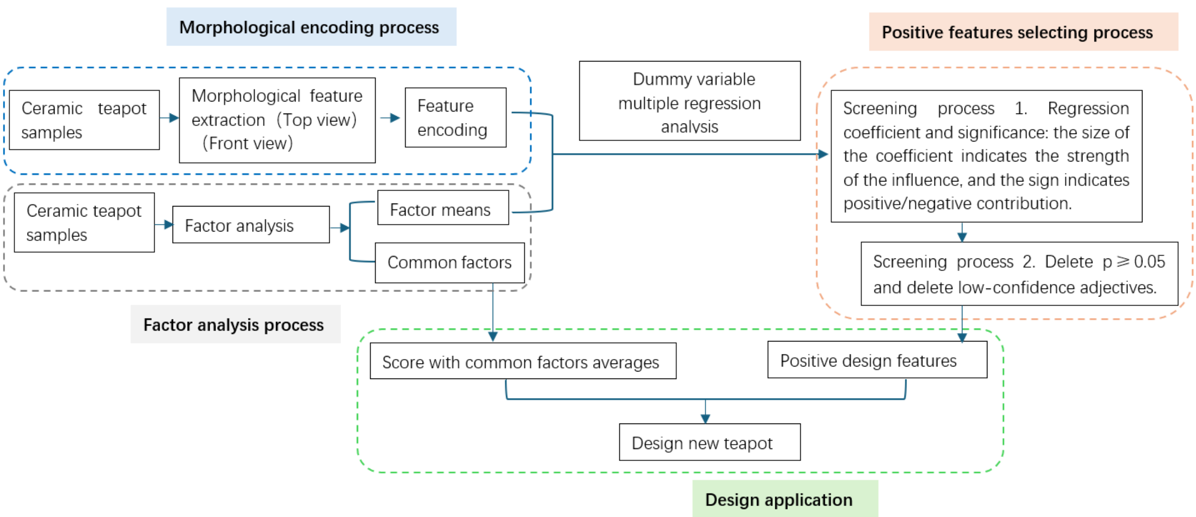


Figure 4.11 The process of design decision

4.4.3 Research limitations

This study has demonstrated that the combination of morphological analysis, SD factor analysis, and dummy variable regression can effectively reveal design–emotion relationships for craft products. The workflow from element extraction to binary coding, factor construction, and regression is transparent and replicable, offering a methodological template that can be extended to other product categories.

However, several limitations should be acknowledged. First, the sample size of 20 teapots, while carefully selected as top sellers, remains limited relative to the diversity of ceramic teapot design. Second, morphological elements were encoded categorically and binarily, which does not capture nuances such as proportion, thickness, or subtle variations in curvature. Third, participants were mainly young students, which may bias the emotional evaluations toward a specific age group.

In future study, we can expand the product set and compare different user groups and image presentation formats. This extension will further enrich and summarize the feature emotion mapping relationship proposed in this chapter.

4.5 Summary

This chapter addressed SRQ1 by systematically identifying the morphological and perceived features of top-selling Chinese and Japanese ceramic teapots and by clarifying how these features map onto consumers' emotional impressions.

First, through SD adjective screening and factor analysis, three higher–order perceived impression factors—elegance, fashion, and practicality—were extracted. These factors form a compact emotional structure that aligns with built emotional design theory and captures over 70% of the variance in consumer evaluations. Among them, elegance emerged as the dominant factor for the examined top sellers, with practicality also playing a strong role, while fashion functioned as a complementary but less central dimension.

Second, a morphological element system for ceramic teapots was constructed by decomposing teapots into body, handle, lid, and spout components and defining their front- and top-view contour types. Using binary coding, these elements were transformed into analyzable variables for 20 top-selling teapots. This operationalization enabled a quantitative investigation of how specific design features relate to emotional responses.

Third, dummy variable multiple regression analysis built the mapping between design features and perceived impressions. The results clarified which morphological elements act as positive or negative contributors for each emotional factor. In particular, front-view handles, lids, and spouts were found to be key determinants of perceived elegance, fashion, and practicality, with some features (e.g., arc or curve-plus-arc handles, straight spouts, straight-plus-curve lids) supporting multiple emotional goals, and others (e.g., purely curved bodies, certain lid forms, absence of a handle) generating trade-offs between elegance and practicality.

Finally, by synthesizing these results, the chapter proposed three conceptual design directions—an elegant teapot, a fashionable teapot, and a practical teapot—and summarized their corresponding positive and negative morphological elements (see Tables 4.17–4.18). These design guidelines translate empirical findings into actionable principles that can guide the creation of new ceramic teapot concepts oriented toward different emotional priorities.

In sum, Chapter 4 provides a foundational "design feature–emotional response" map for ceramic teapots. It demonstrates that emotional preferences for top-selling Chinese and Japanese teapots can be systematically explained by a limited set of morphological rules, and it offers a replicable workflow for bridging the gap between qualitative craft intuition and quantitative emotional evaluation. The insights and feature–emotion mappings built here serve as a key input for Chapter 5, where they are further operationalized within emotion quality classification models, and for Chapter 6, where they are related to consumer review texts in real e-commerce environments.

Chapter 5

Emotional quality evaluation model and its application to new teapot design

5.1 Introduction

In the emotional research of craft product design, how to transform consumers' subjective emotional reactions into quantifiable and analyzable design indicators is an important issue to achieve the scientific implementation of emotional design. The previous chapter revealed the potential correlation between shape and emotional impression by analyzing the emotional design features of top-selling Chinese and Japanese ceramic teapots. However, relying solely on factor analysis and regression models is difficult to fully describe the complexity of emotional qualities. Therefore, this chapter further constructs an "emotional quality classification model" for ceramic teapots to achieve a systematic transformation from sensory description to rational judgment.

The research objective of this chapter is to answer SRQ2, which involves developing an emotional quality model to evaluate the emotional quality of ceramic teapots and exploring its application in the design of novel emotional craft products. Specifically, it aims to address the question of how the emotional quality of ceramic teapots can be evaluated? In addition, by building a reproducible emotional evaluation process, it not only aids designers in understanding the impact of various design elements on emotional responses, but also provides an objective emotional prediction tool for the product development stage, thereby offering scientific support for "emotion-driven design".

5.2 Methods

5.2.1 Data pre-processing

The dissertation used the facial emotion recognition software FaceReader 9.1 (Noldus Information Technology, Wageningen, Netherlands) for emotion classification. A validation study using the Amsterdam Dynamic Facial Expression Set (ADFES) dataset demonstrated that FaceReader 9.1 achieves an average accuracy of 99.0% for emotion classification (Dupré, D. et al.,2020), (Dupré, D. et al.,2023). FaceReader 9.1 detects facial expressions and recognizes eight basic emotions: neutral, happy, sad, angry, surprised, afraid, disgusted, and contempt, as illustrated in Figure 5.1. Subsequently, we employed FaceReader 9.1 to analyze the facial emotion photos of the 60 participants.

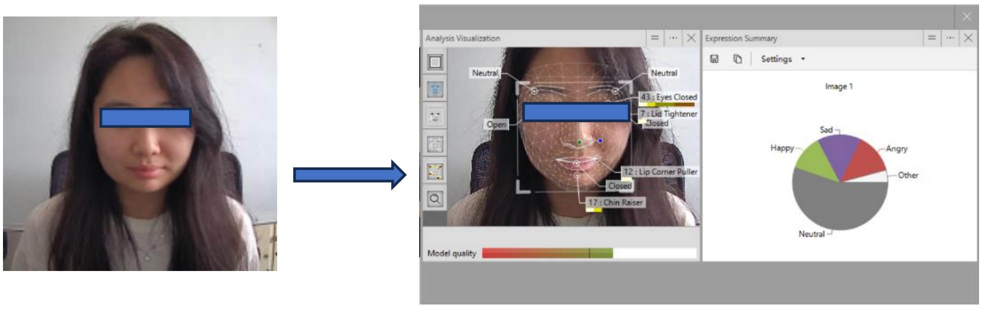


Figure 5.1 Dominant expression is neutral display expression intensity using a pie chart.

Images that the software could not identify were excluded from the dataset. Of the 1,200 photos captured, 20 were deemed invalid and were removed, resulting in 1,180 valid records for further analysis. 1) Invalid photo cleaning: cleared up photos of participants with closed eyes; 2) Invalid data cleaning: cleaned up photos that the software could not recognized (As shown in Figure 5.2).

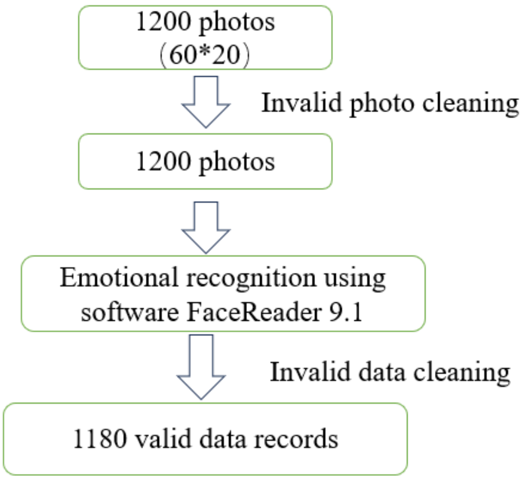


Figure 5.2 Data cleaning process

5.2.2 Classification model building

This dissertation builds the Model using facial recognition data and SAM scale data. the following figure shows the process of building the facial emotion recognition and classification model (As shown in Figure 5.3).

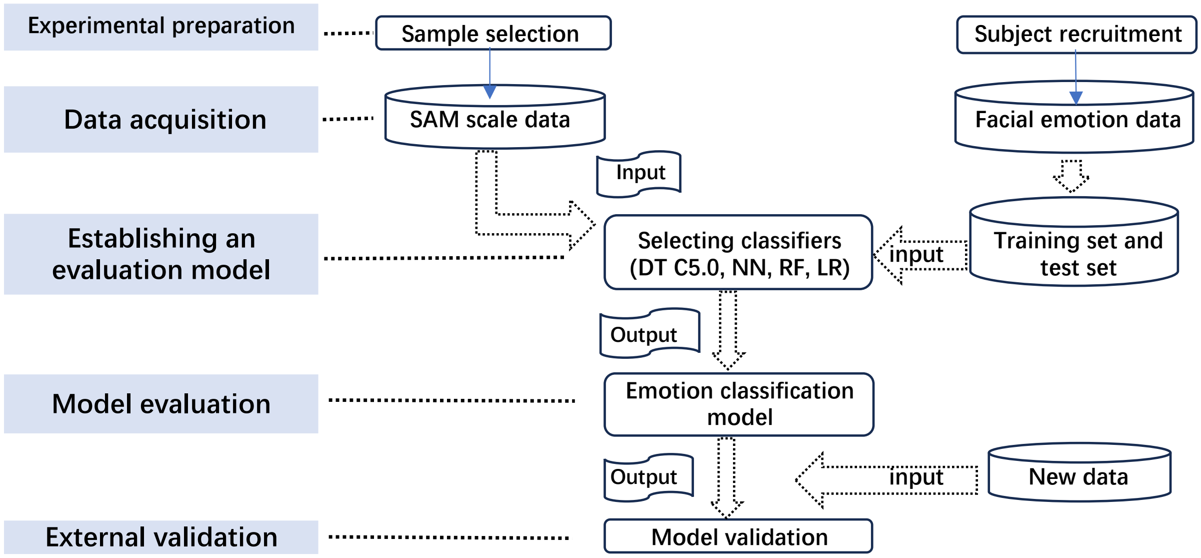


Figure 5.3 The process of building the facial emotion recognition and classification model.

During the experiment, emotional information was obtained from participants' responses to the SAM questionnaire. As the SAM questionnaire is an odd-numbered emotion measurement tool, it provides three, five, and seven emotion levels. To build binary, ternary, and quinary classification models, negative emotional valence was labeled -2 and -1, positive emotional valence was labeled 1 and 2, and the middle level represented samples with zero emotional valence.

Due to the presence of missing values in the original dataset, we preprocessed all data before building the models. Firstly, the dataset was randomly divided into a 70% training set and a 30% test set for all modeling. Secondly, due to the inherent differences in the capabilities of the algorithms, we handled missing values differently. For logistic regression (LR), since SPSS Modeler cannot handle missing values, we removed any instances with missing values from both the training and test sets after splitting. For the three models—decision tree C5.0 (DT C5.0), random forest (RF), and neural network (NN)—we employed mean imputation. The mean of each feature was calculated solely on the training set. This calculated mean was then used to impute missing values in both the training set and the test set. This approach aims to maximize data retention while preventing data leakage. Thirdly, considering the sensitivity of LR and NN to feature scales, we standardized the features for these models, while the DT C5.0- and RF-based models were trained on the original, unscaled features. Therefore, due to the different preprocessing strategies, the final number of test samples varied slightly across the different models.

Additionally, the statistical results of the SAM scale indicated that participants had a weaker understanding of emotional arousal than of emotional valence (positive or negative). Owing to the limited emotional stimulation caused by the ceramic teapot photos, participants found it difficult to distinguish between emotional arousal and psychological stress. Therefore, emotional arousal was excluded from the analysis and only emotional valence was used as the target variable to construct a valence classification model. The process of model building and evaluation is illustrated in Figure 5.3.

This dissertation takes each participant's emotional valence towards each teapot as the dependent (target) variable and their facial data as the independent variable, an emotion classification model was constructed using the SPSS Modeler 18.2. LR, DT C5.0, RF, and NN were used as classifiers to build the model. The dataset was divided into a training set and a testing set in a 7:3 ratio. After specifying the data type, applying filters, and balancing the samples, the dataset was inputted into the SPSS Modeler 18.2 data stream. Upon execution, binary, ternary, and quinary classification models were generated using LR, DT C5.0, RF, and NN classifiers, along with their respective recognition accuracies.

The three figures below are the valence (binary, ternary, and quinary) classification flow built in SPSS Modeler 18.2 (Figure5.4-5.6).

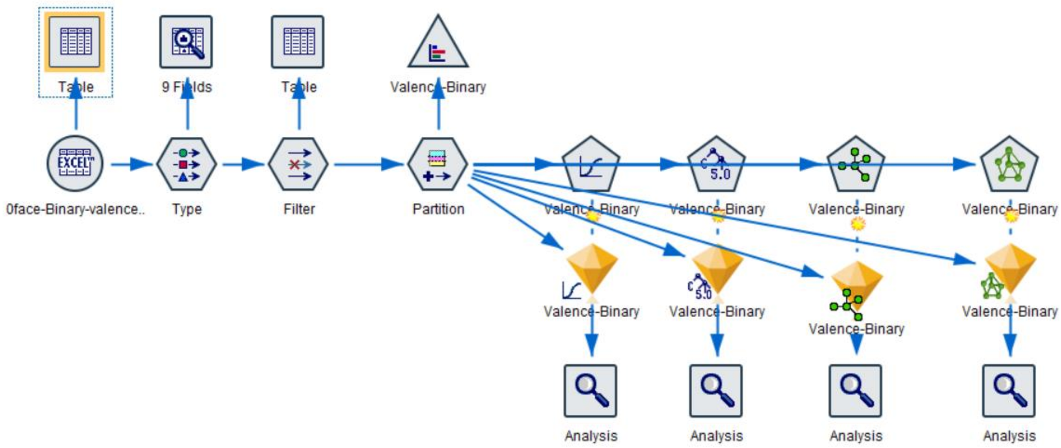


Figure 5.4 The valence(binary) classification flow built in SPSS Modeler.

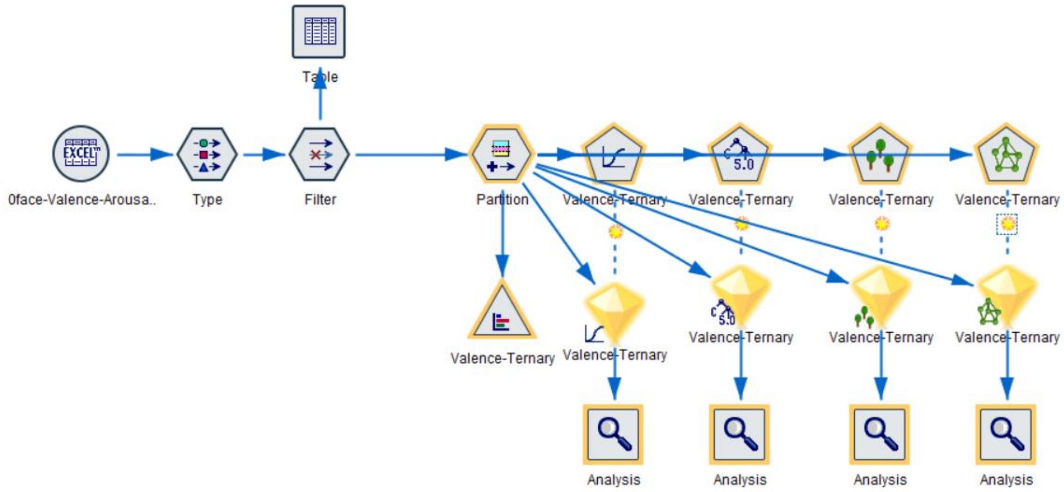


Figure 5.5 The valence (ternary) classification flow built in SPSS Modeler.

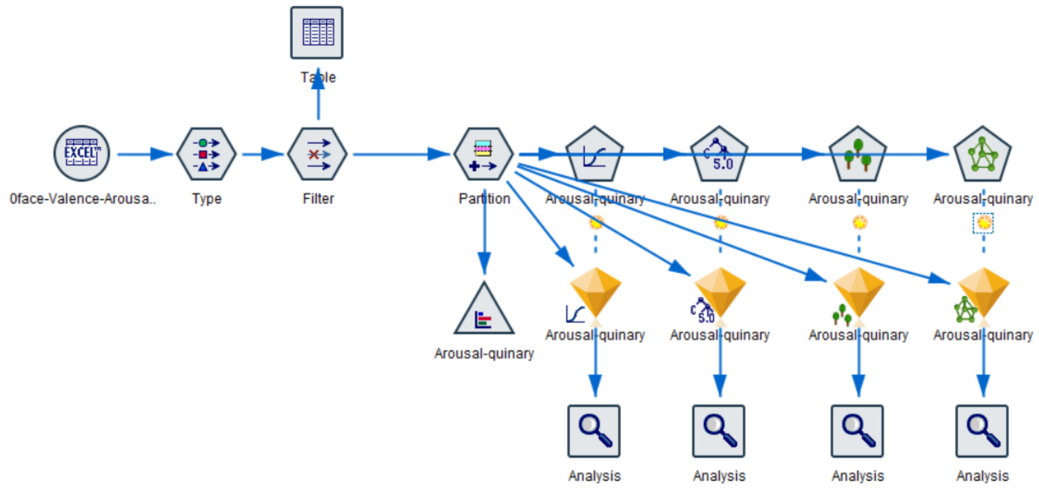


Figure 5.6 The valence (quinary) classification flow built in SPSS Modeler.

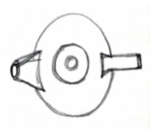
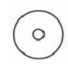
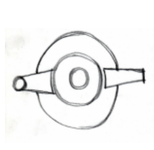
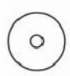
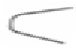
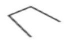
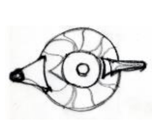
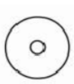
5.2.3 Design practice and Experiments

5.2.3.1 Emotional design of ceramic teapots

Emotional design refers to the consideration of users' emotional responses during the product design process to create a more attractive and pleasant user experience (Triberti, S. et al.,2017). The purpose of this design is to test the applicability of the design method for ceramic teapots based on consumer emotional reactions and to validate the correctness of the research results and the effectiveness of the prediction model.

Based on the analysis results from the previous chapter and the positive design feature lines (Table 4.18) obtained from the multiple regression analysis with dummy variables, this study designed sketches for the three new types of teapots. Through factor analysis, we obtained the factor loading coefficient rankings for the impression factors of the three new types of teapots (Table 4.11). Based on the extracted positive design elements, we designed the new appearance for the teapots, the design analysis sketches of the three ceramic teapots were completed (as shown in Table 5.1). and then combined the results of factor analysis based on perceived evaluation to generate rendering images for three types of teapots (see Table 5.2).

Table 5.1 Sketch of ceramic teapot based on dummy regression analysis results.

Three types of ceramic teapots	The results of multiple regression analysis		Pot lid	Pot body	Pot handle	Spout	Design sketch
Design of Elegant Teapot	Top view	Morphological elements	Circle\ circle+straight line+curve	Circle	Straight line+curve\straight line	Straight line	
		key					
	Front view	Morphological elements	Straight line+curve	Arc+straight line	Curve+arc\arc	Straight line\Curve+straight line	
		key					
Design of Practical Teapot	Top view	Morphological elements	Circle\ circle+straight line+curve	Circle	Straight line \ straight line+arc	Straight line	
		key					
	Front view	Morphological elements	Straight line+curve	Straight line	Curve+arc\arc	Straight line	
		key					
Design of Fashionable Teapot	Top view	Morphological elements	Circle	Circle+straight line+curve	Curve+straight line	Straight line	
		key					
	Front view	Morphological elements	Straight line	hyperbola+straight line\ curve	Arc\straight line+curve	Curve+straight line	
		key					

The following are the design processes for three types of new teapots:

① Design of Elegant Teapot

According to the perceived image features of common factors, the design features of teapots with elegance as the theme mainly include delicate texture, elegance, roundness, expensive, interesting, warm, etc., among which delicate texture and expensiveness have the highest scores and should be paid attention to in the design (Figure 5.7-1, 2).

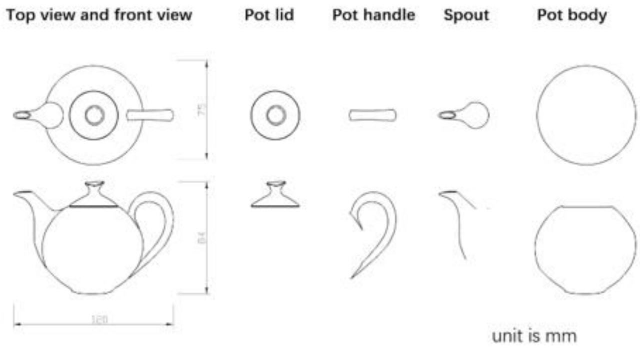


Figure 5.7-1 Analysis of Fashionable Teapot Design Elements.

Figure 5.7-2 Rendering of Elegant Teapot.

② Design of Fashionable Teapot

According to the perceived image features of common factors, the design features of teapots with fashion as the theme mainly include colorful, rich patterns, gloss, exaggeration, complexity, and a fragile appearance fragility, etc., among which rich colors and rich patterns have the highest scores and should be paid attention to in the design (Figure 5.8-1, 2).

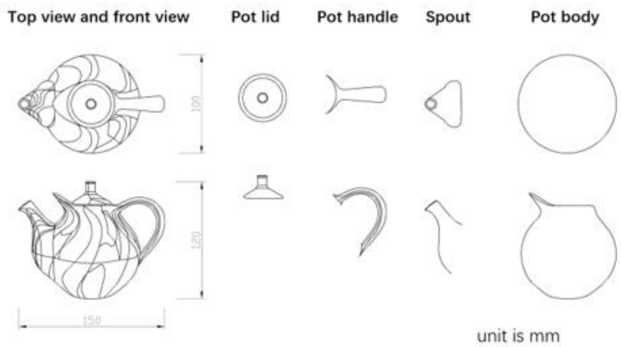


Figure 5.8-1 Analysis of Fashionable Teapot Design Elements.

Figure 5.8-2 Rendering of Fashionable.

③ Design of Practical Teapot

According to the perceived image features of common factors, the design features of teapots with practicality as the theme mainly include regular shape, modern, easy to use, etc., among which regular shape and easy to use have the highest scores and should be paid attention to in the design (Figure 5.9-1, 2).

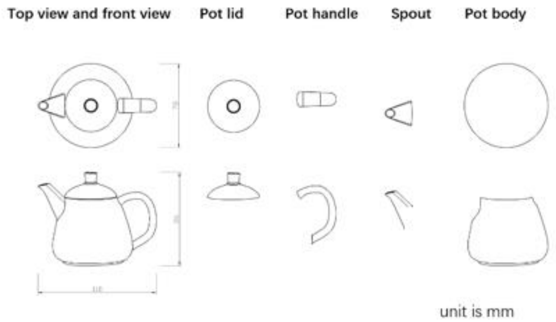


Figure 5.9-1 Analysis of Practical Teapot Design Elements.

Figure 5.9-2 Rendering of Practical Teapot.

The design analysis of the three ceramic teapots is summarized in the following Table:

Table 5.2 Design analysis and rendering display of three new ceramic teapots.

Three new types of ceramic teapots	Selection of positive morphological features for ceramic teapots						Design sketch	Design intention factor(Sort by factor load coefficient in descending order)	Ceramic Teapot Rendering
	Items		Morphological elements				Legend for the Dimensional Drawing		
			Lid	Handle	Spout	Body			
Design of Elegant Teapot	Top view	Legend for the feature Lines						Expensive Delicate texture Graceful Interesting Rounded Warm	
		Feature Lines	C1:Circular	B3:Straight line	D2:Curve	A2:Circular			
	Front view	Legend for the feature Lines							
		Feature Lines	G2:Straight line+Curve	F3:Curve+Arc	H2:Curve+Straight line	E1:Arc+Straight line			
Design of Practical Teapot	Top view	Legend for the feature Lines						Regular shape Easy to use Modern Light	
		Feature Lines	C1:Circular	B1: Straight line+Curve	D1: Straight line+Curve	A2:Circular			
	Front view	Legend for the feature Lines							
		Feature Lines	G2:Straight line+Curve	F2:Arc	H3:Straight line	E1:Arc+Straight line			
Design of Fashionable Teapot	Top view	Combination analysis						Rich patterns Colorful Complex Exaggerated Glossy Breakable	
		Feature Lines	C3:Circular+Straight line+Curve	B3:Straight line	D2:Curve	A2:Circular			
	Front view	Legend for the feature Lines							
		Feature Lines	G2:Straight line+Curve	F2:Arc	H2:Curve+Straight line	E4:Hyperbola+Straight line			

Note: The unit is millimeters (mm)

5.2.3.2 Experiments on three newly designed ceramic teapots

1) The experimental participants comprised 15 randomly selected master's students, with an average age of 24.3 years. The data collection process followed the same procedure as that used for the facial emotion recognition experiment described earlier

(see Figure 5.10). Consequently, we obtained 45 valid facial photos and emotional valence from 15 participants for each set of ceramic teapots.

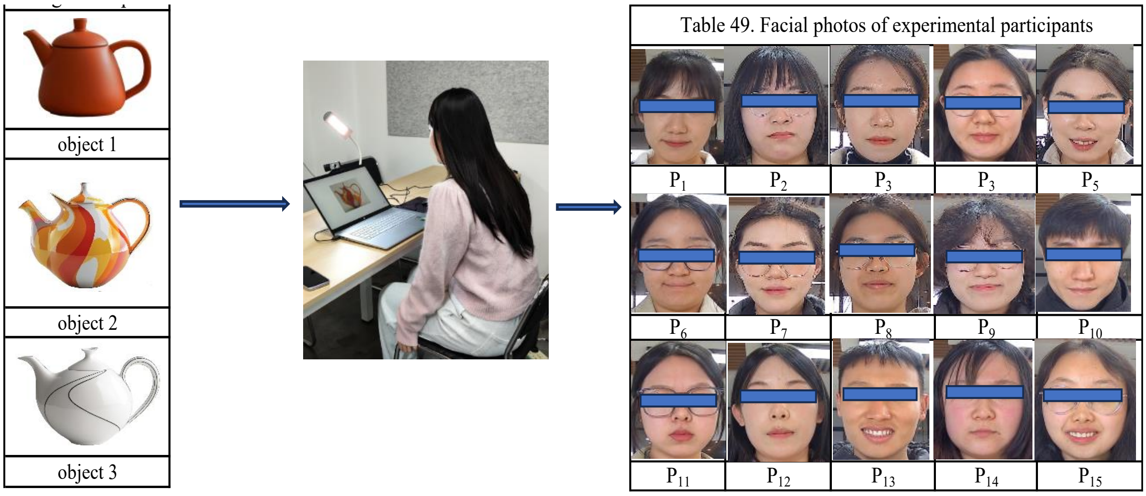


Figure 5.10 The process of collecting facial photos of participants.

5.3 Results

5.3.1 Model evaluation

The model was trained using facial emotion recognition data and its performance was evaluated. The confusion matrix of the test set was used to calculate four performance metrics: the accuracy (Eq.1), and precision (Eq.2), and recall (Eq.3), and F1-score (Eq.4). These metrics were computed for the binary, ternary, and quinary classification models built by the LR, DT C5.0, RF, and NN classifiers.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

We generated binary, ternary, and quinary classification models using LR, DT C5.0, RF, and NN classifiers. In the binary classification model, the accuracy of the LR classifier model is 71.4%, the accuracy of the DT C5.0 classifier model is 76.2%, the accuracy of the NN classification model is 79.3%, and the accuracy of the RF classifier model is 91.0%. The RF classifier model achieves the highest accuracy.

In the ternary and quinary classification models, the accuracies of valence classification using RF were 81.3% and 63.6%, respectively. These values were also higher than those achieved by the LR, DT C5.0, and NN (see Table 5.3). Therefore, among the four types of models, the classification accuracy of RF met the requirements for the emotional design evaluation of ceramic teapots.

The results in the table above indicate that the classification accuracy of the built emotional machine learning model for ceramic teapots demonstrated that the binary and ternary classifiers using RF achieved high classification accuracy. This suggests that RF may be suitable for evaluating the design of new ceramic teapots. Additionally, the precision, recall, and F1-score indicators were all above 81.0%, which was higher than the recognition rates of the models built by other classifiers. Thus, the RF classifier can be used as a reliable model for facial emotion recognition.

Table 5.3 Evaluation metrics for four classifier models.

	Classifiers	Accuracy	Precision	Recall	F1-score
LR	Binary classification	71.4%	99.0%	72.0%	83.3%
	Ternary classification	46.5%	72.0%	47.0%	57.0%
	Quinary classification	44.8%	51.0%	50.0%	61.0%
DT C5.0	Binary classification	76.2%	99.0%	80.0%	86.0%
	Ternary classification	54.3%	66.0%	56.0%	58.0%
	Quinary classification	51.1%	51.0%	54.0%	55.0%
NN	Binary classification	79.3%	89.0%	83.0%	86.0%
	Ternary classification	53.3%	68.0%	55.0%	61.0%
	Quinary classification	45.9%	52.0%	54.0%	56.0%
RF	Binary classification	91.0%	99.0%	97.0%	94.0%
	Ternary classification	81.3%	83.0%	89.0%	82.0%
	Quinary classification	63.6%	62.0%	68.0%	68.0%

In addition to the overall performance of the classifier, the recognition performance for each category is equally important. Table 5.4 shows the precision, recall, and F1 score for each class, along with the 95% confidence intervals (percentile bootstrap, B=1000) calculated on the test set. Support (n) represents the number of true instances

Table 5.4 Binary, Ternary, and Quinary classification: per-class metrics.

	Algorithm	Class	Support(n)	Precision	Recall	F1 Score	F1 95% CI	Accuracy (overall)
Binary classification: per-class metrics	LR	-1	43	0.00%	0.00%	0.00%	[0.0%, 0.0%]	71.40%
		1	111	71.90%	99.10%	83.30%	[77.8%, 87.6%]	
		Macro-F1	154			41.70%	[40.7%, 44.3%]	
	DT	-1	37	80.00%	10.80%	19.00%	[4.7%, 35.0%]	76.20%
		1	106	76.10%	99.10%	86.10%	[81.0%, 90.4%]	
		Macro-F1	143			52.60%	[43.9%, 61.8%]	
	NN	-1	61	66.70%	55.70%	60.70%	[49.6%, 70.6%]	79.30%
		1	152	83.30%	88.80%	86.00%	[81.6%, 89.7%]	
		Macro-F1	213			73.40%	[66.7%, 79.6%]	
	RF	-1	54	97.40%	68.50%	80.40%	[70.8%, 88.5%]	91.00%
		1	146	89.50%	99.30%	94.20%	[91.4%, 96.6%]	
		Macro-F1	200			87.30%	[81.4%, 92.5%]	
Ternary classification: per-class metrics	LR	-1	63	0.00%	0.00%	0.00%	[0.0%, 0.0%]	46.50%
		0	127	46.70%	38.60%	42.20%	[33.7%, 50.0%]	
		1	154	46.60%	72.10%	56.60%	[50.4%, 62.2%]	
		Macro-F1	344			33.00%	[29.0%, 36.6%]	
	DT	-1	48	100%	4.20%	8.00%	[0.0%, 19.2%]	54.30%
		0	126	51.60%	65.90%	57.80%	[50.7%, 64.5%]	
		1	152	56.40%	60.50%	58.40%	[51.4%, 64.5%]	
		Macro-F1	326			41.40%	[36.4%, 46.7%]	
	NN	-1	78	44.40%	20.50%	28.10%	[17.0%, 38.6%]	53.30%
		0	138	52.80%	54.30%	53.60%	[46.0%, 60.4%]	
		1	167	55.10%	67.60%	60.80%	[54.6%, 66.3%]	
		Macro-F1	383			47.50%	[42.0%, 52.5%]	
	RF	-1	73	88.90%	76.70%	82.40%	[74.6%, 88.7%]	81.30%
		0	140	79.30%	82.10%	80.70%	[75.5%, 85.4%]	
		1	173	80.30%	82.70%	81.50%	[76.7%, 85.6%]	
		Macro-F1	386			81.50%	[77.1%, 85.3%]	
Quinary classification: per-class metrics	LR	-1	56	50.00%	1.80%	3.40%	[0.0%, 0.110]	44.80%
		-2	14	0.00%	0.00%	0.00%	[0.0%, 0.0%]	
		0	148	44.60%	98.00%	61.30%	[56.0%, 66.4%]	
		1	98	50.00%	4.10%	7.50%	[1.7%, 14.6%]	
		2	19	0.00%	0.00%	0.00%	[0.0%, 0.0%]	
		Macro-F1	335			14.50%	[12.3%, 16.7%]	
	DT	-1	52	40.30%	59.60%	48.10%	[37.2%, 57.9%]	51.10%
		-2	11	25.00%	72.70%	37.20%	[17.1%, 54.9%]	
		0	164	64.80%	49.40%	56.10%	[49.0%, 63.1%]	
		1	104	53.70%	55.80%	54.70%	[46.1%, 62.4%]	
		2	19	100%	5.30%	10.00%	[0.0%, 29.6%]	
		Macro-F1	350			41.20%	[34.9%, 47.6%]	
	NN	-1	65	40.00%	3.10%	5.70%	[0.0%, 13.8%]	45.90%
		-2	12	0.00%	0.00%	0.00%	[0.0%, 0.0%]	
		0	168	46.90%	94.00%	62.60%	[57.3%, 67.4%]	
		1	86	30.00%	7.00%	11.30%	[3.6%, 19.8%]	
		2	31	0.00%	0.00%	0.00%	[0.0%, 0.0%]	
		Macro-F1	362			15.90%	[13.5%, 18.5%]	
	RF	-1	51	46.70%	82.40%	59.60%	[49.6%, 68.6%]	63.60%
		-2	17	70.00%	82.40%	75.70%	[57.9%, 89.5%]	
		0	171	75.70%	62.00%	68.20%	[61.9%, 73.9%]	
		1	100	68.30%	56.00%	61.50%	[52.6%, 69.5%]	
		2	24	41.90%	54.20%	47.30%	[29.8%, 62.7%]	
		Macro-F1	363			62.40%	[56.1%, 68.0%]	

for each class (the final number of test samples (Support) varies slightly across models due to the different preprocessing strategies; see Section 1) Building Models). The tables also show the Macro-F1, which is the unweighted average of the F1 scores for each class, to mitigate the impact of class imbalance. Across all tasks, the random forest consistently yields the strongest Macro-F1 (binary: 87.3%; ternary: 81.5%; quinary: 62.4%), while LR and NN are less competitive, particularly on minority or extreme classes, reflecting the impact of class imbalance.

The following figures show the heat map analysis of model confusion matrix (Figures 5.11-5.14). In the confusion matrix, the labels on the horizontal axis represent the true labels for the binary, ternary, and quinary classifications, whereas those on the vertical axis represent the predicted labels. The darker the color, the higher the recognition accuracy. so, it can be intuitively observed from the figures that the heat map recognition accuracy of the binary, ternary, and quinary model confusion matrices for RF was the highest.

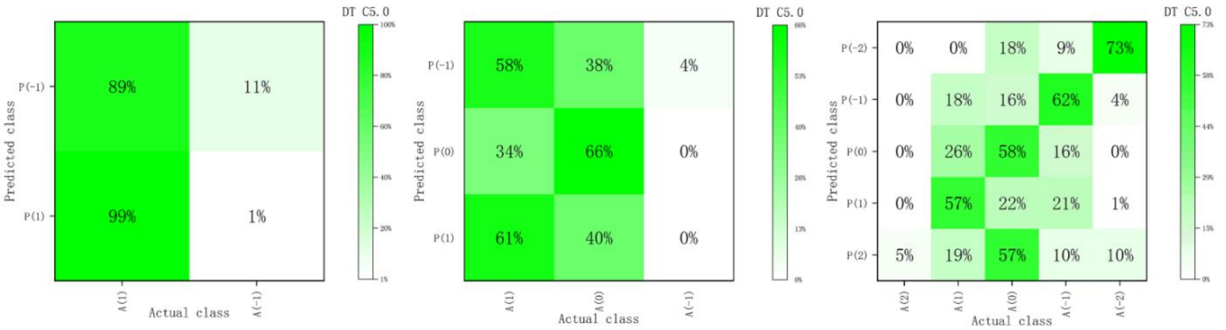


Figure 5.11 Heat map analysis of confusion matrix of the model built by DT C5.0 classifier.

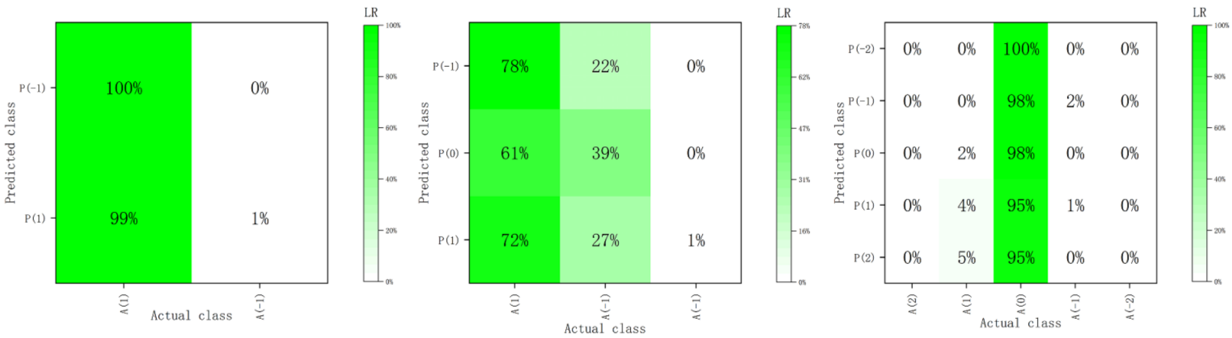


Figure 5.12 Heat map analysis of confusion matrix of the model built by LR classifier.

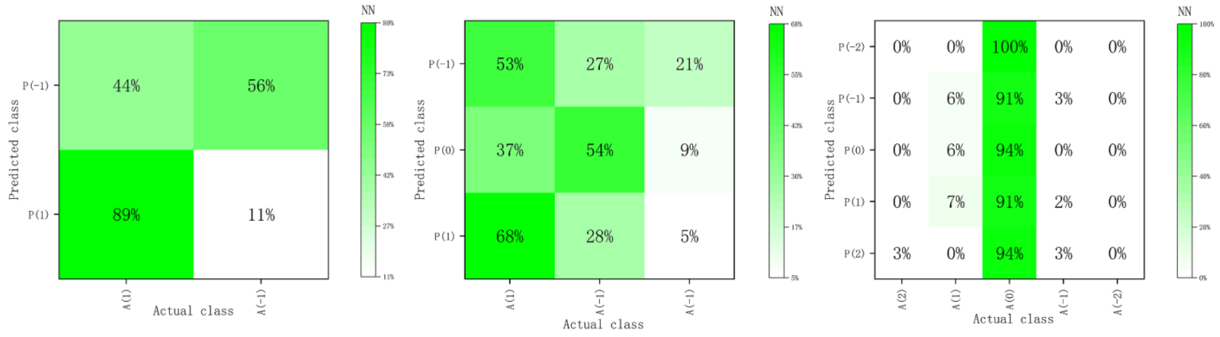


Figure 5.13 Heat map analysis of the confusion matrix of the model built by NN classifier.

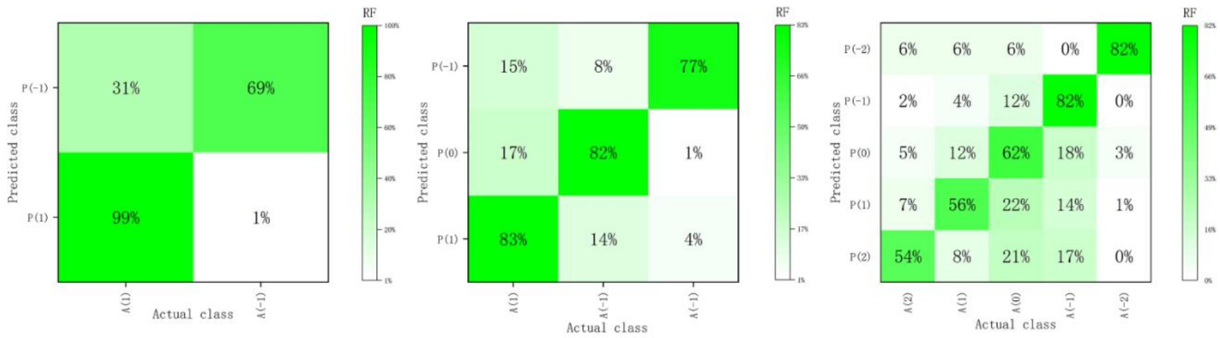


Figure 5.14 Heat map analysis of confusion matrix of the model built by RF classifier.

The classification accuracy of the built emotional machine learning model for ceramic teapots shows that the binary classifier Random Forest has the highest classification accuracy and can be applied to the design evaluation of new ceramic teapots (as show in Figure 5.15).

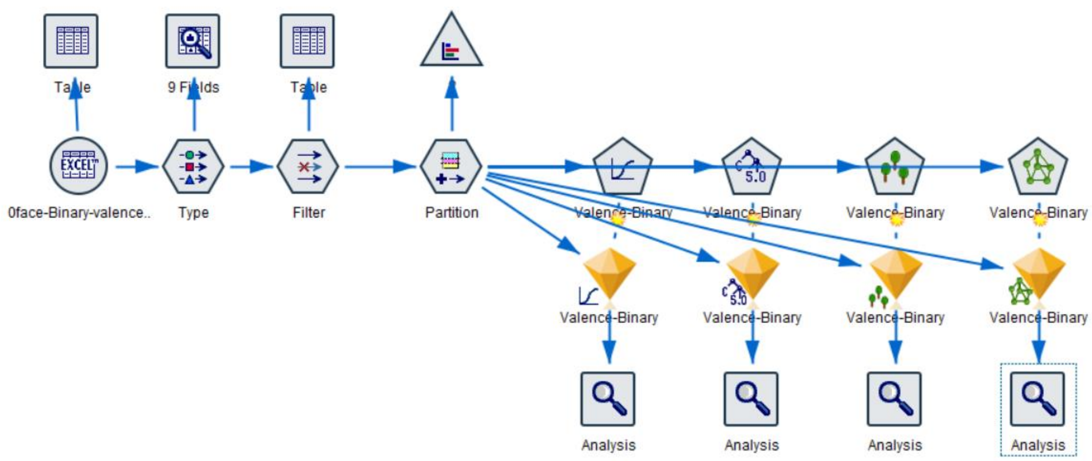


Figure 5.15 The valence(binary) classification flow built in SPSS Modeler 18.2.

5.3.2 New ceramic teapot evaluation

To ensure the independence and rigor of the evaluation process and to address potential concerns regarding circular reasoning, this external validation phase was meticulously designed: 1) the three new teapots, while their design principles were derived from the morphological and perceived analysis of the original 20 samples, served as novel and independent stimuli; 2) Crucially, the facial emotion data for validation were collected from a completely new cohort of participants who did not participate in the initial model training phase; 3) The predictive models (binary and ternary RF classifiers) were frozen and applied directly to this new dataset without any retraining or parameter adjustment. This approach ensures a strict separation between the data used for model development and the data used for testing, thereby providing a genuine assessment of the model's generalizability to new designs rather than merely reflecting its performance on the original data distribution.

After collecting new data, the facial photos of the participants were input into the facial recognition processing software FaceReader 9.1 for analysis. Subsequently, the facial emotion recognition data were input into the binary and ternary models built by RF for external validation, yielding (obtaining) the following results (Figure 5.16-5.17). The results showed that the proportion of external validation for “1” in the binary classification model reached 91.1%, while the proportion for “1” in the ternary classification model was 64.5%. This result is significantly higher than the average proportion of the "1" category for the original 20 teapots (37.4% and 28.9% for the binary and ternary classification, respectively (see Table 5.5). These results indicate that the newly designed teapot significantly increased the proportion of participants' positive emotional responses. This supports the generalizability of the RF-based evaluation model to new designs.

While the design features are derived from the initial analysis, the validation experiment itself is independent. The strong performance on the new teapots demonstrates the model's ability to generalize to new designs created based on the discovered principles, which is a key goal of this research.

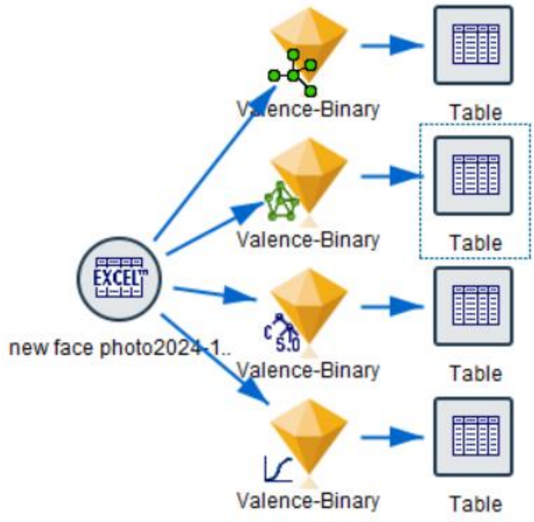


Figure 5.16 The valence (binary) classification flow was built after inputting new data.

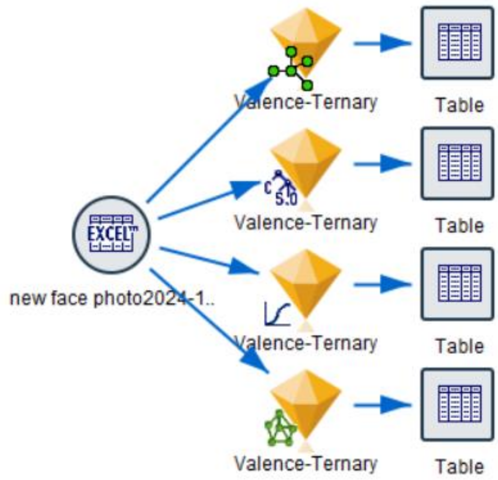


Figure 5.17 The valence (ternary) classification flow was built after inputting new data.

Table 5.5 Comparison of classification results between the samples and new teapots.

Teapots	Predicted valence distribution in external validation (%)				
	Binary		Ternary		
	-1	1	-1	0	1
Original 20 teapots (average proportion)	62.6%	37.4%	56.4%	14.7%	28.9%
Three newly designed teapots (average proportion)	8.9%	91.1%	2.2%	33.3%	64.5%

Note: Binary: -1 = negative, 1 = positive; Ternary: -1 = negative, 0 = neutral, 1 = positive.
Original samples: average across the 20 top-selling teapots;
New teapots: external validation set of the three newly designed teapots.

5.3.3 Application of an evaluation process

To further illustrate the practical applicability of our approach, this dissertation proposes a replicable evaluation workflow that translates research findings into actionable design guidance. As depicted in Figure 5.18, this process begins with designers proposing new teapot concepts, which are then evaluated through participant

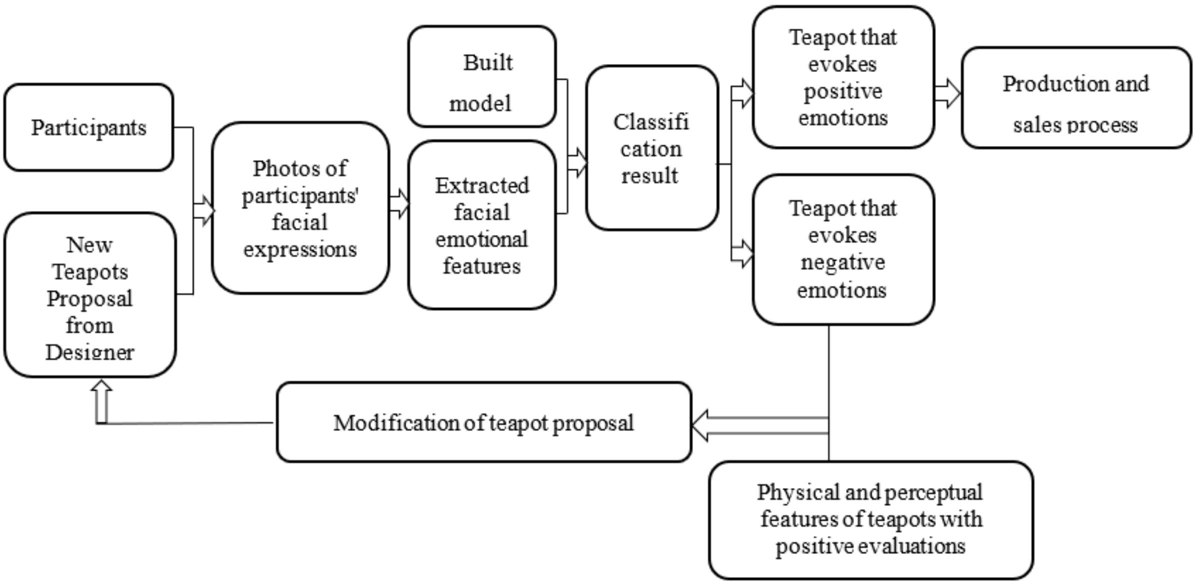


Figure 5.18 The replicable evaluation procedure of the results of this study in practice.

facial expression analysis. The extracted emotional features are fed into our pre-trained classification model to determine whether the design evokes positive or negative emotions. Based on these results, designers can iteratively refine the teapot proposals, incorporating the physical and perceived features associated with positive emotional responses. This closed-loop system not only validates the model's predictive capability but also provides a structured, data-driven framework for guiding the production and marketing of emotionally resonant ceramic teapots. Such a workflow exemplifies how emotional design evaluation can be seamlessly integrated into the craft development process, bridging the gap between affective research and practical design iteration.

5.4 Discussion

This chapter successfully built and evaluated an emotional quality classification model for ceramic teapots, and evaluated the newly designed teapot addressing SRQ2. The integration of facial emotion recognition with machine learning has provided a robust support for quantifying the often-elusive consumer emotional experience.

5.4.1 Performance of Machine Learning Classifiers

The comparative analysis of four machine learning algorithms (LR, DT C5.0, NN, and RF) revealed that the Random Forest (RF) classifier consistently outperformed the others across binary, ternary, and quinary classification tasks. Specifically, the RF binary classification model achieved an accuracy of 91.0%, with precision and recall exceeding 97% for positive emotional responses. This suggests that ensemble learning methods like Random Forest are better satisfying the requirements for evaluating the non-linear and high-dimensional nature of facial emotion data compared to linear models or simple decision trees. The heat map analysis of confusion matrices further corroborated the superior stability of the RF model in correctly identifying positive emotional states.

5.4.2 Evaluation of new ceramic teapot design

A significant contribution of this chapter is the evaluation process. Three new teapots (Elegant, Fashionable, and Practical) were designed using the positive feature lines identified in Chapter 4. The facial emotion analysis of a new participant group showed that these new designs elicited a 91.1% positive response rate in the binary model, a substantial increase compared to the 37.4% average of the original top-selling samples. This result not only validates the predictive capability of the RF model but also empirically proves the effectiveness of the "feature-emotion" mapping rules built in the previous chapter. It demonstrates that explicitly incorporating "positive" morphological elements (e.g., specific handle curvatures or spout shapes) directly translates to measurable positive emotional reactions.

5.4.3 A replicable evaluation process

The study moves beyond theoretical modeling to propose a practical, replicable evaluation process (Figure 5.18). By creating a closed-loop system—where design concepts are evaluated by the model, and results feed back into design iteration—this research bridges the gap between subjective craft intuition and objective engineering evaluation. This process provides designers with design guidance for prompt the craft industry.

5.4.4 Research limitations

1) Due to objective limitations, the evaluation objects of the experiment cannot use real products as experimental samples. The experiment is mainly conducted using sample photos. The subjects evaluate the morphology of the experimental samples by visual means, so the experiment has certain limitations.

2) Due to changes in head posture, lighting, occlusion, etc., collecting photos of the subjects' facial expressions may result in low recognition accuracy. In addition, although facial expressions can be used as the main representation of emotion recognition, these expressions can be self-controlled and sometimes do not reflect real emotions.

3) Due to the length of this article, no comparative analysis of the design features of best-selling Chinese and Japanese ceramic teapots was conducted.

In future research, we will conduct a comparative study of Chinese and Japanese ceramic teapots; and use multimodal fusion methods to study the emotional responses of ceramic teapot consumers to improve the scientific validity of the research.

5.5 Summary

This chapter focuses on answering SRQ2, which is the question of objective evaluation of the emotional quality of ceramic teapots.

Data Processing: Facial expression data from 60 participants were processed using FaceReader 9.1, and combined with SAM scale data to create a labeled dataset for training.

Model Construction: Four machine learning models were constructed and compared. The Random Forest (RF) model performed best, achieving an accuracy of 91.0% in binary classification of valence.

Design Practice & Validation: Based on the regression analysis from Chapter 4, three new teapots were designed and subjected to new teapots evaluation. The results showed a dramatic improvement in positive emotional responses (from 37.4% to 91.1%), verifying both the design guidelines and the evaluation model.

In summary, this chapter provides the methodological core for quantitative sentiment assessment. A standardized and replicable 'design-evaluation-iteration' workflow is proposed to help designers predict consumer emotions, thereby providing them with a basis for design decisions.

Chapter 6

Comparative analysis of design features based on online reviews and emotional questionnaires

6.1 Introduction

In the contemporary e-commerce environment, consumers' emotional reactions to products are influenced by various forms of information. For ceramic teapots, emotional responses may be elicited directly by product images, whereas online reviews provide textual expressions of consumers' evaluations formed in actual market contexts. Given the structure of the present study, these two sources are examined as two distinct evaluative contexts: an online-reviews context and an emotional questionnaires context. This distinction is particularly relevant for ceramic teapots, which, as craft products, embody not only functional utility but also formal, decorative, and so on. Although previous studies have addressed emotional design, emotional questionnaires-based product evaluation, and sentiment in online reviews, relatively limited research has systematically compared these two contexts within the same set of ceramic teapots (Hassenzahl, 2003; Ladhari et al., 2020).

Against this background, Chapter 6 explores SRQ3 within the broader context of the "design features-emotional response" relationship in this dissertation. Specifically, the chapter compares online reviews-based emotional expressions with emotional questionnaires-based emotional responses for the same set of top-selling Chinese and Japanese ceramic teapots. To do so, it brings together laboratory-based data, including SAM valence ratings, perceptual evaluation results, coded morphological features, and textual emotion-related information extracted from 1,316 valid pieces of data. Through this integrated analytical design, the chapter examines how ceramic teapot design features are associated with consumer emotion across different evaluative contexts.

Methodologically, this chapter combines generalized linear mixed models (GLMM), generalized estimating equations (GEE), and text analysis to investigate the relationships between perceptual and morphological design cues and emotional outcomes derived from images and reviews. The purpose is not to infer a direct temporal transition in the same consumers, but rather to clarify how different forms of design information are linked to different forms of emotional response. By comparing these two contexts, the chapter seeks to identify design features that remain salient across contexts, those whose effects vary by context, and the implications of such differences for evidence-based ceramic teapot design.

The fourth and fifth chapters of this dissertation use a consumer emotional quality model to study consumers' perception of popular teapot images. This chapter further extends the research from laboratory scenarios to e-commerce scenarios, aiming to respond to the research objectives of SRQ3: What are the differences in ceramic teapot design features based on emotional responses elicited by online reviews versus those derived from emotional questionnaires?

Regarding SRQ3, this chapter raises three core questions:

SRQ3.1. Based on online reviews, which design features have the impact on consumers' emotional responses?

SRQ3.2. Based on emotional questionnaires, which design features have the impact on consumers' emotional responses?

SRQ3.3. What are the differences in design features of ceramic teapots based on emotional evaluation from online reviews and emotional questionnaires?

To answer these three questions, this chapter conducts text mining (such as word frequency analysis and cluster analysis) on 1,316 valid pieces of data from the same batch of teapots, and uses the generalized linear mixture model (GLMM) and generalized estimating equations (GEE) to analyze and compare emotional responses based on images and online reviews, to identify the design features that are most likely to trigger emotional responses.

And then, the research in this chapter is divided into the following steps (Figure 6.1).

Step 1: Analysis of online reviews-based consumers' emotional responses and ceramic teapot design features

This chapter summarizes the emotional ratings of each consumer's online reviews for each ceramic teapot, with a total of 1791 data points. We removed 475 invalid data points and 119 data points with a rating of "0", leaving 1197 valid data points as binary dependent variables. Then, in IBM SPSS Statistics 24 software, the generalized estimating equations (GEE) were used to analyze the correlation between the morphological characteristics of ceramic teapots and the emotional ratings of each consumer's online reviews of each ceramic teapot. Thus, the correlation between consumer emotional responses to online reviews-based and the perceived and morphological characteristics of ceramic teapots can be obtained.

Step 2: Analysis of emotional questionnaires-based consumers' emotional responses and ceramic teapot design features.

This chapter has compiled 1200 valid data points from the SAM values (Valence values of SAM) of each ceramic teapot sample. Among them, there are 523 data points with a value of "1", 206 data points with a value of "-1", and 471 data points with a value of "0". After deleting the data with a value of "0", the remaining 729 valid data were used as binary dependent variables and analyzed using a generalized linear mixed effects model (GLMM) with the average perceived characteristic adjectives of ceramic teapots in factor analysis. Then, in IBM SPSS Statistics 24 software, the generalized estimating equations (GEE) were used to analyze the correlation between the morphological characteristics of ceramic teapots and the Valence value of SAM. Thus, the relationship between consumers' emotional responses to emotional questionnaires-based and the perception and morphological features of ceramic teapots can be obtained.

Step 3: Text data analysis of Chinese and Japanese ceramic teapots, word frequency statistics, and text clustering, and to explore the relationship between the design features of craft products and consumers' emotional responses.

This chapter will clean up the collected 1791 online comment data, delete 475 invalid data, and leave 1316 valid data. This includes 664 comments for Chinese ceramic teapots and 652 reviews for Japanese ceramic teapots. Then use SPSSAU international version to perform word frequency statistics and text clustering analysis, and compare and analyze the emotional responses of consumers. ceramic teapots to obtain the design focus of designers when designing ceramic teapots. Provide the basis for designers to create the top-selling ceramic teapot on the market, thereby promoting the development of craft product design.

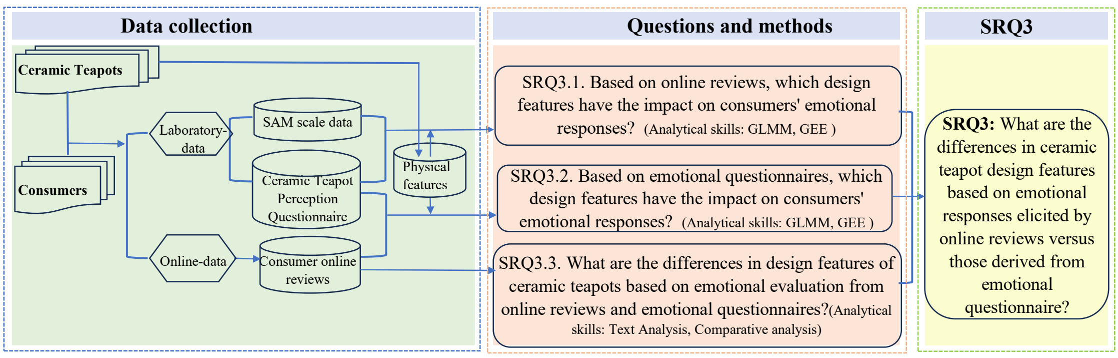


Figure 6.1 Research flowchart of Chapter 6

6.2 Methods

6.2.1 Generalized regression analysis

6.2.1.2 Analysis of online reviews-based consumers' emotional responses and ceramic teapot design features

1. Correlation analysis between Perception features of ceramic teapots and sentiment from online reviews using GLMM (Generalized linear mixed effects model analysis).

1) Data pre-processing

This chapter has compiled sentiment scores for each online review of ceramic teapot consumers, with a total of 1791 data points. Delete 475 invalid data and 119 data with a rating of 0, leaving 1197 valid data as the dependent variable for binary classification (see Table 6.1). Using the Average score of perceived features for each teapot as the independent variable (see Table 6.2), in IBM SPSS Statistics 24 software was applied for analysis Generalized linear mixed effects model (GLMM)analysis (see Table 6.3).

Table 6.1 The sentiment tendency value of each comment in the teapot sample (Partial data).

A	B	C	D	E	F	G	H	I
	Ceramic Teapot Sample	Emotional inclination value						
	1	-1						
		1						
		1						
		-1						
		1						
		-1						
		1						
		-1						
		1						
		1						
		1						
		-1						
		-1						
		-1						
		1						
		0						
		-1						
		1						
		0						

... | 文本分析情感数据与感知得分结合 | 文本分析每个茶壶的情感值与SD每个茶壶的特征 ...

Table 6.2 Average score of perceived features for each teapot (Partial data).

Table:The average score of perceptual features for each teapot

Samples	Colorful/Monochromatic	Rich patterns/Simple patterns	Glossy/lackluster	Delicate texture/Rough texture	Regular shape/Irregular shape	Modern/Traditional	Interesting/Serious	graceful/Ugly	Low-key/Exaggerated	Light/Heavy	Concise/Complex	Warm/Cold	Rounded/Hard	Expensive/Cheap	Easy to use/Inconvenient to use	Unbreakable/fragile
Teapot 01	-0.71667	-0.46667	0.933333	1.066667	1.216667	-0.35	-0.03333	0.95	1.15	0.716667	1.333333	-0.16667	1.2	-0.06667	1.116667	-0.78333
Teapot 02	-2.65	-2.66667	0.066667	1.166667	1.466667	0.4	-0.61667	1.033333	1.816667	1.033333	2.233333	0.633333	1.216667	0.516667	1.45	-0.21667
Teapot 03	1.733333	1.283333	1.983333	1.833333	1.35	0.766667	0.5	0.933333	-0.03333	0.4	0.016667	0.633333	0.733333	0.1	0.966667	-0.46667
Teapot 04	-0.9	-1.8	1.266667	1.366667	0.75	0.4	0.666667	0.583333	1.016667	-0.26667	1.1	0.866667	1.166667	1.1	0.733333	0.9
Teapot 05	2.266667	2.483333	1.616667	0.6	0.15	-0.25	1.4	0.766667	-0.38333	-0.56667	-0.9	0.466667	0.25	0.616667	0.75	-0.55
Teapot 06	-2.61667	-2.65	0.2	1.333333	1.8	0.466667	0.166667	1.433333	1.75	1.416667	2.166667	1.016667	1.966667	1.233333	1.233333	-0.05
Teapot 07	2.233333	2.416667	0.233333	0.3	0.266667	1.066667	0.966667	0.583333	-0.71667	0.166667	-0.98333	0.283333	-0.78333	-0.25	0.616667	-0.4
Teapot 08	-2.75	-2.6	0.883333	1.85	1.366667	0.416667	0.416667	1.5	1.666667	1.183333	2.316667	0.9	2.166667	1.183333	1.15	-0.2
Teapot 09	2.05	1.733333	1.25	1.433333	0.733333	0.916667	1.1	1.183333	0.033333	-0.2	-0.08333	0.766667	0.766667	0.533333	0.516667	0.333333
Teapot 10	-2.66667	0.55	0.766667	1.483333	-1.28333	-0.51667	1.45	1.716667	-0.13333	0.033333	-0.43333	0.616667	0.8	1.65	-0.58333	-0.5
Teapot 11	-1.06667	-1.9	0.366667	0.583333	0.116667	0.4	0.383333	0.166667	-0.35	0.033333	0.466667	0.05	0.6	0.75	0.316667	-0.26667
Teapot 12	-1.73333	-2.06667	-1.13333	-1.41667	-0.21667	-0.73333	-0.86667	-0.51667	0.45	-1.26667	0.633333	-0.48333	-0.36667	0.4	0.55	0.983333
Teapot 13	-0.98333	-2.15	-0.38333	1.216667	1.55	0.283333	0.516667	1.5	1.3	0.616667	1.466667	0.466667	1.283333	0.983333	1.166667	0.033333
Teapot 14	-2.13333	-2.1	0.433333	1.1	0.866667	1.533333	1.05	1.016667	0.916667	0.583333	1.466667	0.466667	1.4	0.716667	1.05	0.433333
Teapot 15	-0.88333	-1.73333	0.566667	-0.01667	-0.08333	0.333333	-0.13333	-0.4	0.133333	-0.91667	0.266667	-0.21667	0.083333	0.116667	0.216667	0.533333
Teapot 16	2.466667	2.316667	2.433333	1.8	0.983333	0.3	0.716667	0.116667	-1.55	0.233333	-1.05	1.266667	0.6	0.533333	0.583333	-0.71667
Teapot 17	-0.11667	0.45	0.166667	0.866667	-0.28333	0.533333	0.833333	0.833333	0.083333	0.483333	0.233333	0.55	0.666667	0.583333	-0.15	0.15
Teapot 18	-0.78333	-1.23333	0.316667	-0.66667	-0.36667	-0.4	-0.21667	-0.28333	-0.11667	-1.05	0.55	0.033333	-0.76667	0	0.366667	0.9
Teapot 19	-1.1	0.983333	1.566667	1.566667	1.4	0.433333	0.633333	1.566667	1.35	1.4	1.083333	0.75	1.35	0.783333	1.1	-0.31667
Teapot 20	1.166667	1.683333	1.35	1.3	1.133333	0.216667	1.35	1.316667	0.15	0.483333	0.066667	1.016667	1.35	0.5	0.883333	-0.2
Average value	-0.45917	-0.37333	0.744167	0.938333	0.645833	0.310833	0.514167	0.8	0.426667	0.225833	0.5975	0.495833	0.784167	0.599167	0.701667	-0.02
Standard deviation	1.816675	1.910278	0.83909	0.847323	0.817818	0.552805	0.64729	0.67575	0.908366	0.772565	1.038686	0.458636	0.799094	0.480542	0.501019	0.540186

Table 6.3 Data table of emotional values of online comments and perceived features, average values of teapots (Partial data).

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R
CeramicTeapotSample	Emotionalinclinationvalue	Monochromatic_Colorful	Rich_in_patterns_Simple_patterns	Glossy_lackluster	Delicate_texture_Rough_texture	Regular_shape_Irregular_shape	Modern_Traditional	Interesting_Serious	Graceful_Ugly	Lowkey_Exaggerated	Light_Heavy	Concise_Complex	Warm_Cold	Rounded_Hard	Expensive_Cheap	Easy_to_use_Inconvenient_to_use	Unbreakable_fragile
1	-1	-0.71666667	-0.46666667	0.933333	1.066667	1.216667	-0.35	-0.03333333	0.95	1.15	0.716667	1.33333333	-0.16667	1.2	-0.06667	1.116667	-0.78333
1	1	-0.71666667	-0.46666667	0.933333	1.066667	1.216667	-0.35	-0.03333333	0.95	1.15	0.716667	1.33333333	-0.16667	1.2	-0.06667	1.116667	-0.78333
1	1	-0.71666667	-0.46666667	0.933333	1.066667	1.216667	-0.35	-0.03333333	0.95	1.15	0.716667	1.33333333	-0.16667	1.2	-0.06667	1.116667	-0.78333
1	-1	-0.71666667	-0.46666667	0.933333	1.066667	1.216667	-0.35	-0.03333333	0.95	1.15	0.716667	1.33333333	-0.16667	1.2	-0.06667	1.116667	-0.78333
1	1	-0.71666667	-0.46666667	0.933333	1.066667	1.216667	-0.35	-0.03333333	0.95	1.15	0.716667	1.33333333	-0.16667	1.2	-0.06667	1.116667	-0.78333
1	-1	-0.71666667	-0.46666667	0.933333	1.066667	1.216667	-0.35	-0.03333333	0.95	1.15	0.716667	1.33333333	-0.16667	1.2	-0.06667	1.116667	-0.78333
1	1	-0.71666667	-0.46666667	0.933333	1.066667	1.216667	-0.35	-0.03333333	0.95	1.15	0.716667	1.33333333	-0.16667	1.2	-0.06667	1.116667	-0.78333
1	-1	-0.71666667	-0.46666667	0.933333	1.066667	1.216667	-0.35	-0.03333333	0.95	1.15	0.716667	1.33333333	-0.16667	1.2	-0.06667	1.116667	-0.78333
1	1	-0.71666667	-0.46666667	0.933333	1.066667	1.216667	-0.35	-0.03333333	0.95	1.15	0.716667	1.33333333	-0.16667	1.2	-0.06667	1.116667	-0.78333
1	1	-0.71666667	-0.46666667	0.933333	1.066667	1.216667	-0.35	-0.03333333	0.95	1.15	0.716667	1.33333333	-0.16667	1.2	-0.06667	1.116667	-0.78333
1	1	-0.71666667	-0.46666667	0.933333	1.066667	1.216667	-0.35	-0.03333333	0.95	1.15	0.716667	1.33333333	-0.16667	1.2	-0.06667	1.116667	-0.78333
1	-1	-0.71666667	-0.46666667	0.933333	1.066667	1.216667	-0.35	-0.03333333	0.95	1.15	0.716667	1.33333333	-0.16667	1.2	-0.06667	1.116667	-0.78333
1	-1	-0.71666667	-0.46666667	0.933333	1.066667	1.216667	-0.35	-0.03333333	0.95	1.15	0.716667	1.33333333	-0.16667	1.2	-0.06667	1.116667	-0.78333
1	-1	-0.71666667	-0.46666667	0.933333	1.066667	1.216667	-0.35	-0.03333333	0.95	1.15	0.716667	1.33333333	-0.16667	1.2	-0.06667	1.116667	-0.78333
1	1	-0.71666667	-0.46666667	0.933333	1.066667	1.216667	-0.35	-0.03333333	0.95	1.15	0.716667	1.33333333	-0.16667	1.2	-0.06667	1.116667	-0.78333
1	0	-0.71666667	-0.46666667	0.933333	1.066667	1.216667	-0.35	-0.03333333	0.95	1.15	0.716667	1.33333333	-0.16667	1.2	-0.06667	1.116667	-0.78333
1	-1	-0.71666667	-0.46666667	0.933333	1.066667	1.216667	-0.35	-0.03333333	0.95	1.15	0.716667	1.33333333	-0.16667	1.2	-0.06667	1.116667	-0.78333
1	1	-0.71666667	-0.46666667	0.933333	1.066667	1.216667	-0.35	-0.03333333	0.95	1.15	0.716667	1.33333333	-0.16667	1.2	-0.06667	1.116667	-0.78333
1	0	-0.71666667	-0.46666667	0.933333	1.066667	1.216667	-0.35	-0.03333333	0.95	1.15	0.716667	1.33333333	-0.16667	1.2	-0.06667	1.116667	-0.78333
1	1	-0.71666667	-0.46666667	0.933333	1.066667	1.216667	-0.35	-0.03333333	0.95	1.15	0.716667	1.33333333	-0.16667	1.2	-0.06667	1.116667	-0.78333
1	0	-0.71666667	-0.46666667	0.933333	1.066667	1.216667	-0.35	-0.03333333	0.95	1.15	0.716667	1.33333333	-0.16667	1.2	-0.06667	1.116667	-0.78333
1	1	-0.71666667	-0.46666667	0.933333	1.066667	1.216667	-0.35	-0.03333333	0.95	1.15	0.716667	1.33333333	-0.16667	1.2	-0.06667	1.116667	-0.78333
1	-1	-0.71666667	-0.46666667	0.933333	1.066667	1.216667	-0.35	-0.03333333	0.95	1.15	0.716667	1.33333333	-0.16667	1.2	-0.06667	1.116667	-0.78333
1	0	-0.71666667	-0.46666667	0.933333	1.066667	1.216667	-0.35	-0.03333333	0.95	1.15	0.716667	1.33333333	-0.16667	1.2	-0.06667	1.116667	-0.78333
1	1	-0.71666667	-0.46666667	0.933333	1.066667	1.216667	-0.35	-0.03333333	0.95	1.15	0.716667	1.33333333	-0.16667	1.2	-0.06667	1.116667	-0.78333
1	1	-0.71666667	-0.46666667	0.933333	1.066667	1.216667	-0.35	-0.03333333	0.95	1.15	0.716667	1.33333333	-0.16667	1.2	-0.06667	1.116667	-0.78333
1	1	-0.71666667	-0.46666667	0.933333	1.066667	1.216667	-0.35	-0.03333333	0.95	1.15	0.716667	1.33333333	-0.16667	1.2	-0.06667	1.116667	-0.78333
1	1	-0.71666667	-0.46666667	0.933333	1.066667	1.216667	-0.35	-0.03333333	0.95	1.15	0.716667	1.33333333	-0.16667	1.2	-0.06667	1.116667	-0.78333
1	1	-0.71666667	-0.46666667	0.933333	1.066667	1.216667	-0.35	-0.03333333	0.95	1.15	0.716667	1.33333333	-0.16667	1.2	-0.06667	1.116667	-0.78333

And then, this chapter performed dimensionality reduction on the data. Through preliminary data analysis (preprocessing) on 16 independent variables, 5 irrelevant variables were removed, leaving 11 independent variables, namely: Colorful-Monochromatic, Rich in patterns-Simple patterns, Glossy-Lacklust, Delicate texture-Rough texture, Regular shape-Irregular shape, Interesting-Serious, Graceful-Ugly, Lowkey-Exaggerated, Light-Heavy, Concise-Complex, Expensive-Cheap. Consumers' online reviews and perceived features of ceramic teapots using GLMM (the Generalized Linear Mixed Effects Model).

2) The GLMM analysis results

The GLMM analysis results show that Concise-Complex has the highest correlation with Emotion from text analysis consumer text sentiment tendency; Rich in patterns-Simple patterns, Glossy-Lackluster, Delicate texture-Rough texture, Graceful-Ugly Highly correlated with Emotion from text analysis; Lowkey-Exaggerated, Light-Heavy, Expensive-Cheap are weakly correlated with Emotion from text analysis; Colorful-Monochromatic, Regular Shape-Irregular Shape, Interesting Serious are not correlated with Emotion from text analysis (see Table 6.4).

Table 6.4 The GLMM analysis results

Term	Estimate	Std_Error	z_value	P-value	Significance
(Intercept)	0.9442	0.3256	2.899	0.003738	**
Colorful-Monochromatic	-0.4719	0.4181	-1.129	0.258999	
Rich in patterns-Simple patterns	1.9069	0.6115	3.118	0.001818	**
Glossy-Lackluster	-1.8758	0.6147	-3.052	0.002276	**
Delicate texture-Rough texture	2.6673	0.9108	2.929	0.003405	**
Regular shape-Irregular shape	1.0832	0.6598	1.642	0.100664	
Interesting-Serious	0.7861	0.4977	1.579	0.114239	
Graceful-Ugly	-3.0732	0.9995	-3.075	0.002107	**
Lowkey-Exaggerated	-2.2459	0.9308	-2.413	0.015832	*
Light-Heavy	-1.7687	0.7093	-2.494	0.012646	*
Concise-Complex	3.7701	0.989	3.812	0.000138	***
Expensive-Cheap	0.8382	0.4175	2.008	0.044673	*

3) Correlation visualization:

The following figure shows a visualization of regression coefficients and confidence intervals (See Figure 6.4)

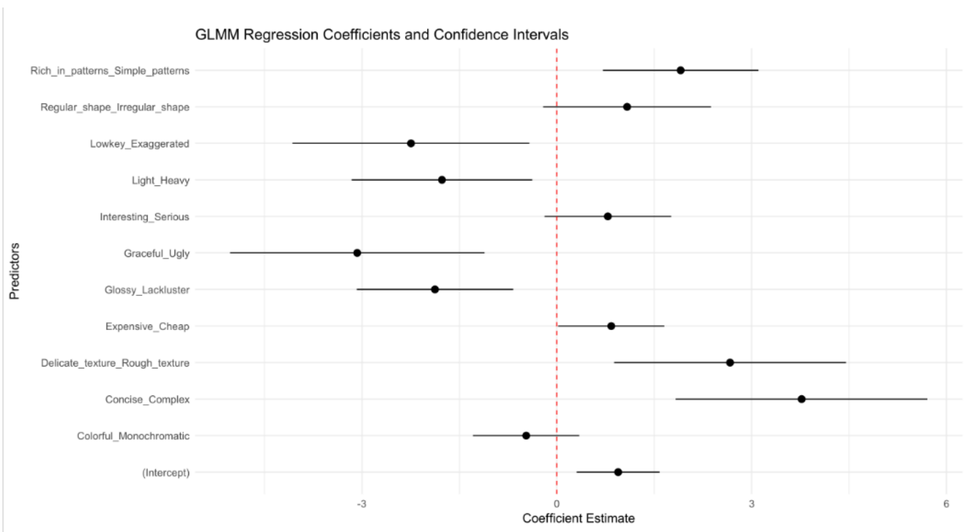


Figure 6.2 Visualization of regression coefficients and confidence intervals (GLMM).

2. Correlation analysis between morphological features of ceramic teapots and sentiment from online reviews using GEE (Generalized estimating equations analysis).

1) Data pre-processing

Correlation analysis between consumer online reviews and the morphological characteristics of ceramic teapots using GEE. Taking the sentiment tendency value of each comment in the teapot sample as the dependent variable (see Table 6.1), and the encoding table for design features of 20 ceramic teapot samples (see Table 4.3) as independent variables, generalized estimating equations (GEE) analysis was conducted using IBM SPSS Statistics 24 software (see Table 6.5).

And then, this study performed dimensionality reduction on the data. Through preliminary data analysis (preprocessing) of 25 independent variables, 14 irrelevant variables were removed, leaving 11 independent variables, namely B2, C2, C3, D1, E1, E4, F1, F3, F4, G1, and G3. Since the independent variable does not come from the questionnaire, there is no need for reliability and validity testing.

2) The GEE analysis results

We perform generalized estimating equations (GEE) regression analysis, and the

Table 6.5 The emotional value of online comments on teapots and the code of teapot morphological features (Partial data).

A	B	S	T	U	V	W	X	Y	Z	AA	AB	AC	AD	AE	AF	AG
CeramicTeapotSample	Emotional inclinationvalue	A1	A2	B1	B2	B3	B4	D1	D2	F1	F2	F3	F4	H1	H2	H3
1	-1	0	1	1	0	0	0	0	1	0	1	0	0	0	1	0
1	1	0	1	1	0	0	0	0	1	0	1	0	0	0	1	0
1	1	0	1	1	0	0	0	0	1	0	1	0	0	0	1	0
1	-1	0	1	1	0	0	0	0	1	0	1	0	0	0	1	0
1	1	0	1	1	0	0	0	0	1	0	1	0	0	0	1	0
1	-1	0	1	1	0	0	0	0	1	0	1	0	0	0	1	0
1	1	0	1	1	0	0	0	0	1	0	1	0	0	0	1	0
1	-1	0	1	1	0	0	0	0	1	0	1	0	0	0	1	0
1	1	0	1	1	0	0	0	0	1	0	1	0	0	0	1	0
1	1	0	1	1	0	0	0	0	1	0	1	0	0	0	1	0
1	1	0	1	1	0	0	0	0	1	0	1	0	0	0	1	0
1	-1	0	1	1	0	0	0	0	1	0	1	0	0	0	1	0
1	-1	0	1	1	0	0	0	0	1	0	1	0	0	0	1	0
1	-1	0	1	1	0	0	0	0	1	0	1	0	0	0	1	0
1	1	0	1	1	0	0	0	0	1	0	1	0	0	0	1	0
1	0	0	1	1	0	0	0	0	1	0	1	0	0	0	1	0
1	-1	0	1	1	0	0	0	0	1	0	1	0	0	0	1	0
1	1	0	1	1	0	0	0	0	1	0	1	0	0	0	1	0
1	0	0	1	1	0	0	0	0	1	0	1	0	0	0	1	0
1	1	0	1	1	0	0	0	0	1	0	1	0	0	0	1	0
1	0	0	1	1	0	0	0	0	1	0	1	0	0	0	1	0
1	1	0	1	1	0	0	0	0	1	0	1	0	0	0	1	0
1	-1	0	1	1	0	0	0	0	1	0	1	0	0	0	1	0
1	0	0	1	1	0	0	0	0	1	0	1	0	0	0	1	0
1	1	0	1	1	0	0	0	0	1	0	1	0	0	0	1	0
1	1	0	1	1	0	0	0	0	1	0	1	0	0	0	1	0
1	1	0	1	1	0	0	0	0	1	0	1	0	0	0	1	0
1	1	0	1	1	0	0	0	0	1	0	1	0	0	0	1	0
1	1	0	1	1	0	0	0	0	1	0	1	0	0	0	1	0

Sheet1

The analysis results are as follows: The morphological feature codes with the highest correlation with Emotion from text analysis are F4 and G3, followed by C3. The morphological feature codes with the lowest correlation are E4 and G1, while the uncorrelated ones are B2, C2, D1, E1, F1, and F3 (see Table 6.6).

Table 6.6 The GEE analysis results

Term	Estimate	Std.err	Wald	Pr_W	Significance
(Intercept)	1.0855	0.0561	373.8700	< 2e-16	***
B2	0.0465	0.0631	0.5400	0.4618	
C2	0.0246	0.0899	0.0800	0.7841	
C3	0.2115	0.0749	7.9700	0.0047	**
D1	-0.0939	0.1522	0.3800	0.537	
E1	0.0005	0.0983	0.0000	0.9963	
E4	0.1357	0.0581	5.4500	0.0196	*
F1	-0.0189	0.0564	0.1100	0.7382	
F3	0.0247	0.1262	0.0400	0.8449	
F4	0.1884	0.0317	35.3200	2.8e-09	***
G1	0.2125	0.0909	5.4600	0.0195	*
G3	0.5117	0.0849	36.3500	1.6e-09	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

3) Correlation visualization:

The following figure shows a visualization of regression coefficients and confidence intervals (See Figure 6.5)

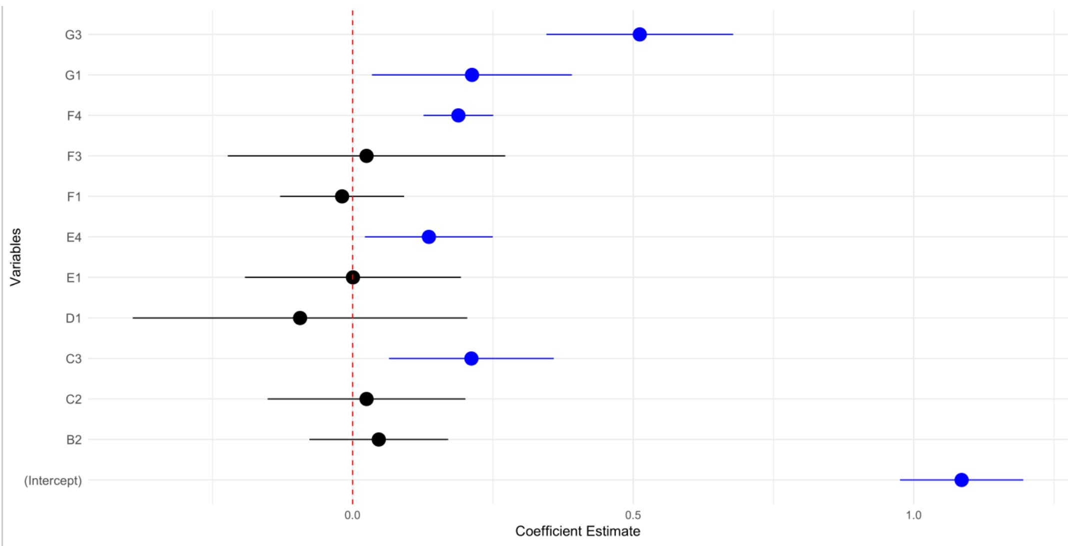


Figure 6.3 Visualization of regression coefficients and confidence intervals (GEE).

6.2.1.2 Analysis of emotional questionnaires-based consumers' emotional responses and ceramic teapot design features

1. Correlation analysis between Perception features of ceramic teapots and Valence from SAM using GLMM (Generalized linear mixed effects model (GLMM)analysis).

1) Data pre-processing

This chapter compiled the valence values from the SAM values of each ceramic teapot sample, with a total of 1200 valid data points. Among them, there were 523 data points with a valence value of "1", 206 data points with a valence value of '-1', and 471 data points with a valence value of '0'. Delete the data with a rating of "0", leaving a total of 729 valid data as the dependent variable for binary classification (see Table 6.7). Using the Average score of perceived features for each teapot as the independent variable (see Table 6.2), in IBM SPSS Statistics 24 software was applied for analysis Generalized linear mixed effects model (GLMM)analysis (see Table 6.8).

And then, perform dimensionality reduction on the data. Through preliminary data analysis (preprocessing) on 16 independent variables, 3 irrelevant variables were removed, leaving 13 independent variables, namely: Colorful-Monochromatic, Regular shape-Irregular shape, Modern-Traditional, Interesting-Serious, Graceful-Ugly, Lowkey-Exaggerated, Light-Heavy, Concise-Complex, Warm-Cold, Rounded-Hard, Expensive-Cheap, Easy to use-Inconvenient to use, Unbreakable-Fragile.

Table 6.7 The Valence value of each teapot sample (Partial data).

	A	B
1	Teapots ample	Valenc
2	1	1
3	4	1
4	7	-1
5	8	1
6	11	1
7	14	1
8	17	1
9	19	1
10	20	-1
11	1	1
12	3	1
13	7	1
14	9	1
15	10	1
16	16	1
17	19	1
18	20	1
19	1	-1
20	2	1
21	4	-1
22	6	1
23	7	1

Table 6.8 Data table of valence emotional values of SAM and perceived features, average values of teapots (Partial data).

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R
1	Teapotsample	Valence	Colorful_Monochromatic	Rich_in_patterns_Simple_patterns	Glossy_Lackluster	Delicate_texture_Rough_texture	Regular_shape_Irregular_shape	Modern_Traditional	Interesting_Serious	Graceful_Ugly	Lowkey_Exaggerated	Light_Heavy	Concise_Complex	Warm_Cold	Rounded_Hard	Expensive_Cheap	Easy_to_use_Inconvenient_to_use	Unbreakable_Fragile
2	1	1	-0.71666667	-0.46666667	0.93333333	1.06666667	1.21666667	-0.35	-0.03333333	0.95	1.15	0.71666667	1.33333333	-0.16666667	1.2	-0.06666667	1.11666667	-0.78333333
3	4	1	-0.9	-1.8	1.26666667	1.36666667	0.75	0.4	0.666666667	0.583333	1.016667	-0.2666667	1.1	0.866666667	1.166667	1.1	0.73333333	0.9
4	7	-1	2.233333333	2.416666667	0.23333333	0.3	0.26666667	1.066667	0.966666667	0.583333	-0.71667	0.16666667	-0.9833333	0.283333333	-0.78333	-0.25	0.61666667	-0.4
5	8	1	-2.75	-2.6	0.88333333	1.85	1.36666667	0.416667	0.416666667	1.5	1.666667	1.18333333	2.31666667	0.9	2.166667	1.183333333	1.15	-0.2
6	11	1	-1.06666667	-1.9	0.36666667	0.58333333	0.11666667	0.4	0.383333333	0.166667	-0.35	0.03333333	0.46666667	0.05	0.6	0.75	0.31666667	-0.26666667
7	14	1	-2.13333333	-2.1	0.43333333	1.1	0.86666667	1.533333	1.05	1.016667	0.916667	0.58333333	1.46666667	0.466666667	1.4	0.716666667	1.05	0.433333333
8	17	1	-0.11666667	0.45	0.16666667	0.86666667	-0.2833333	0.533333	0.833333333	0.833333	0.083333	0.48333333	0.23333333	0.55	0.666667	0.583333333	-0.15	0.15
9	19	1	-1.1	0.983333333	1.56666667	1.56666667	1.4	0.433333	0.633333333	1.566667	1.35	1.4	1.08333333	0.75	1.35	0.783333333	1.1	-0.31666667
10	20	-1	1.166666667	1.683333333	1.35	1.3	1.13333333	0.216667	1.35	1.316667	0.15	0.48333333	0.06666667	1.016666667	1.35	0.5	0.88333333	-0.2
11	1	1	-0.71666667	-0.46666667	0.93333333	1.06666667	1.21666667	-0.35	-0.03333333	0.95	1.15	0.71666667	1.33333333	-0.16666667	1.2	-0.06666667	1.11666667	-0.78333333
12	3	1	1.733333333	1.283333333	1.98333333	1.83333333	1.35	0.766667	0.5	0.933333	-0.03333	0.4	0.01666667	0.633333333	0.733333	0.1	0.96666667	-0.46666667
13	7	1	2.233333333	2.416666667	0.23333333	0.3	0.26666667	1.066667	0.966666667	0.583333	-0.71667	0.16666667	-0.9833333	0.283333333	-0.78333	-0.25	0.61666667	-0.4
14	9	1	2.05	1.733333333	1.25	1.43333333	0.73333333	0.916667	1.1	1.183333	0.033333	-0.2	-0.0833333	0.766666667	0.766667	0.533333333	0.51666667	0.333333333
15	10	1	-2.66666667	0.55	0.76666667	1.48333333	-1.2833333	-0.51667	1.45	1.716667	-0.13333	0.03333333	-0.4333333	0.616666667	0.8	1.65	-0.5833333	-0.5
16	16	1	2.466666667	2.316666667	2.43333333	1.8	0.98333333	0.3	0.716666667	0.116667	-1.55	0.23333333	-1.05	1.266666667	0.6	0.533333333	0.58333333	-0.71666667
17	19	1	-1.1	0.983333333	1.56666667	1.56666667	1.4	0.433333	0.633333333	1.566667	1.35	1.4	1.08333333	0.75	1.35	0.783333333	1.1	-0.31666667
18	20	1	1.166666667	1.683333333	1.35	1.3	1.13333333	0.216667	1.35	1.316667	0.15	0.48333333	0.06666667	1.016666667	1.35	0.5	0.88333333	-0.2
19	1	-1	-0.71666667	-0.46666667	0.93333333	1.06666667	1.21666667	-0.35	-0.03333333	0.95	1.15	0.71666667	1.33333333	-0.16666667	1.2	-0.06666667	1.11666667	-0.78333333
20	2	1	-2.65	-2.66666667	0.06666667	1.16666667	1.46666667	0.4	-0.61666667	1.033333	1.816667	1.03333333	2.23333333	0.633333333	1.216667	0.516666667	1.45	-0.21666667
21	4	-1	-0.9	-1.8	1.26666667	1.36666667	0.75	0.4	0.666666667	0.583333	1.016667	-0.2666667	1.1	0.866666667	1.166667	1.1	0.73333333	0.9
22	6	1	-2.61666667	-2.65	0.2	1.33333333	1.8	0.466667	0.166666667	1.433333	1.75	1.41666667	2.16666667	1.016666667	1.966667	1.233333333	1.23333333	-0.05
23	7	1	2.233333333	2.416666667	0.23333333	0.3	0.26666667	1.066667	0.966666667	0.583333	-0.71667	0.16666667	-0.9833333	0.283333333	-0.78333	-0.25	0.61666667	-0.4
24	8	1	-2.75	-2.6	0.88333333	1.85	1.36666667	0.416667	0.416666667	1.5	1.666667	1.18333333	2.31666667	0.9	2.166667	1.183333333	1.15	-0.2
25	10	-1	-2.66666667	0.55	0.76666667	1.48333333	-1.2833333	-0.51667	1.45	1.716667	-0.13333	0.03333333	-0.4333333	0.616666667	0.8	1.65	-0.5833333	-0.5
26	11	-1	-1.06666667	-1.9	0.36666667	0.58333333	0.11666667	0.4	0.383333333	0.166667	-0.35	0.03333333	0.46666667	0.05	0.6	0.75	0.31666667	-0.26666667
27	12	-1	-1.73333333	-2.06666667	-1.1333333	-1.4166667	-0.2166667	-0.73333	-0.86666667	-0.51667	0.45	-1.2666667	0.63333333	-0.48333333	-0.36667	0.4	0.55	0.983333333
28	13	-1	-0.98333333	-2.15	-0.3833333	1.21666667	1.55	0.283333	0.516666667	1.5	1.3	0.61666667	1.46666667	0.466666667	1.283333	0.983333333	1.16666667	0.033333333
29	15	-1	-0.88333333	-1.73333333	0.56666667	-0.0166667	-0.0833333	0.333333	-0.13333333	-0.4	0.133333	-0.9166667	0.26666667	-0.21666667	0.083333	0.116666667	0.21666667	0.533333333

2) The GLMM analysis results.

The results of the GLMM analysis showed that 'Colorful-Monochromatic', 'regular shape-irregular shape', 'light-heavy', and 'unbreakable-fragile' had the strongest correlation with SAM valence; 'elegant-ugly' had a relatively high correlation with SAM valence; 'lowkey-exaggerated' and 'expensive-cheap' had a weak correlation with SAM valence; and 'modern-traditional', 'interesting-serious', 'simple-complex', 'warm-cold', 'rounded-hard', and ' easy to use-inconvenient to use ' did not correlate with SAM valence (See Table 6.9).

Table 6.9 The GLMM analysis results

Predictor	Estimate	Std_Error	Z_value	P_value	Signif.	Lower_CI	Upper_CI
(Intercept)	2.2027	0.4897	4.4979	0.0000	***	1.2765	3.2030
Colorful-Monochromatic	1.0430	0.3093	3.3716	0.0007	**	0.4638	1.6790
Regular shape-Irregular shape	-3.0219	0.9094	-3.3228	0.0009	***	-4.8439	-1.2718
Modern-Traditional	-0.3497	0.2952	-1.1845	0.2362		-0.9322	0.2269
Interesting-Serious	-0.5023	0.5838	-0.8604	0.3895		-1.6603	0.6328
Graceful-Ugly	-1.5509	0.5391	-2.8766	0.0040	**	-2.6222	-0.5040
Lowkey-Exaggerated	1.3402	0.5436	2.4656	0.0137	*	0.2823	2.4176
Light-Heavy	4.0677	0.7615	5.3420	0.0000	***	2.6588	5.6527
Concise-Complex	-0.7565	0.5570	-1.3583	0.1744		-1.8560	0.3316
Warm-Cold	-0.8398	0.5137	-1.6347	0.1021	.	-1.8544	0.1635
Rounded-Hard	0.9090	0.5500	1.6528	0.0984	.	-0.1657	1.9941
Expensive-Cheap	1.2605	0.5234	2.4084	0.0160	*	0.2342	2.2895
Easy to use-Inconvenient to use	1.1616	0.9078	1.2795	0.2007		-0.6068	2.9602
Unbreakable-Fragile	2.0658	0.6384	3.2357	0.0012	***	0.8396	3.3491

3) Correlation visualization

A confidence interval (CI) is a range used in statistics to estimate population parameters (such as mean, proportion, etc.), representing our uncertainty about the true values of the parameters. The confidence interval does not contain zero, indicating its correlation. The further away from zero, the higher the correlation. The following figure is a visualization of the GLMM analysis results, specifically a visualization of the regression coefficients and their confidence intervals (See Figure 6.2).

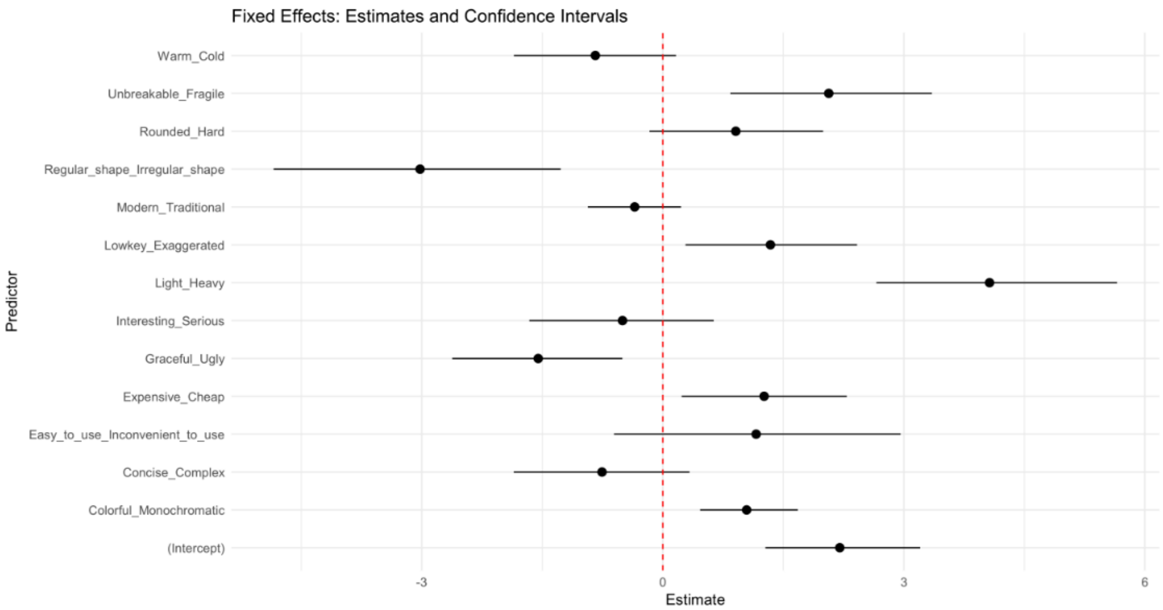


Figure 6.4 Visualization of regression coefficients and confidence intervals (GLMM).

2. Correlation analysis between morphological features of ceramic teapots and Valence from SAM using GEE (Generalized estimating equations (GEE) analysis).

1) Data pre-processing

Taking the Valence value of each teapot sample as the dependent variable (see Table 6.7), and the Encoding table for design features of 20 ceramic teapot samples (see Table 4.3) as independent variables, generalized estimating equations (GEE) analysis was conducted using IBM SPSS Statistics 24 software (see Table 6.10).

Table 6.10 Data table of valence emotional values of SAM and the code of teapot morphological features (Partial data).

1	Teapots ample	Valen	A1	A2	B1	B2	B3	B4	C1	C2	C3	D1	D2	E1	E2	E3	E4	F1	F2	F3	F4	G1	G2	G3	H1	H2	H3
2	1	1	0	1	1	0	0	0	1	0	0	0	1	1	0	0	0	0	1	0	0	1	0	0	0	1	0
3	4	1	0	1	0	1	0	0	1	0	0	0	1	1	0	0	0	0	0	1	0	1	0	0	0	1	0
4	7	-1	0	1	1	0	0	0	0	1	0	1	0	0	0	0	1	0	0	1	0	1	0	0	0	1	0
5	8	1	0	1	1	0	0	0	1	0	0	0	1	1	0	0	0	0	0	0	1	1	0	0	1	0	0
6	11	1	0	1	0	1	0	0	1	0	0	0	1	1	0	0	0	0	1	0	0	1	0	0	1	0	0
7	14	1	1	0	0	0	1	0	0	0	1	1	0	1	0	0	0	1	0	0	0	1	0	0	1	0	0
8	17	1	0	1	0	0	0	1	1	0	0	0	1	1	0	0	0	1	0	0	0	0	0	1	0	0	1
9	19	1	0	1	1	0	0	0	1	0	0	1	0	1	0	0	0	0	0	1	0	1	0	0	1	0	0
10	20	-1	0	1	0	0	1	0	1	0	0	1	0	1	0	0	0	1	0	0	0	1	0	0	1	0	0
11	1	1	0	1	1	0	0	0	1	0	0	0	1	1	0	0	0	0	1	0	0	1	0	0	0	1	0
12	3	1	0	1	1	0	0	0	1	0	0	0	1	0	0	0	1	0	0	0	1	1	0	0	1	0	0
13	7	1	0	1	1	0	0	0	0	1	0	1	0	0	0	0	1	0	0	1	0	1	0	0	0	1	0
14	9	1	0	1	0	1	0	0	1	0	0	1	0	1	0	0	0	0	1	0	0	1	0	0	0	1	0
15	10	1	1	0	0	0	0	1	0	1	0	1	0	0	1	0	0	0	0	1	0	0	1	0	1	0	0
16	16	1	0	1	1	0	0	0	1	0	0	0	1	1	0	0	0	1	0	0	0	1	0	0	0	1	0
17	19	1	0	1	1	0	0	0	1	0	0	1	0	1	0	0	0	0	0	1	0	1	0	0	1	0	0
18	20	1	0	1	0	0	1	0	1	0	0	1	0	1	0	0	0	1	0	0	0	1	0	0	1	0	0
19	1	-1	0	1	1	0	0	0	1	0	0	0	1	1	0	0	0	0	1	0	0	1	0	0	0	1	0
20	2	1	0	1	1	0	0	0	1	0	0	1	0	0	0	1	0	0	1	0	0	0	1	0	0	1	0
21	4	-1	0	1	0	1	0	0	1	0	0	0	1	1	0	0	0	0	0	1	0	1	0	0	0	1	0
22	6	1	0	1	1	0	0	0	1	0	0	0	1	1	0	0	0	1	0	0	0	1	0	0	0	0	1
23	7	1	0	1	1	0	0	0	0	1	0	1	0	0	0	0	1	0	0	1	0	1	0	0	0	1	0
24	8	1	0	1	1	0	0	0	1	0	0	0	1	1	0	0	0	0	0	0	1	1	0	0	1	0	0
25	10	-1	1	0	0	0	0	1	0	1	0	1	0	0	1	0	0	0	0	1	0	0	1	0	1	0	0
26	11	-1	0	1	0	1	0	0	1	0	0	0	1	1	0	0	0	0	1	0	0	1	0	0	1	0	0
27	12	-1	0	1	0	1	0	0	1	0	0	0	1	1	0	0	0	0	1	0	0	1	0	0	1	0	0
28	13	-1	0	1	1	0	0	0	1	0	0	0	1	1	0	0	0	0	1	0	0	1	0	0	1	0	0
29	15	-1	0	1	0	1	0	0	1	0	0	1	0	1	0	0	0	1	0	0	0	1	0	0	0	0	1
30	17	1	0	1	0	0	0	1	1	0	0	0	1	1	0	0	0	1	0	0	0	0	0	1	0	0	1
31	18	1	0	1	0	1	0	0	1	0	0	1	0	0	0	1	0	1	0	0	0	1	0	0	0	0	1
32	19	1	0	1	1	0	0	0	1	0	0	1	0	1	0	0	0	0	0	1	0	1	0	0	1	0	0
33	2	1	0	1	1	0	0	0	1	0	0	1	0	0	0	1	0	0	1	0	0	0	1	0	0	1	0
34	3	1	0	1	1	0	0	0	1	0	0	0	1	0	0	0	1	0	0	0	1	1	0	0	1	0	0
35	4	1	0	1	0	1	0	0	1	0	0	0	1	1	0	0	0	0	0	1	0	1	0	0	0	1	0
36	5	1	1	0	0	0	1	0	1	0	0	0	1	0	1	0	0	1	0	0	0	1	0	0	0	0	1
37	6	1	0	1	1	0	0	0	1	0	0	0	1	1	0	0	0	1	0	0	0	1	0	0	0	0	1
38	8	1	0	1	1	0	0	0	1	0	0	0	1	1	0	0	0	0	0	0	1	1	0	0	1	0	0
39	9	1	0	1	0	1	0	0	1	0	0	1	0	1	0	0	0	0	1	0	0	1	0	0	0	1	0
40	10	1	1	0	0	0	0	1	0	1	0	1	0	0	1	0	0	0	0	1	0	0	1	0	1	0	0

And then, this study performed dimensionality reduction on the data. Through preliminary data analysis (preprocessing) of 25 independent variables, 15 irrelevant variables were removed, leaving 10 independent variables, namely B1, C2, C3, D1, E1, E4, F1, F3, F4, and G1. Since the independent variable does not come from the questionnaire, there is no need for reliability and validity testing.

2) The GEE analysis results

Perform generalized estimating equations (GEE) regression analysis, and the analysis results are as follows: The morphological feature codes with the highest correlation with Valence from SAM are C2, F3 and G1, the morphological feature codes with the lowest correlation are E1, while the uncorrelated one is B2, C3, D1, E4, F1, F4 (See Table 6.11).

3) Correlation visualization

The following figure shows a visualization of regression coefficients and confidence intervals (See Figure 6.3)

Table 6.11 The GEE analysis results

Variable	Estimate	Std.err	Wald	Pr_W	Significance
(Intercept)	1.7990	0.3760	22.9000	0.0000	***
B2	-0.4604	0.2442	3.5500	0.0590	
C2	-2.2818	0.5556	16.8600	0.0000	***
C3	0.4974	0.5266	0.8900	0.3450	
D1	0.0145	0.2377	0.0000	0.9510	
E1	0.6049	0.2488	5.9100	0.0150	*
E4	0.4510	0.4125	1.2000	0.2740	
F1	0.0984	0.2301	0.1800	0.6690	
F3	1.7678	0.4500	15.4300	0.0001	***
F4	-0.5224	0.3644	2.0500	0.1520	
G1	-1.5101	0.2815	28.7800	0.0000	***

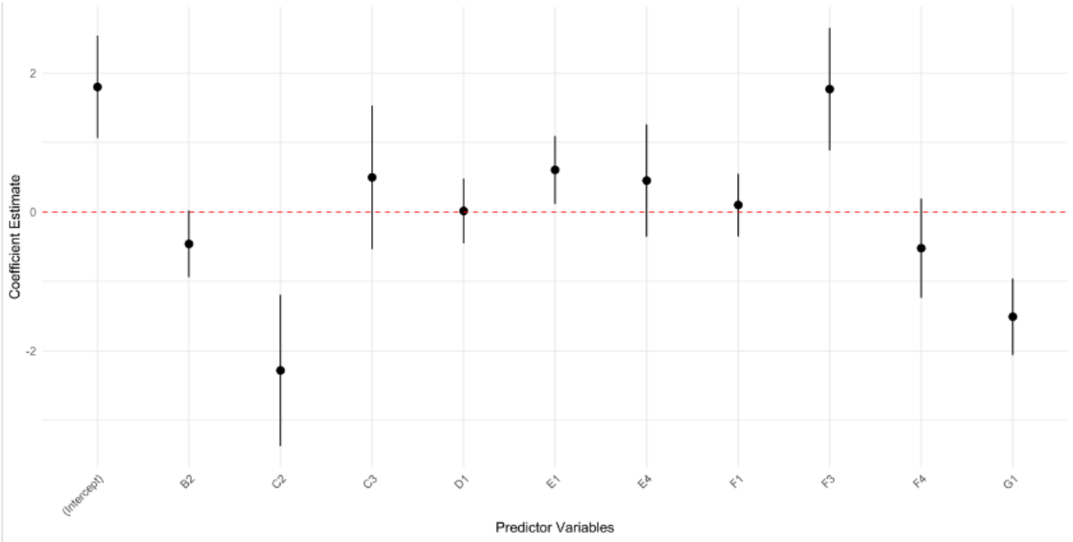


Figure 6.5 Visualization of regression coefficients and confidence intervals (GEE).

The following emotional perception features of ceramic teapots do not affect consumer emotional reactions: Modern-Traditional, Warm-Cold, Interesting-Serious, Rounded-Hard, Easy to use-Inconvenient to use. Before purchasing, consumers pay more attention to the following emotional design features of ceramic teapots, while after purchasing, the opposite is true: Colorful-Monochromatic, Regular shape -Irregular shape, Unbreakable-Fragile.

6.2.2 Text feature analysis

With the popularization of the Internet and the continuous growth of online commodity sales, consumer reviews are also growing. Consumers leave their own experiences and feelings in the product review system, becoming an important window for designers to understand consumers and for consumers to understand other consumers. Therefore, the analysis of review data has important practical significance.

1. Data cleaning

This chapter will collect 1791 online comments for data cleaning. After removing blank comments, excess spaces, invalid, duplicated, highly similar reviews, and stop-word, etc., a total of 475 invalid data were eliminated, leaving 1316 valid data. This includes 664 comments for Chinese ceramic teapots and 652 comments for Japanese ceramic teapots. Then use SPSSAU international version for word frequency statistics and text clustering analysis.

2. Text data analysis of Chinese and Japanese ceramic teapots

This chapter utilizes SPSSAU International Edition (SPSSAU International Version Website: https://spssau.net/indexs.html.) for text analysis. SPSSAU is an intelligent online statistical analysis platform. The analysis process is shown in the following figure (Figure 6.6).

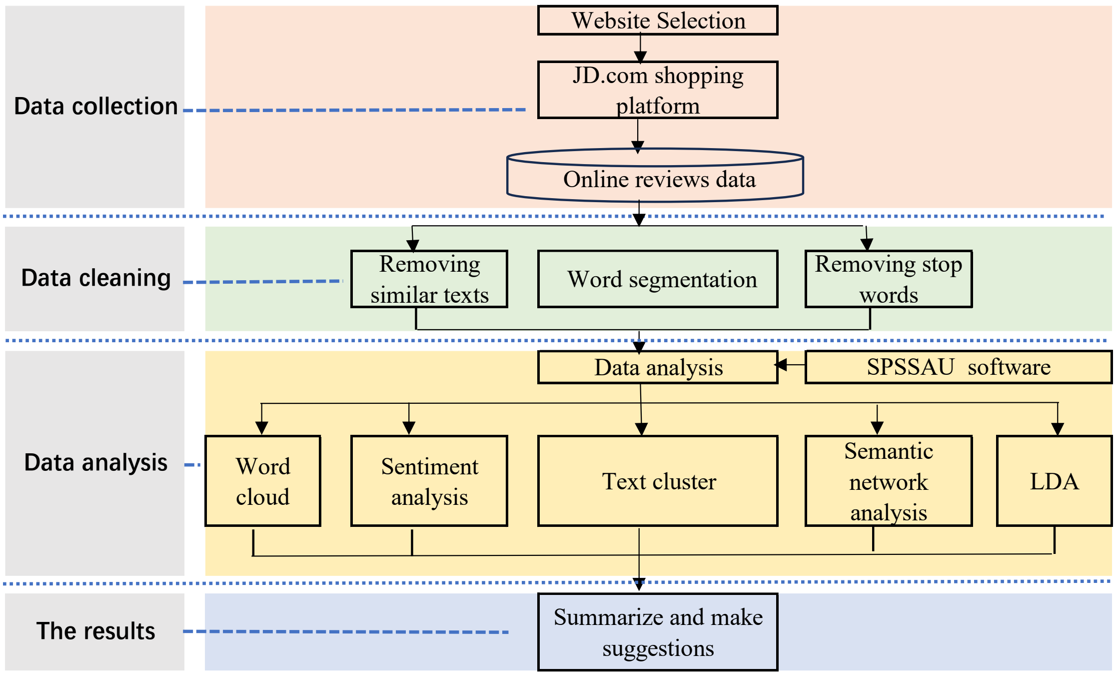


Figure 6.6 Text analysis flowchart.

1) Word cloud visualization

Word cloud visualization is a technique that uses natural language processing technology to analyze the frequency of text data and generate visual images. The color and size of words in the word cloud reflect their frequency and importance in all comments. The higher the frequency of a word, the more prominent it is in the word cloud, which can intuitively display the most frequent and important information in comments.

① Word frequency visualization

In order to explore the key information in the crawled text data of ceramic teapot comments, and to mine the product features that consumers are most concerned about and the comment features that merchants are most concerned about, this dissertation visualizes the 1316 valid comments crawled with a word cloud map. Figure 6.7 is a visual chart of word frequency for consumer evaluations of Chinese and Japanese ceramic teapots generated using SPSSAU software.

Figure 6.7 Word cloud chart.

As can be seen from Figure 6.7, the word-frequency visualization indicates that consumers' overall evaluations of both top-selling Chinese and Japanese ceramic teapots are highly positive. The most salient terms appearing in the word cloud are evaluative adjectives (e.g., "good") and product/usage descriptors (e.g., "teapot," "tea," "water," "quality"), suggesting that post-purchase emotions are strongly shaped by both perceived quality and practical use experience. Consistent with this pattern, high-frequency words reported for Chinese and Japanese ceramic teapot reviews include "good," "packaging," "workmanship," "exquisite," "elegant," "beauty," "quality," and "material," which collectively highlight a combined focus on craftsmanship aesthetics, and delivery/service assurance. The overall evaluation of Chinese and Japanese ceramic teapots is good.

② TF-IDF keyword visualization

About TF-IDF Word Cloud Visualization, TF-IDF measures a word's importance in a document relative to a corpus. It combines Term Frequency (how often a word appears in a document) and Inverse Document Frequency (how rare the word is across all documents). High TF-IDF words are frequent locally but rare globally, making them good keywords. It's widely used for search, text mining, and as a baseline feature for ML models. (Sparck Jones, K.1972), (Manning, C. D.2008), (Salton, G., & Buckley, C.1988). Visualize TF-IDF word cloud with SPSSAU. As can be seen from Figure 6.8, High-frequency tf-idf words of ceramic teapot consumers' evaluation: commonly, texture, served, spotless, impeccable, useful, atmosphere, etc.

The TF-IDF word cloud (see Table 6.12 and Figure 6.8) highlights discriminative keywords that are locally frequent yet globally distinctive. The high-TF-IDF terms (e.g., "commonly," "texture," "spotless," "impeccable," "useful," "atmosphere") reveal that consumers not only evaluate general satisfaction, but also emphasize experience-proximal attributes such as surface texture, cleanliness/finish, perceived refinement, and contextual atmosphere during use. These TF-IDF results, therefore, provide a more feature-diagnostic view of what differentiates consumer narratives beyond generic praise.

Table 6.12 The top 100 tf-idf words are shown (Partial data).

A	B	C	D
ID	Tokens	Row Number	TF-IDF
1	commonly	"179, 274"	1
2	spotless	"19"	0.82340735
3	poor	"132, 417, 590"	0.71820754
4	hee	"1188"	0.7043544
5	served	"605"	0.6984853
6	atmosphere	"529, 817"	0.6485459
7	stuff	"150, 185, 341, 455, 471, 656, 799"	0.62484425
8	ha	"920, 1045, 1236"	0.62192625
9	leader	"1215, 1221"	0.61813426
10	grand	"55, 494, 523, 815"	0.6172984
11	toy	"409, 432"	0.6072357
12	user	"293, 641, 642, 645, 695, 699, 700, 1273, 1321"	0.6044163
13	card	"874, 893, 896"	0.60419154
14	discharge	"561, 1209, 1259, 1260"	0.6024078
15	reassuring	"764, 962, 1134"	0.6014245
16	satisfaction	"1052, 1184"	0.5812646
17	air	"17"	0.5756543
18	tightness	"17"	0.5756543
19	spot	"1030"	0.5731231
20	gray	"122, 275"	0.56783503
21	useful	"114, 136, 351, 726, 735"	0.5606665
22	extremely	"7, 433"	0.544384
23	impeccable	"1198, 1296"	0.54278255
24	publicity	"167, 229"	0.540798
25	textured	"218, 262, 550, 875"	0.5375521
26	mountains	"540"	0.5363514
27	tatami	"880, 991"	0.5343866
28	smells	"38"	0.52785224

Figure 6.8 The word cloud shows high tf-idf words from text analysis.

2) Sentiment Analysis

Sentiment Analysis is a technique in the field of Natural Language Processing (NLP) aimed at identifying and extracting emotional states expressed in text, typically classified into three categories: positive, negative, or neutral (Sentiment Analysis). Also known as “Opinion Mining”, it is used to identify, extract, and quantify emotional attitudes contained in text. Its goal is not only to judge whether people are positive, negative, or neutral in text expression, but also to further distinguish more segmented emotions such as anger, joy, sadness, and satire. Through sentiment analysis of 1316 valid data, it is concluded that Positive Comments: 77%, Negative Comments: 4%, Overall Sentiment: Positive. (Refer to Table 6.13 and Figure 6.9)

Table 6.13 The top 100 most frequent words are displayed (Partial data).

ID	Word	Word Frequ	TF-IDF	Occurrence	Sentiment Score	Sentiment Direction
1	good	754	0.2314391	555	0.4404	Positive
2	very	704	0.2212216	470	0	Slightly Positive
3	tea	276	0.1980237	186	0	Slightly Positive
4	like	238	0.2400904	215	0.3612	Positive
5	quality	207	0.2236099	188	0	Slightly Positive
6	water	206	0.1951062	156	0	Slightly Positive
7	pot	191	0.2092634	146	0	Slightly Positive
8	beautiful	188	0.2431717	183	0.5994	Positive
9	easy	153	0.2635906	121	0.4404	Positive
10	teapot	149	0.2237505	136	0	Slightly Positive
11	ha	148	0.6219263	3	0.34	Positive
12	small	147	0.2775275	129	0	Slightly Positive
13	exquisite	136	0.2732449	132	0	Slightly Positive
14	size	133	0.2279065	125	0	Slightly Positive
15	packaging	126	0.2063969	115	0	Slightly Positive
16	cup	126	0.2364139	104	0	Slightly Positive
17	workmanshi	119	0.2195959	115	0	Slightly Positive
18	much	115	0.2444188	113	0	Slightly Positive
19	use	112	0.2314671	105	0	Slightly Positive
20	little	111	0.2549405	99	0	Slightly Positive
21	bought	109	0.2289862	92	0	Slightly Positive
22	also	99	0.1893966	89	0	Slightly Positive
23	can	96	0.1776621	84	0	Slightly Positive
24	color	90	0.2479782	78	0	Slightly Positive
25	time	89	0.213217	78	0	Slightly Positive
26	has	88	0.2177448	75	0	Slightly Positive
27	smooth	85	0.2127055	74	0	Slightly Positive
28	you	83	0.2471454	68	0	Slightly Positive

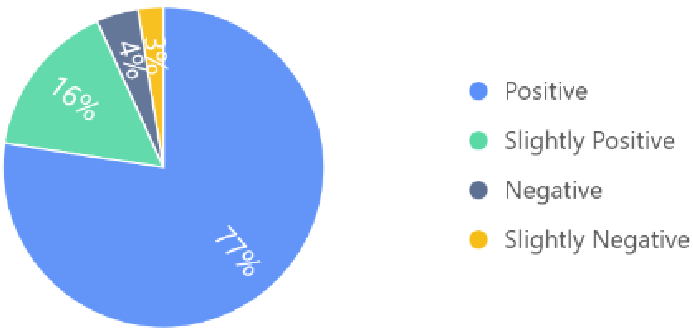


Figure 6.9 The chart shows sentiment analysis results by word.

3) Text Cluster

Text clustering is a machine learning method that aggregates similar texts through algorithms to extract information from unstructured data and belongs to the category of natural language processing techniques. Cluster analysis refers to the process of dividing a given set of objects into different subsets, to make the elements within each subset as similar as possible and the elements between different subsets as dissimilar as possible. These subsets are also known as clusters and generally have no intersection. The concept of clustering is shown in Figure 6.10. Document Clustering refers to the clustering of documents and is widely used in the fields of text mining and information retrieval.

Figure 6.11 shows word distribution in 3 adjustable clusters. Bubble size indicates frequency, color represents the cluster, and analyze the relationships. Some words may lack vectors and can't be clustered.

4) Semantic network analysis

Semantic network analysis is a method of constructing concept graphs through nodes and relationship arcs to enable machines to understand and reason about semantics. The common steps include: first, extracting keywords or concepts from the text as nodes; second, analyzing the semantic relationships between these nodes, such as frequency of co-occurrence, similarity, etc., and annotating them with relationship arcs; Finally, constructing a semantic network diagram to visually display knowledge associations, facilitating applications such as topic analysis and knowledge reasoning. The following table shows that the analysis uses the top 20 words by frequency (see Table 6.14).

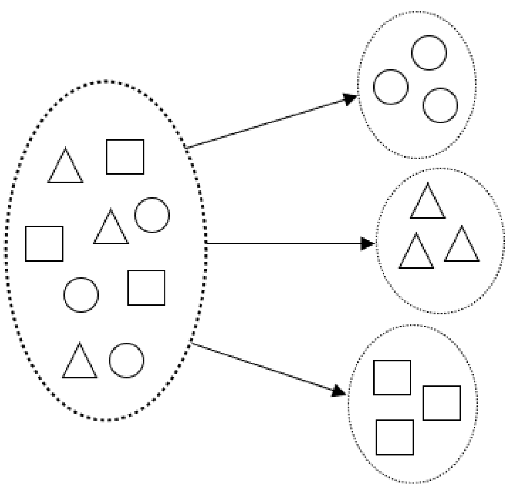


Figure 6.10 The diagram of the clustering concept.

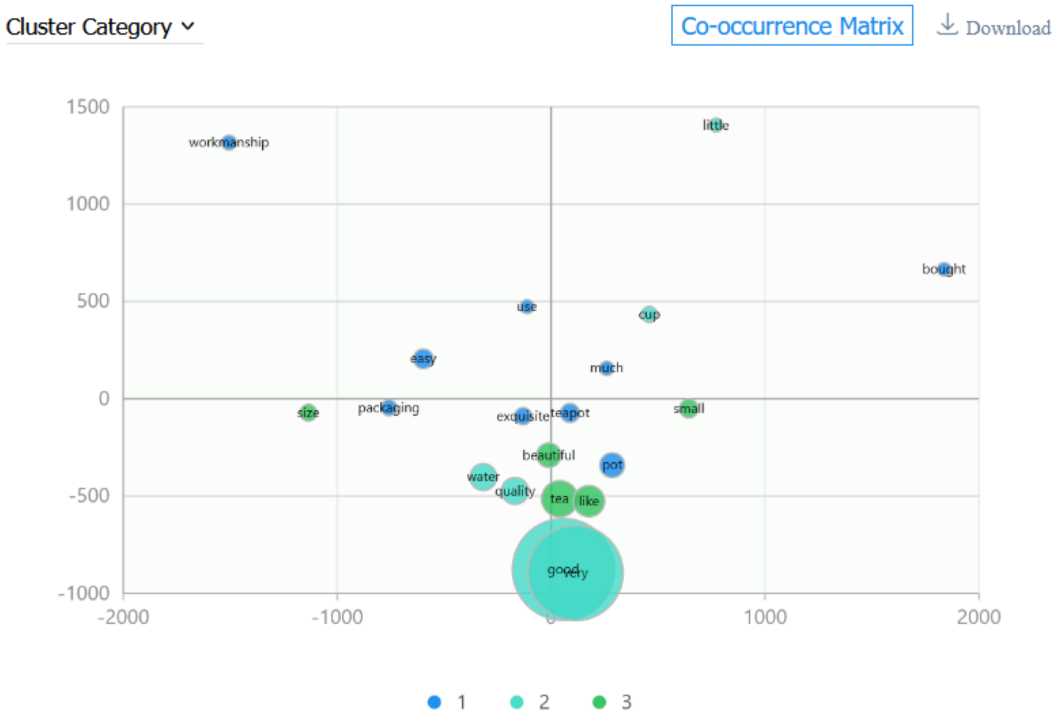


Figure 6.11 Word distribution in 3 adjustable clusters

Table 6.14 The analysis uses the top 20 words by frequency.

ID	Word	Word Frequency
1	good	754
2	quality	207
3	water	206
4	pot	191
5	beautiful	188
6	easy	153
7	teapot	149
8	small	147
9	exquisite	136
10	size	133
11	packaging	126
12	cup	126
13	workmanship	119
14	use	112
15	bought	109
16	color	90
17	smooth	85
18	satisfied	79
19	price	76
20	clean	73

The semantic network shows word relationships (see Figure 6.12). The closer the words are to the central node (core node), the closer they are to the words in the central node. The denser the lines are, the higher the frequency of co-occurrence is. The denser the lines are, the more times they are co-linear. In sum, the semantic network further clarifies how key terms co-occur and form higher-level evaluation structures. As shown in Table 6.18, the network density indicates frequent co-occurrence among evaluation words and concrete product cues. Importantly, "good," "workmanship," "packaging," "beautiful," "quality," and "color" emerge as core nodes, meaning that they act as hubs linking multiple related concepts in review narratives. This pattern suggests that after-sales emotional responses are not driven by a single factor; rather, they are composed of (1) aesthetics/appearance cues (e.g., "beautiful," "color"), (2) performance and usability cues (e.g., water-related terms, ease of use, size), and (3) service and protection cues (e.g., "packaging"). In other words, consumers' positive emotions are reinforced when craftsmanship, appearance, and actual use performance are supported by reliable delivery/packaging experiences.

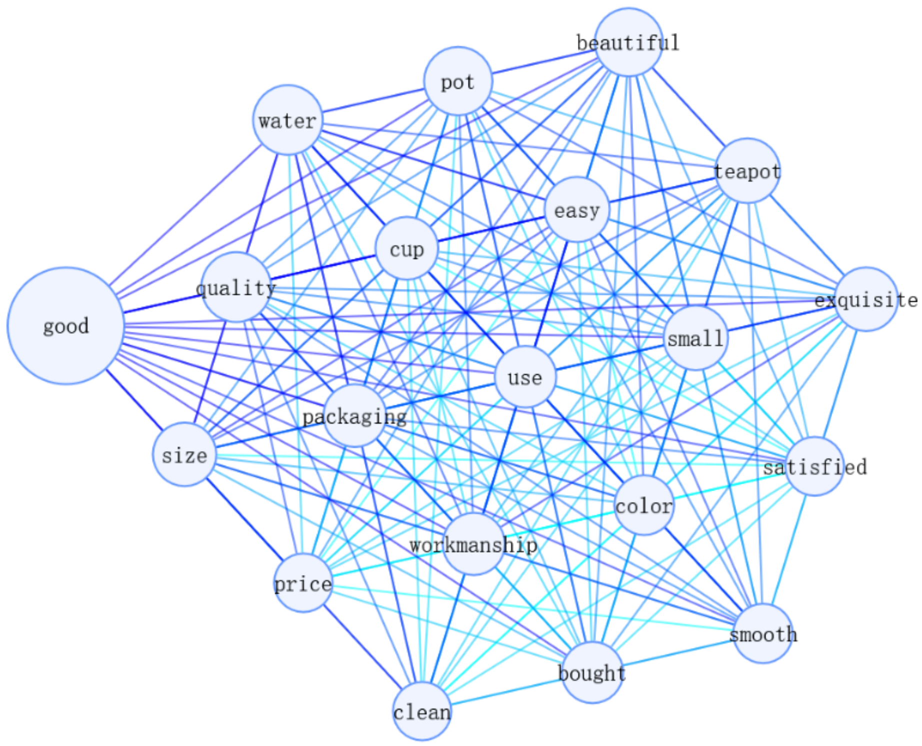


Figure 6.12 The semantic network analysis of ceramic teapot reviews

5) LDA Theme Analysis

LDA topic analysis (Latent Dirichlet Allocation) is an unsupervised machine learning model used to automatically discover potential topics from text data. The LDA topic model can obtain the probability distribution of a certain word in a certain topic through calculation, and divide a specific word into the topic with the highest probability, thus achieving the division of "exquisite" to determine which topic it belongs to with the highest probability. Meanwhile, the LDA topic model is an unsupervised model that only requires training documents to automatically train the probability values between documents and topics, topics and keywords, without any manual annotation. Therefore, it has wide applications in text clustering, topic analysis, similarity calculation, and other fields.

From Figure 6.13, it can be seen that through LDA Theme Analysis, firstly, Bubble size reflects how strongly a word relates to a topic. Larger bubbles indicate a stronger connection. Second: Analyze topics by looking at the word relationships (bubble size). Third: Words with low weights may not appear in the chart (see Figure 6.13). Further analysis of consumer demand is mainly conducted based on the results of LDA topic clustering. Firstly, identify user needs based on the specific clustering results of the topic, and then express them in a standardized manner. Then, based on the identified user needs, summarize and generalize the composition of user demand elements.

Based on the results of LDA topic clustering mentioned above, combined with high-frequency words in the word frequency table, the identification of user needs is as follows: overall, in the clustering results, the user needs of “Practical and functional” can be identified from words such as “particularly”, “body”, “water”, “easy”, “packaging”, “feature”, as well as “clean”, “use”, “size”, and “filter”; The user demand for ‘Aesthetics and Experience’ can be identified by words such as ‘very good’, ‘beautiful’, ‘small’, ‘perfect’, etc. The user demand for “Fashion and Value” can be identified from words such as “pot”, “bought”, “time”, “cute”, “exquisite”, etc., and a total of three theme categories can be identified.

6) Composition of user requirement elements

Through a series of processes such as online comment acquisition, cleaning, LDA topic model clustering, and consumer demand identification based on clustering results, consumers' demand for ceramic teapots has gradually been discovered. Through standardized expression and classification of user needs, a total of conclusions have been drawn. Topic 1: Fashion and Value, Topic 2: Aesthetics and Experience, and Topic 3: Practical and functional. There are three main types of needs. The composition of user demand elements is shown in Table 6.15.

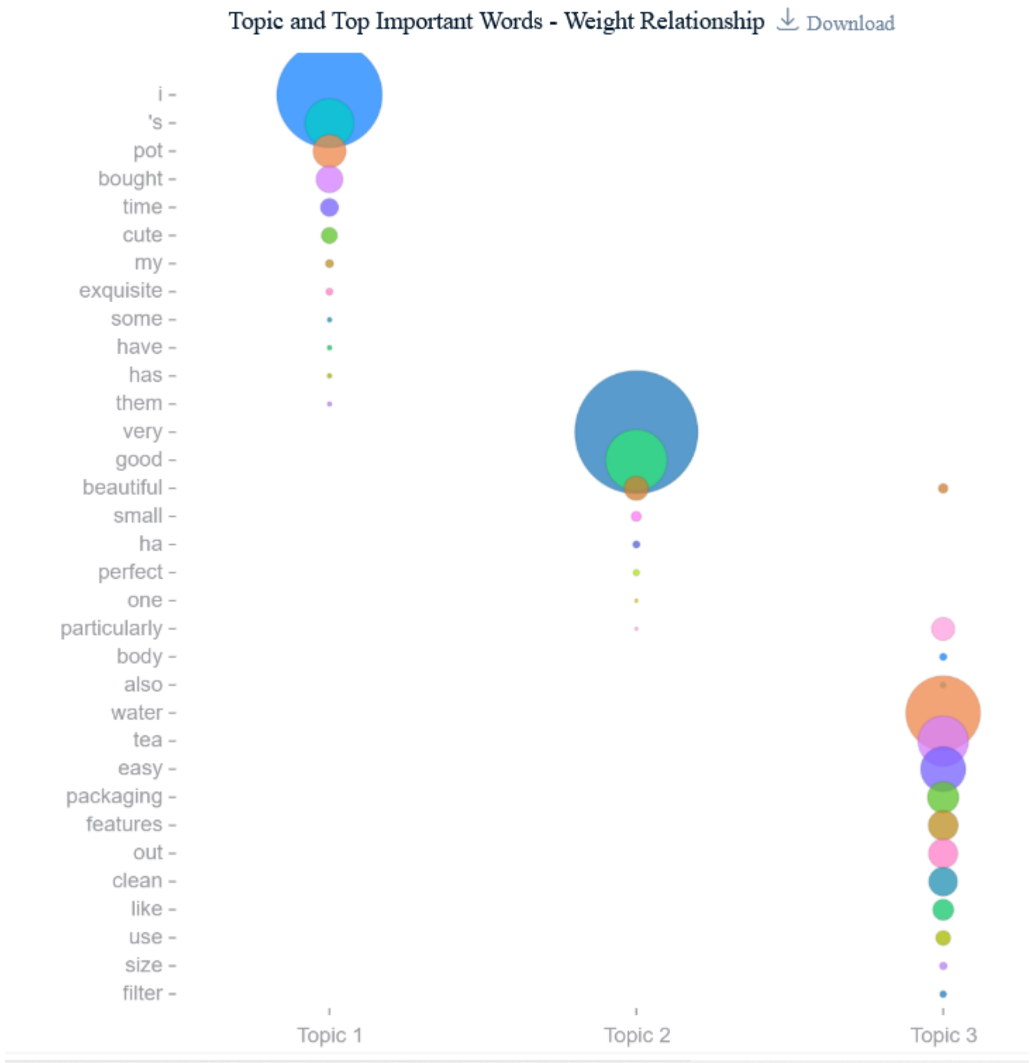


Figure 6.13 The LDA topic-word relationships visualization.

Table 6.15 The composition of consumer demand elements

Topic		Topic weight	Row count	Percentage
Topic 1	Fashion and Value	32.6%	956	70.3%
Topic 2	Aesthetics and Experience	33.1%	269	19.8%
Topic 3	Practical and functional	34.3%	135	9.9%
	Total	100%	1316	100%

6.3 Results

6.3.1 Analysis results of online reviews-based and emotional questionnaires-based consumers' emotional responses and ceramic teapot design features.

6.3.1.1 Analysis results of online reviews-based and emotional questionnaires-based consumers' emotional responses and perceived impressions of ceramic teapot.

It can be seen from the table (see Table 6.16) that the relationship between perceived impressions of ceramic teapots and consumer emotional responses. The following perceived impressions of ceramic teapots have no effect on consumers' emotional responses: Modern-Traditional, Warm-Cold, Interesting-Serious, Rounded-Hard, Easy to use-Inconvenient to use; on emotional questionnaires-based context, consumers pay more attention to the following emotional design features of ceramic teapots: Colorful-Monochromatic, Regular shape-Irregular shape, Unbreakable-Fragile, However, on online reviews-based context, the situation is exactly the opposite; The perceived features of ceramic teapots that consumers are particularly concerned about on online reviews-based context include: Concise-Complex, Delicate texture-Rough texture, Glossy-Lackluster, Rich in patterns-Simple patterns, on emotional questionnaires-based context, consumers do not pay attention; The perceived features of ceramic teapots that are weakly correlated with consumers on emotional questionnaires-based and on online reviews-based context include Expansive-Cheap and Lowkey-Exaggerated; The perceived feature of ceramic teapots that consumers pay close attention to on emotional questionnaires-based context, but their attention decreases on online reviews-based context, is Graceful-Ugly.

6.3.1.2 Analysis results of online reviews-based and emotional questionnaires-based consumers' emotional responses and Morphological features of ceramic teapot.

1) The correlation between the top view feature lines of ceramic teapots and consumer emotional responses: Whether on online reviews-based and on emotional questionnaires-based context, ceramic teapots with straight spouts and curved or straight-combined handles show no correlation with consumers' emotional responses; on emotional questionnaires-based context, ceramic teapots with round and curved-combined lids can arouse consumer interest, but on online reviews-based context, consumers no longer pay attention to these features of the teapots; Ceramic teapots with round, curved, and straight-combined lids are closely related to consumers' online reviews-based emotional responses but show no connection with their emotional

questionnaires-based emotional responses.

Table 6.16 The correlation analysis result between independent and dependent variables

Emotional design features			Emotion from text analysis (Online review-based)		Valence from SAM (Emotional questionnaire-based)	
			P-value	Signif.	P-value	Signif.
Perceived features of ceramic teapots		Colorful-Monochromatic	0.258999		0.0007	**
		Regular shape-Irregular shape	0.100664		0.0009	***
		Modern-Traditional	x		0.2362	
		Interesting-Serious	0.114239		0.3895	
		Graceful-Ugly	0.002107	**	0.0040	**
		Lowkey-Exaggerated	0.015832	*	0.0137	*
		Light-Heavy	0.012646	*	0.0000	***
		Concise-Complex	0.000138	***	0.1744	
		Warm-Cold	x		0.1021	.
		Rounded-Hard	x		0.0984	.
		Expensive-Cheap	0.044673	*	0.0160	*
		Easy to use-Inconvenient to use	x		0.2007	
		Unbreakable-Fragile	x		0.0012	***
		Delicate texture-Rough texture	0.003405	**	x	
		Glossy-Lackluster	0.002276	**	x	
		Rich in patterns-Simple patterns	0.001818	**	x	
Morphological characteristics of ceramic teapots	Top view contour line (A-D)	**B2** Kettle handle: Arc+ Straight line	0.4618		0.0590	.
		C2 Pot lid: Circular+ Curve	0.7841		0.0000	***
		C3 Pot lid: Circular+ Straight line+ Curve	0.0047	**	0.3450	
		D1 Spout: Straight line	0.537		0.9510	
	Front view contour line (E-H)	**E1** Kettle body: Arc + Straight line	0.9963		0.0150	*
		E4 Kettle body: Straight line + Hyperbola	0.0196	*	0.2740	
		F1 Kettle handle: Curve+ Straight line	0.7382		0.6690	
		F3 Kettle handle: Curve + Arc	0.8449		0.0001	***
		F4 Kettle handle: No handle	2.8e-09	***	0.1520	
		G1 Pot lid: Arc+ Straight	0.0195	*	0.0000	***
		G3 Pot lid: Straight line	1.6e-09	***	x	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
x' represents the independent variable of dimensionality reduction and deletion

2) The correlation between the front view feature lines of ceramic teapots and consumer emotional responses: Whether on online reviews-based and on emotional questionnaires-based context, the ceramic teapot with a handle combining curves and straight lines shows no correlation with consumers' emotional responses; The ceramic teapot with a handle combining curves and arcs, and a lid blending arcs and straight lines, attracts significant consumer attention on emotional questionnaires-based context, but the opposite is true on online reviews-based context; The ceramic teapot with no handle and the one with a lid featuring straight feature lines show a high correlation

with consumers' online reviews-based emotional responses, though consumers show little interest in these features on emotional questionnaires-based context; The ceramic teapot with a body combining arcs and straight lines is weakly correlated with consumers' emotional questionnaires-based emotional responses but shows no correlation with their online reviews-based emotional responses; The ceramic teapot with a body combining straight lines and hyperbolas shows no correlation with consumers' emotional questionnaires-based emotional responses but exhibits a weak correlation with their online reviews-based emotional responses.

6.3.1.3 Analyzes the differences in consumer emotional responses based on online reviews and emotional questionnaires.

In addition, this study analyzes the differences in consumer emotional responses based on online reviews and emotional questionnaires. as shown in the table below (Table17). As can be seen from the table 17, Emotional questionnaires-based: Emotions are more conservative and neutral, with a significantly higher negative proportion (Negative 17.2%). (Images/SAM, N=1180). Review-based: Overall significantly more positive (77% positive, 3% negative). (Reviews, 1,316 pieces of data). The key finding: Emotions become significantly more positive online reviews-based.

Explanation of this result: 1) Different sample groups (student/real purchasing audience) and measurement tools. 2) Differences in information content/experience.3) Positive bias in comments: People who are willing to write reviews are more likely to be satisfied.

Table 6.17. The result of emotional questionnaires-based vs. online reviews-based emotional responses.

Stage	Positive	Neutral	Negative
Images / SAM valence (Image-based)	43.6%	39.2%	17.2%
Reviews sentiment (Online review-based)	77.0%	20.0%	3.0%

6.3.2 Comparison of design features and emotional responses between Chinese and Japanese ceramic teapots

1) This chapter uses SPSSAU international version online statistical analysis software to analyze the top-selling Chinese and Japanese ceramic teapots. It is found that the overall polarity difference between the word frequency and TF-IDF visualization, the semantic network, and the emotional tendency distribution of Chinese and Japanese ceramic teapots is very small (Table 6.18). From Table 6.18, it can be seen that there is a little difference in sentiment outcomes between Chinese ceramic teapots (positive76%) and Japanese ceramic teapots (positive79%) (Table 6.18), indicating that Chinese consumers demonstrate strong acceptance of both product types when these teapots are selected from the top-selling segment. So, this suggests emotional drivers were more related to differences between emotional questionnaires-based and review-based responses.

While the sentiment analysis shows that both top-selling Chinese and Japanese ceramic teapots elicit overwhelmingly positive emotions with only minor differences in overall polarity, the TF-IDF terms and network hubs reveal what consumers repeatedly anchor their positive evaluations to: (1) craftsmanship and aesthetic refinement (e.g., workmanship, texture, exquisite/elegant, color/beauty), (2) use-related performance and practicality (e.g., usefulness, water/tea-related cues), and (3) service-related assurance, most notably packaging, which frequently co-occurs with quality-related terms.

While the sentiment analysis shows that both top-selling Chinese and Japanese ceramic teapots elicit overwhelmingly positive emotions with only minor differences in overall polarity, the TF-IDF terms and network hubs reveal what consumers repeatedly anchor their positive evaluations to: (1) craftsmanship and aesthetic refinement (e.g., workmanship, texture, exquisite/elegant, color/beauty), (2) use-related performance and practicality (e.g., usefulness, water/tea-related cues), and (3) service-related assurance, most notably packaging, which frequently co-occurs with quality-related terms.

On the other hand, this research also discussed the comparison of the Chinese and Japanese ceramic teapots in emotional responses from valence ratings. There was no significant difference in valence ratings: the valence ratings for Chinese ceramic teapots indicated an average of 3.2, and the valence ratings for Japanese ceramic teapots indicated an average of 3.4. This result indicates that there is little difference in preference for Chinese and Japanese ceramic teapots among Chinese consumers (Table 6.19).

Table 6.18. Comparison of Chinese and Japanese ceramic teapots (online reviews based).

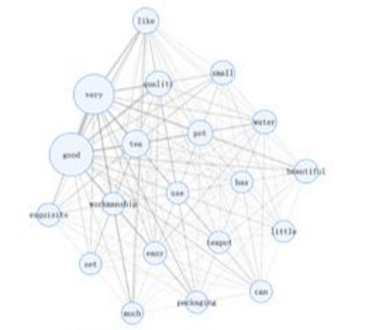
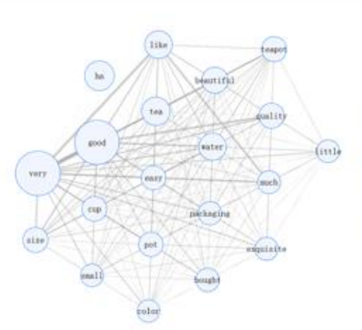
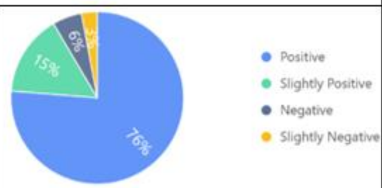
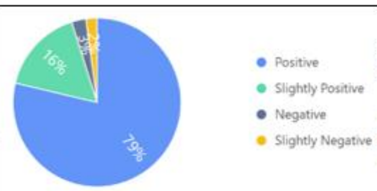
<table>
<tr><th>Items</th><th>Top-selling Chinese Ceramic Teapots</th><th>Top-selling Japanese ceramic teapot</th><th>Comparison of Results and Findings</th></tr>
<tr><td>The visual chart of word frequency</td><td>
</td><td>
</td><td>Both share “good/quality/tea/water”; Japan shows more “packaging/workmanship/exquisite/elegant/material.”</td></tr>
<tr><td>The word cloud shows high tf-idf</td><td>
</td><td>
</td><td>Both highlight sensory/finish terms (“texture/spotless/impeccable”) and use value (“useful/atmosphere”); origin effect is weak.</td></tr>
<tr><td>The semantic network analysis</td><td></td><td></td><td>Both are dense “quality–appearance–use” clusters; Japan links “good” tightly with “workmanship/packaging/beautiful/color.”</td></tr>
<tr><td>The sentiment analysis</td><td>
</td><td>
</td><td>Both are strongly positive (>75%); Japan slightly higher positive and slightly lower negative; differences are small.</td></tr>
</table>

Table 6.19. The comparison of the Chinese and Japanese ceramic teapots in emotional responses from valence ratings

Sample	Dataset (Total number of ratings)	Total score	Mean value
Chinese ceramic teapots	600	1922	3.2
Japanese ceramic teapots	600	2071	3.4

However, this study targeted the Chinese and Japanese ceramic teapots to increase the diversity of the sample. And then, to illustrate the diversity of the Chinese and Japanese ceramic teapots in a Chinese e-commerce platform, this study showed the differences in the perceived impressions and morphological features between Chinese and Japanese ceramic teapots.

1) Differences in perceived impressions: Chinese ceramic teapots were more closely associated with delicate texture, rounded, low-key, graceful, warm, light, and expensive, forming an elegant perceived impression. In contrast, Japanese ceramic teapots were more closely related to colorful, rich patterns, interesting, unbreakable, forming a decorative perceived impression (Figure 6.14).

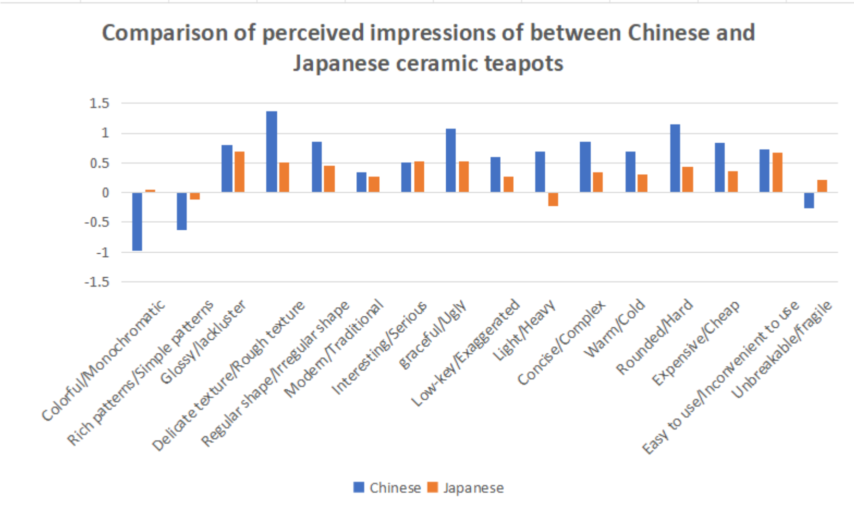


Figure 6.14. Comparison of perceived impressions between Chinese and Japanese ceramic teapots.

2) Differences in morphological features: There were differences in local contour features such as handles, spouts, and lids. Chinese teapots showed a stronger tendency toward curved and flexible forms, especially in the top-view handle and spout, as well as in the front-view spout and handle, reflecting a softer and more fluid morphological style. By contrast, Japanese teapots exhibit a more standardized and structurally stable tendency, particularly in the top-view handle and the highly unified front-view lid contour, suggesting a more orderly and regulated morphological language. Therefore, the difference lies in the contrast between the curve-oriented flexible style and the structure-oriented stable style (Table 6.20).

Therefore, the Chinese and Japanese ceramic teapots had a diversity of samples by comparing the one-sided ceramic teapots.

Table 6.20. The differences in the morphological features of Chinese and Japanese ceramic teapots.

Dimension	Feature	Code Item	Chinese Teapot Coding Performance	Japanese Teapot Coding Performance
Main Differences	Top View (Handle)	B	Mainly concentrated in B1, with a small amount of B4	Mainly concentrated in B2, B3
	Top View (Spout)	D	Predominantly D2	D1 and D2
	Front View (Lid)	G	G1, G2, G3	G1
	Front View (Spout)	H	Tends more towards H1	Distributed across H1, H2, H3,
	Front View (Handle)	F	Dispersed distribution, with F1, F2, F3, and F4.	Mainly concentrated in F1, F2, with no F4
Morphological Feature Cluster	A–H Combination A–H Combination		Round top view body (A2); mixed curved-straight or weakened top view handle (B1/B4); curved top view spout (D2); softer front view spout (H1); more varied handle designs (dispersed F).	Round top view body (A2); more structured top view handle (B2/B3); more balanced spout types (D1/D2); highly uniform front view lid (G1); more conventional, stable front view handle (F1/F2).
Overall Conclusion	Morphological Tendency		More rounded, flowing, softer, with more variation.	More regular, stable, with a stronger sense of structure.

6.3.3 The results of text analysis.

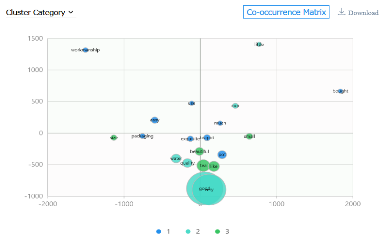
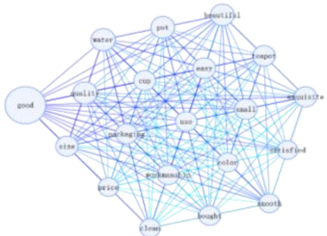
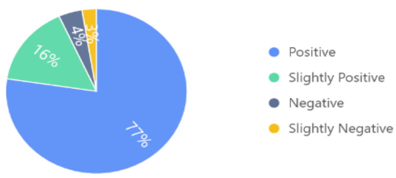
The results from the high-frequency words and semantic network analysis of the text indicate that words such as “good”, “quality”, “water”, “beautiful”, “easy”, “size”, “packaging", and "workmanship" repeatedly appear in consumer reviews. Furthermore, “good”, “workmanship”, “packaging”, “beautiful”, “quality”, and “color” are core nodes in the semantic network. TF–IDF and semantic network analyses further indicate that perceptions of craftsmanship, appearance, and usability are the core drivers of sentiment, which motivates the subsequent LDA topic modeling to summarize three major themes (Table 6.21).

Based on the analysis results, the sentiment derived from online reviews typically consists of three factors: 1) aesthetics and appearance (beautiful, color); 2) actual performance/user experience (water, easy, size); 3) service and delivery protection (packaging). Meanwhile, the LDA theme categorizes demands into three types: practicality and functionality, aesthetics and experience, and fashion and value. This guides the design of emotional craft products that will be welcomed by the market in the future.

6.4 Discussion

In the e-commerce environment, comparative research on the design features of craft products remains limited (Yang, X. et al., 2023), There is a lack of transforming empirical evidence into actionable design guidance. (van Kuijk, J. et al.,2017) This chapter addressed SRQ3 by comparing online reviews-based emotional expressions and emotional questionnaires-based emotional responses for the same set of top-selling Chinese and Japanese ceramic teapots.

Table 6.21. The results of text analysis

Text Analysis method	Visualization	Results
Word cloud of word frequency		High-frequency words of Chinese and Japanese ceramic teapots consumers' evaluation: good, packaging, workmanship, exquisite, suitable, elegant, beauty, white, quality, material etc.
Word cloud of high tf-idf		High-frequency tf-idf words of ceramic teapot consumers' evaluation: commonly, texture, served, spotless, impeccable, useful, atmosphere, etc.
Text cluster		The chart shows word distribution in 3 adjustable clusters.
Semantic network analysis		There are the words "good," " workmanship," "packaging," " beautiful," "quality," and "color" are the core nodes.
Sentiment analysis		Positive Comments: 77% Negative Comments: 3% Overall Sentiment: Positive

1) The statistical results show that, in the online-reviews context, emotional expressions were more strongly associated with Concise–Complex, Delicate texture–Rough texture, Glossy–Lackluster, and Rich in patterns–Simple patterns. By contrast, in the emotional questionnaires context, perceived features such as Colorful – Monochromatic, Regular shape–Irregular shape, and Unbreakable–Fragile were more

strongly associated with emotional outcomes. This contrast suggests that consumers rely on different evaluative logics across the two contexts. When only images are available, emotional responses are more easily elicited by design features that can be judged immediately from appearance, such as color contrast, formal regularity, and perceived solidity. In online reviews, however, consumers tend to articulate emotions through qualities that imply direct encounter with the ceramic teapot, such as surface finish, tactile refinement, decorative density, and the practicality of product usage.

2) The results also suggest that some perceptual dimensions remain relevant across contexts, although their relative importance changes. Graceful – Ugly, Lowkey – Exaggerated, Light – Heavy, and Expensive – Cheap all showed associations with emotional responses in at least part of the comparative analysis, indicating that certain evaluative meanings can operate across both review-based and emotional questionnaires-based data contexts.

3) The GEE results show that the contour features associated with emotional outcomes are not identical across the two evaluative contexts. In the online-reviews context, emotional expressions were more strongly associated with C3, F4, G3, and, to a lesser extent, E4 and G1, whereas in the emotional- questionnaires context, several lid and handle configurations, such as C2, F3, and G1, were more salient. This suggests that some morphological features may support immediate visual preference, while others become meaningful only when they are connected to the process of use, convenience, and handling.

4) The text analysis further deepens this interpretation by showing that online reviews-based emotional expressions are embedded in a broader experiential structure than emotional questionnaires-based evaluations. High-frequency words and semantic network analysis indicate that terms such as "good," "quality," "water," "beautiful," "easy," "size," "packaging," and "workmanship" recur prominently in consumer reviews, while core nodes such as "good," "workmanship," "packaging," "beautiful," "quality," and "color" organize the semantic structure of review narratives. In addition, the LDA results summarize consumer concerns into three themes: Practical and functional, Aesthetics and experience, and Fashion and value. Together, these findings suggest that emotional expressions in reviews are not limited to visual appreciation. They are jointly shaped by appearance, practical use, perceived craftsmanship, and

service-related assurance, especially packaging and delivery protection. This is an important reminder that emotional design for ceramic teapots in online retail settings extends beyond form itself and includes the broader system through which the product is presented, delivered, and experienced.

5) The comparison between Chinese and Japanese ceramic teapots. The results indicate that the overall difference in emotional responses between the two groups is relatively small, both in valence ratings and in online review sentiment. Chinese consumers showed similarly positive attitudes toward both top-selling Chinese and Japanese ceramic teapots, suggesting that the major analytical contrast in this chapter lies less in national origin than in the difference between the emotional-questionnaires context and the online-reviews context. At the same time, the two groups still showed identifiable differences in perceived impressions and morphological tendencies: Chinese teapots were more closely associated with delicate, rounded, graceful, and light impressions, whereas Japanese teapots were more closely associated with colorful, patterned, interesting, and structurally stable impressions. These differences support the diversity of the sample set, but they do not overturn the broader conclusion that contextual differences in evaluation are more pronounced than nationality-based differences in overall emotional polarity.

6) From a practical perspective, the findings imply that designers and online sellers should avoid relying on a single type of emotional cue. For the emotional-questionnaires context, product presentation should communicate those cues that are immediately legible in images, such as color clarity, shape regularity, and perceived solidity. For the online-reviews context, greater attention should be paid to tactile refinement, glaze quality, decorative control, handling experience, and packaging reliability, because these are the aspects most likely to appear in consumers' emotional expressions after product use.

7) Suggestions for emotional craft product design.

Evaluation Context: Emotional questionnaires (images/SAM) and online reviews (post-use). ①The strong correlation of " regular - irregular," "light-heavy," and "unbreakable-fragile" with SAM valence reflects consumers' /users' intuitive first impressions, aligning with Norman's visceral level of appearance-based emotion. ②In online reviews, consumers' /users' emotional responses shift from appearance to usage experience, functional performance, and durability after actual purchase and use. This is exactly the embodiment of Norman's behavioral level. ③The "Fashion & Value" theme dominates 70.3% of reviews with the highest sentiment, showing that post-use reflection on taste, identity, and aesthetics enters Norman's reflective level.

Based on the findings of this chapter, designers can divide the emotional craft product design path into two contexts: The emotional questionnaires-based evaluation context involves design features under visual image cues, which are related to the visceral level. The online reviews-based evaluation context involves design features under usage experience cues, which are related to the behavioral and reflective levels (Figure 6.15).

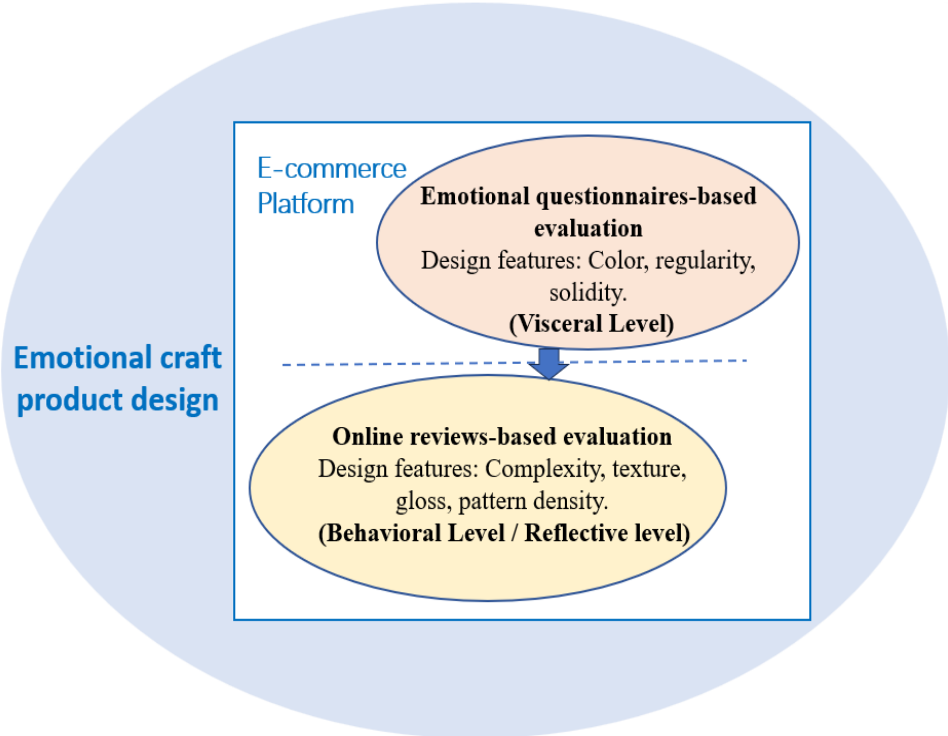


Figure 6.15 The emotional craft product design path into two contexts

The construction of a design decision pathway enables research findings to specifically guide design practice, thereby providing designers with an operable decision-making basis for creating market-bestselling ceramic teapots and promoting the development of craft product design.

8) limitations

Several limitations should also be acknowledged. First, the online reviews-based emotional expressions and the emotional questionnaires-based emotional responses were derived from different participant groups and different measurement formats, and therefore should not be interpreted as sequential observations from the same consumers. Second, the online review data were collected from top-selling products within a specific platform and time window, which may limit the generalizability of the results.

These limitations do not reduce the value of the present comparison, but they suggest that future studies could strengthen the framework through cross-platform data, longitudinal sampling, and more directly comparable participant groups.

6.5 Summary

This chapter explored how the design features of ceramic teapots are associated with consumer emotion across two distinct evaluative contexts: an online reviews-based context and an emotional questionnaires-based context. Using GLMM, GEE, and text analysis, the chapter compared online reviews-based emotional expressions with emotional questionnaires-based emotional responses for the same set of top-selling Chinese and Japanese ceramic teapots. The results show that emotional associations with design features are clearly context-dependent. In the online reviews-based context, emotional expressions were more strongly associated with Concise–Complex, Delicate texture–Rough texture, Glossy–Lackluster, and Rich in patterns–Simple patterns. In the emotional questionnaires context, emotional responses were more strongly associated with Colorful–Monochromatic, Regular shape–Irregular shape, and Unbreakable–Fragile.

The analysis of morphological features further showed that the formal features linked to emotion also differ across contexts. Certain lids and handles were more important in the emotional questionnaires-based context, whereas other lids, bodies, and handles were more strongly associated with online reviews-based emotional expressions. This finding indicates that the emotional meaning of the ceramic teapot's morphological features is not fixed, but rather varies depending on different contexts.

The text analysis results provide additional support for this conclusion. high-frequency words, semantic network analysis, and LDA topic modeling show that online reviews emphasize not only aesthetic appreciation, but also use-related performance, craftsmanship, and service-related assurance. The three major themes identified in the review corpus are practical and functional, aesthetics and experience, and fashion and value.

In addition, the comparison between Chinese and Japanese ceramic teapots indicates that the overall difference in emotional polarity between the two groups is relatively small. This suggests that, within the present sample, the more important analytical distinction lies in the contrast between the emotional-questionnaires context and the online-reviews context. Nevertheless, the two groups still contributed useful diversity in perceived impressions and morphological features.

Overall, this chapter answers SRQ3 by showing that ceramic teapot design features are associated with consumer emotion in different ways across online reviews-based and emotional questionnaires-based data contexts. Therefore, this chapter offers empirical support for the link between design features and emotional responses, paving the way for the development of more evidence-based emotional craft design in the e-commerce environment.

Chapter 7

Conclusion, Implication, and Limitations

7.1 Conclusion

This dissertation investigates the emotional design of craft products by examining how design features influence consumers' emotional responses. Ceramic teapots, which combine practical functionality with aesthetic and cultural value, provide an appropriate case for studying emotional craft design. Accordingly, this dissertation focuses on top-selling Chinese and Japanese ceramic teapots and addresses the following main research question (MRQ): How is emotional craft design produced based on the relationship between design features and emotional responses of ceramic teapots? To answer the MRQ, the dissertation formulates three sub-research questions aligned with Chapters 4–6: SRQ1 asks which design features of ceramic teapots are associated with users' perceived impressions? SRQ2 asks how is the emotional quality of ceramic teapots evaluated? and SRQ3 asks, what are the differences in ceramic teapot design features based on emotional responses elicited by online reviews versus those derived from emotional questionnaires?

To address these questions, the dissertation selects 20 top-selling ceramic teapots from JD.com in China (10 Chinese teapots and 10 Japanese teapots) and collects multi-source data, including a semantic differential (SD) questionnaire, the Self-Assessment Manikin (SAM), morphological feature coding, facial-expression data, and 1,791 online reviews. Sixty student participants viewed teapot images while their facial expressions were recorded (1,200 facial images in total) and then completed the SAM and SD questionnaires; review texts were collected via web scraping. The main conclusions are summarized below in relation to SRQ1–SRQ3.

Conclusion for SRQ1: identifying morphological design features associated with the perceived impressions of ceramic teapots;

To answer SRQ1, the dissertation decomposed teapot forms into replicable morphological elements (e.g., body, lid, spout, handle, and their front/top view contours) and quantified users' perceived impressions using an SD-scale adjective system. Factor analysis of SD pairs yielded three higher-order perceived impression factors—elegance, fashion, and practicality—which jointly explained over 70% of the variance and showed a clear salience ranking: elegance was most prominent, followed by practicality, and then fashion.

Morphological analysis is utilized to identify key form elements that shape users' perceived impressions of the top-selling Chinese and Japanese ceramic teapots. Combining users' perceived impressions of ceramic teapots, multiple linear regression is used for analysis to build a mapping relationship between perceived impression words and morphological features. The study finds that for users, they prefer elegant teapots with fine materials and expensive appearance, fashionable teapots with rich colors and rich decorations, and practical teapots that are easy to use and have regular shapes. This result verifies the matching relationship between users' perceived impressions and the design features of top-selling Chinese and Japanese ceramic teapots, which can effectively guide the morphological design of ceramic teapots, successfully convey the target image, and bring users a pleasant emotional response.

In summary, these findings translate the intuition of craft design into statistical relationships, enabling designers to justify design choices with evidence rather than solely relying on experience.

Conclusion for SRQ2: Developing an emotional quality model to evaluate the emotional quality of ceramic teapots and its application in new emotional craft product design.

To answer SRQ2, the dissertation builds and evaluates a predictive emotional model for consumers' emotional quality towards top-selling Chinese and Japanese teapots through experiments and the application of facial emotion recognition technology. Four classifiers—logistic regression (LR), C5.0 decision tree (DT C5.0), random forest (RF), and neural network (NN)—are employed to compare recognition accuracy. It is found that the random forest (RF) ensemble achieved the highest accuracy, reaching 91.0% in binary classification and 81.4% in ternary classification. In addition to intra-sample evaluation, based on the research findings of SRQ1 and combined with Norman's three-level theory of emotional design, the dissertation designed three new ceramic teapots and conducted external validation of the model. The results showed that the proportion of teapots satisfying consumer emotional preferences reached 91.1% for binary classification and 64.5% for ternary classification, exceeding the results of the original 20 teapots, thus verifying the effectiveness of the model. This indicates that the model can be applied to the evaluation and application of new teapots.

To further illustrate the practical applicability of this method, the dissertation proposes a replicable design evaluation process that converts research findings into actionable design guidance. Overall, the results indicate that the data-driven "emotion-quality evaluation tool" can be effectively integrated into the design process of craft products.

Conclusion for SRQ3: Exploring the design features of ceramic teapot by comparing online reviews-based emotional responses with emotional questionnaires-based emotional responses.

To answer SRQ3, The dissertation further extends the research from the laboratory to the e-commerce scenario, conducting text mining (such as word frequency and clustering) on 1,316 valid pieces of online reviews of the same batch of teapots, and using generalized linear mixed models (GLMM) and generalized estimating equations (GEE) to analyze and compare online reviews-based emotions and emotional questionnaires-based emotions in the laboratory, thereby identifying the design features most likely to elicit emotional responses and assessing which features influence emotions both two contexts. By comparing online reviews-based emotional expressions with emotional questionnaires-based evaluations for the same set of ceramic teapots, the study found that different design features become salient at different stages of consumer experience. In the emotional-questionnaires context, emotional responses were more strongly associated with immediately visible appearance-related cues, such as regularity, color, and perceived solidity. In contrast, online reviews-based emotions were more strongly associated with craftsmanship, decorative density, texture, use-related experience, and packaging reliability. The findings indicate that perceived elegance, light, expensiveness, and exaggeration significantly influenced emotions both before and after sales; among these, elegance and light were valued most by consumers.

Through comment clustering analysis, it was found that theme 1 (Fashion and Value) accounts for 70.3% and has the highest score, indicating that the fashion ability and value of ceramic teapots hold an important position in consumer evaluations.

These results reveal that emotional craft design in e-commerce should not focus only on emotional questionnaires-based visual attraction, but must also consider the online reviews-based experiential factors that shape long-term satisfaction and emotional evaluation.

The dissertation further translates these research findings into a two-context design path (as shown in Figure 6.15), Taken together, the overall conclusion of this dissertation is that emotional craft design can be understood as a design procedure in which design features are first encoded and analyzed, then linked to perceived and measured emotional responses, and finally translated into actionable design decisions. In this sense, the dissertation has moved the study of craft product design from an experience-driven mode toward a more data- and theory-driven mode. It has also shown that the emotional appeal of ceramic teapots can be systematically studied, modeled, validated, and reapplied in design practice.

In addition, this dissertation compares the emotional evaluations of Chinese and Japanese ceramic teapots, finding that Chinese consumers have a preference for both types of ceramic teapots. These findings provide decision-making evidence for designers to create market-top-selling ceramic teapots, thereby promoting the development of emotional design in craft products.

Overall conclusion of MRQ:

By integrating (1) morphological features-to-impression mapping, (2) emotional quality evaluation, and (3) comparative analysis of emotional online reviews-based experiential factors and questionnaires-based visual attraction, the dissertation forms a coherent and reusable research path, demonstrating that the "design features-emotional response-design decision" procedure.

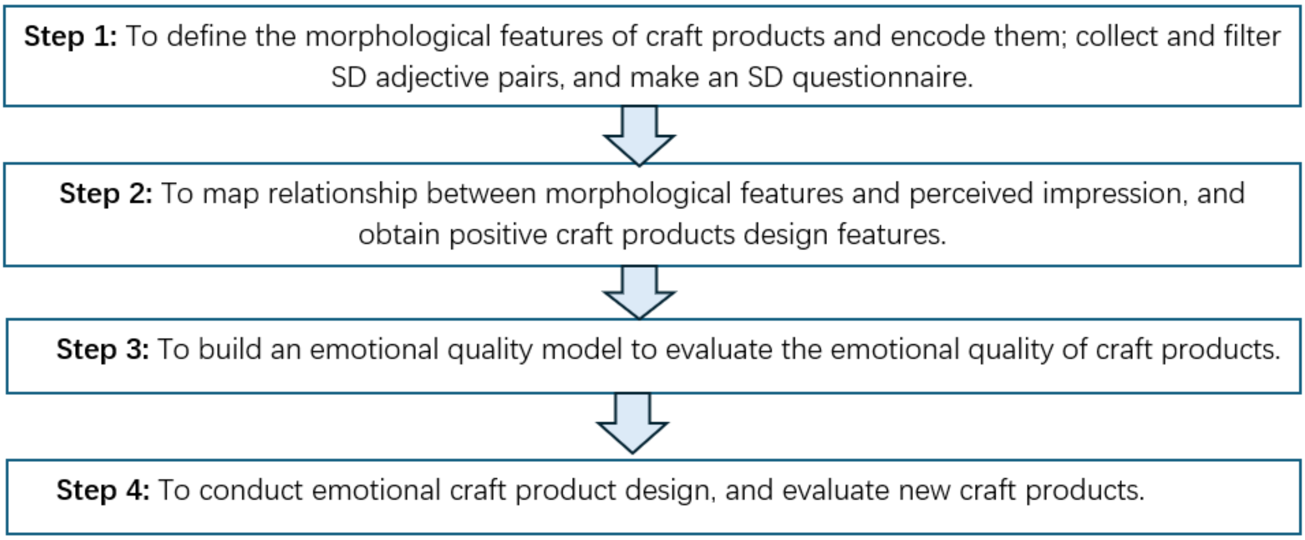


Figure 7.1 Procedure of emotional craft products design.

Therefore, this dissertation ultimately answers the question MRQ: How is emotional craft design produced based on the relationship between design features and emotional responses of ceramic teapots? That is to say, this study provided a data-driven emotional craft product design procedure that included semantic evaluation, morphological encoding, facial emotion recognition, machine learning, and text analysis to address the main research question (MRQ).

At a practical level, this study offered operational design guidance and evaluation tools for the design of ceramic teapots and other craft products.

7.2 Research implications

7.2.1 Theoretical implication and practical implication

7.2.1.1 Theoretical implications.

This dissertation has several important theoretical implications for emotional design research, craft design research, and design evaluation studies.

1) First, this study enriches the theoretical understanding of the relationship between design features and emotional responses in craft products.

Previous studies often emphasized either semantic perception or product evaluation, but relatively few studies clarified how specific morphological features of craft products systematically correspond to emotional impressions and measurable emotional outcomes. By constructing a feature–emotion mapping model for ceramic teapots, this dissertation makes the design–emotion relationship more explicit, analyzable, and empirically grounded. In this sense, the study contributes to transforming emotional design from a mainly descriptive concept into a more operationalized research framework.

2)Second, the study extends emotional design theory by showing that the emotional meaning of craft products can be structured around the three dimensions of elegance, fashion, and practicality.

These three factors not only emerged from the factor analysis, but also correspond well to the broader logic of emotional design discussed in the dissertation. This provides an interpretable conceptual bridge between abstract emotional design theory and the concrete design language of ceramic teapots. Thus, the dissertation offers a middle-level theoretical structure through which designers and researchers can understand how consumers emotionally interpret craft products.

3)Third, this dissertation is an interdisciplinary study that broadens the theory of emotional design.

The study does not stop at semantic evaluation or self-report data, but further combines facial emotion recognition, SAM scales, and machine learning classification. This integration broadens the methodological foundation of emotional design research and shows that emotional design can be studied through a combination of design theory, psychology, and data science.

4) The dissertation adds a theoretical perspective on context-dependent emotional response in e-commerce. The findings show that emotional responses derived from ceramic teapot images are not identical to those expressed in online reviews after ceramic teapot use. This means that the emotional significance of design features changes across different consumption stages and data contexts. Therefore, the study expands emotional craft design theory from a static "design features–emotional responses" relationship to a more dynamic "context–design features–emotional responses" relationship. This is particularly meaningful for craft products sold on digital platforms, where consumers' impressions are shaped first visually and later experientially.

7.2.1.2 Practical implications

This dissertation also offers important practical implications for designers.

1)First, the study provides designers with a more concrete basis for design decision-making. Instead of relying only on personal experience or aesthetic intuition, designers can refer to the positive and negative morphological elements identified in Chapter 4 when developing ceramic teapots for different emotional goals, such as elegance, fashion, or practicality. This makes emotional design more operable at the early concept stage and helps reduce uncertainty in design process.

2)Second, the study proposes a replicable evaluation process that can be used in practice. By combining morphological coding, perceived evaluation, facial emotion recognition, machine learning prediction, and redesign, the dissertation establishes a closed-loop system from design proposal to emotional assessment and redesign. This workflow can help designers test whether a concept is likely to evoke positive emotional responses before production, thereby saving time and reducing market risk.

3)Third, the findings are useful for emotional design guidance.

The comparison between online reviews-based and emotional questionnaires-based emotional responses suggests that products should be designed and communicated differently across two contexts. For image presentation, attention should be paid to visual cues that are immediately legible, such as regular shape, color impression, and perceived solidity. For actual user experience, more attention should be given to craftsmanship, glaze quality, usability, handling, and packaging reliability. These distinctions provide guidance for designing craft products that are popular in the market.

4) Fourth, the practical value of the study extends beyond ceramic teapots. Although the dissertation focuses on one type of craft product, the methodological logic—namely, extracting design features, measuring emotional responses, modeling evaluation, and translating findings into design rules—can be adapted to other categories of craft products (Table 5. Examples of other product categories). Therefore, this research offers a practical reference procedure for broader craft product innovation and emotional design. If I apply this procedure to another product category, the process remains unchanged: from extracting features, emotional quality evaluation to e-commerce assessment, what needs to be modified and adjusted are: morphological decomposition and coding system, semantic adjectives (SD adjective pairs), and domain words of the e-commerce corpus (Figure 2).

Table 7.1. Examples of other product categories.

Categories	Representative Craft Products
Ceramics	Tableware, coffee utensils, vases, pottery jars, etc. (Von Drachenfels, S. 2000; Richerson, D. W. 2012)
Metal products	Jewelry, stationery, tools (handmade scissors), etc. (Agyei, I. K., Adu-Agyem, J., & Tetteh, N. A.; UNNIKRISHNAN, G. 2024).
Wood/bamboo	Furniture, tableware (cutting boards, wooden bowls), kitchenware (spatulas, chopsticks), stationery (pen holders), storage boxes, wooden combs, musical instruments, etc. (Ekhuemelo, D. O., et al., 2018; Obiri, B. D., et al., 2020).
Glass products	Wine glasses, water bottles, vases, fruit plates, seasoning bottles, craft lamps, etc. (Whitacre, L. 2009; Shuman III, J. 2011).
Textiles /Embroidery	Clothing, home textiles (bed sheets, duvet covers, carpets), accessories (scarves, handkerchiefs), soft furnishings (curtains, tablecloths, cushions), etc. Martha Stewart Living Magazine. 2012; Parchure, J. W. 2025)
Lacquerware	Food boxes, trays, jewelry boxes, furniture, etc. (JunGuo, Z. H. A. O. 2022; January, Caraway, G. K. 2012)
Leather products	Leather bags, belts, leather shoes, wallets, laptop covers, key bags, furniture (leather sofas), etc. (MUPPIDI, R. 2025)

7.2.2 Contributions to knowledge science

This dissertation makes a meaningful contribution to knowledge science in several respects (Figure 7.3).

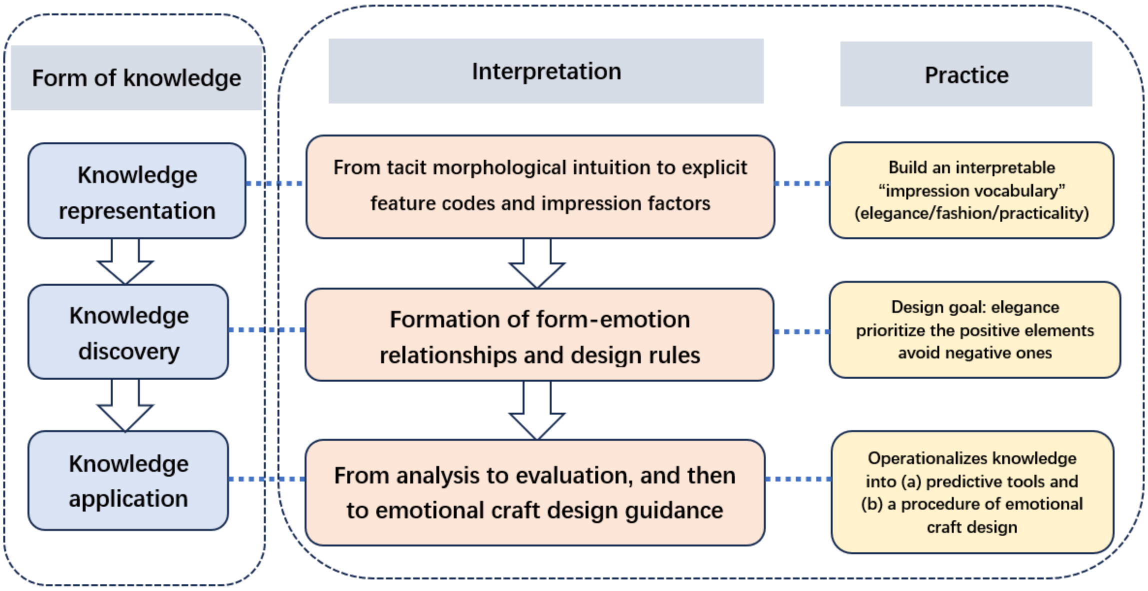


Figure 7.3 Overview of contributions to knowledge science

1) Knowledge representation: from tacit morphological intuition to explicit feature codes and impression factors.

In many craft design contexts, knowledge about what makes a product emotionally appealing often remains implicit in the experience of designers or artisans. This dissertation extracts such tacit knowledge and reconstructs it into analyzable units, including morphological elements, impression factors, emotional classifications, and design rules. In this way, the study supports one of the central concerns of knowledge science: how implicit, experience-based knowledge can be externalized and made shareable.

2) Knowledge discovery: statistical learning of form–emotion relationships and design rules.

Dummy-variable regression reveals which morphological variables significantly contribute to each impression factor, yielding rule-like knowledge ("if design goal is elegance, prioritize the positive morphological elements and avoid negative ones"). This is not merely descriptive; it is generated through a transparent and replicable inference process, supporting the knowledge-science goal of explainable knowledge extraction.

3) Knowledge application: connecting emotional responses with design features and then translating the results into actionable design guidance.

The dissertation's workflow operationalizes knowledge into (a) evaluation tools (emotion-quality classifiers), (b) decision roadmaps (two- context decision from review evidence to design priority), and (c) toward reusable emotional design knowledge for other craft products. This provides a scalable pathway to accumulate domain knowledge across product families.

In summary, this dissertation will provide a scientific methodology and empirical foundation for the field of emotional design of craft products, promoting the development of craft product design. The main contributions to knowledge science are reflected in the following two aspects.

Academic contributions; 1) This study adopted an interdisciplinary research approach by integrating knowledge from multiple disciplines, such as design studies, affective psychology, and information science, into the research on emotional design of ceramic products. This provided a theoretical framework for studying other craft products, promoted the development of interdisciplinary research, and contributed to the field of knowledge science. 2) This study used quantitative analysis to evaluate the impact of design features of ceramic teapot on consumer emotions, offering a new analytical dimension for affective design. Additionally, it conducted design practices and validations based on consumer emotional feedback, providing a replicable methodology for related research and enriching the theory of craft product design.

Practical contributions; 1) The empirical study of ceramic teapots not only deepened the application of affective design theory in the craft field but also provided specific guidance and inspiration for actual design work. It helped designers understand consumer usage and aesthetic needs from the details of craft products, offering clear design recommendations and guiding specific design decisions. 2) The results of this study provided data-driven evidence for the innovative design of ceramic teapots.

7.3 Limitations and future works

7.3.1 Limitations

Despite its contributions, the dissertation has several limitations.

1) Sample size and representativeness of products.

Although the study deliberately included both Chinese and Japanese top-selling ceramic teapots to increase form diversity, the total number of product samples was still relatively small, and all samples were drawn from a single e-commerce platform. These samples do not include ceramic teapots with medium or low sales rankings. This limits the generalizability of the findings to the broader ceramic teapot market or to other kinds of craft products.

2) Participant bias and population inconsistency across stages.

Second, the study has limitations in terms of participant diversity. Emotional evaluations are primarily obtained from young students, which may bias the results toward a specific demographic. In addition, Laboratory participants were primarily university students, whereas online reviews represent heterogeneous real consumers; this inconsistency may bias the comparison between two-context emotional processes.

3) Time-window dependence of “top-selling” attributes.

Top-selling styles are time-sensitive; therefore, findings may be bounded by the specific collection period.

4) Emotion measurement constraints.

The use of facial emotion recognition also has methodological limitations. Factors such as lighting conditions, head posture, partial occlusion, and self-control of facial expressions may affect recognition accuracy. In addition, facial expressions alone may not fully represent emotional experience.

7.3.2 **Future works**

Based on the findings and results of this study, future research will primarily focus on the following aspects.

1) Future studies should expand the sample range by including more product types, more platforms, more price levels, and a wider variety of cultural or regional styles.

2) Future work should test generalizability across age, expertise (tea enthusiasts vs. casual users), and cultural background, and examine whether different segments prioritize different emotional drivers.

3) Future work should recruit more diverse participants and consider paired designs (e.g., follow the same participants from viewing to purchase to use) to measure within-subject emotional transition. In addition, replicate across time windows and platforms (multi-year, multi-platform) to test stability and identify trend-sensitive vs stable drivers.

4) Future research could improve the scientific validity of emotional evaluation by adopting multimodal approaches, such as combining facial emotion recognition with eye tracking, physiological signals, EEG, or other biosensing methods. Although combining FaceReader and SAM provides a cost-effective multimodal measure, facial expressions and self-report are both imperfect proxies for emotion. Future research can incorporate additional signals (e.g., physiological measures, behavioral data such as click/purchase/return records) and compare convergent validity across modalities.

In summary, the dissertation has provided a relatively solid methodological and theoretical foundation for the emotional design of craft products. Future research can continue to expand in areas such as sample size, feature accuracy, and group diversity, in order to promote the further application of this framework in real-world e-commerce and design practices.

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List of publications

- Papers published in journals

1) Xianghui Li, Takaya Yuizono, Van-Nam Huynh, and Ruixuan Li, Toward Emotional Design Feature Evaluation in Craft Development: Understanding the Top-Selling Chinese and Japanese Ceramic Teapots, IEEE Access, vol. 13, pp. 210554-210575, 2025, doi: 10.1109/ACCESS.2025.3642927.

This journal paper is the main content of Chapter 4 and 5 of my doctoral thesis.

-International conference proceedings

1) Li Xianghui, Yuizono Takaya, Li Ruixuan, and Bing Wang, Study on Consumer Acceptance Evaluation Model of Ceramic Tea Set Based on Facial Emotion Recognition Technology. The Proceedings of the 2022 4th International Conference on Economic Management and Model Engineering (ICEMME), 2022.10.

This conference paper is the main content of Chapter 5 of my doctoral thesis.

Appendices

Appendix A. Core rules of JD hot selling list (Sales Ranking).

(The following content comes from the official website of JD.com: https://learn-jdm.jd.com/knowledge/rule)

Core dimension	Specific rules and instructions
Generation logic	Based on the product data of JD website, it is completely generated and sorted automatically by the system algorithm without any manual intervention.
Core sorting according to	The weighted calculation is mainly based on two core indicators: Gross Merchandise Volume (GMV) and Order Volume. Simply put, the more sold and the higher the sales revenue, the higher the ranking.
Data range	Based on the real transaction data of all products on the website, cheating data such as anti-brushing orders and false transactions will be automatically filtered out to ensure the fairness of the ranking.
Update frequency	Updates are very frequent. For example, the hot selling list on the main site is usually updated daily, while the "New Product Hot Selling List" launched during major promotions may even be updated daily based on sales volume. (Daily full update: triggered at 18:00 every day and completed before 9:00 the next day)
Basic threshold for listing	Not all products are eligible to be listed. The system will conduct a preliminary screening, for example, the product's positive review rate is usually not less than 95%, and the store's benchmark ranking also has requirements (such as not less than 20%), while ensuring that the product does not hit any violations.

Appendix B. Participant information.

Study stage	Participant group	No. of participants (n)	Affiliation	Major	Age (years)	Male: female ratio
Adjective screening stage	Expert teachers	10	School of Art and Design, DPU, China	Product design	35-55	1:1
	Undergraduate students	10		Product design	21	2:3
		10		Art and design	21	3:2
Evaluation of the emotional quality stage	Undergraduate students	60	School of Art and Design, DPU, China	Art and design	21-22	6:13
Evaluation of the new teapot stage	Postgraduate students	15	School of Art and Design, DPU, China	Art and design	23-25	1:5

Appendix C Survey questionnaire on ceramic teapot imagery vocabulary.

Dear friends, I am a doctoral student at the Advanced Institute of Science and Technology in Japan. I am currently conducting a survey titled "Toward Emotional Craft Design: Exploration of Design Features on Emotional Responses within top-selling Chinese and Japanese Ceramic Teapots". This questionnaire contains a total of 72 words (adjectives) related to emotional imagery, arranged in random order. Please make a subjective judgment based on your own experience and tick the box below (put a " √ " on the question number). You think that the best number of adjectives that match the shape of the ceramic teapot is about 20. If the emotional image words listed in the questionnaire do not meet your expectations, please supplement them at the bottom of the questionnaire. Your valuable feedback will be of great help to this study. Thank you for your enthusiastic participation and support!			
Safe	Pure	Bright	Advanced
Practical	Simple	Lightweight	Delicate texture
Rich patterns	Unbreakable	Expensive	Low-key
Metallic	Bright	Clean	Fresh
Durable	Rustic	Refreshing	Distinctive
Popular	Transpicuous	Concise	Cold
Fashionable	Neutral	Elegant	Light
Interesting	Colorful	Regular shape	Prosaic
Gorgeous	Artificial	Unique	Easy to use
Fantastic	Monotonous	Exquisite	Rhythmic
Graceful	Modern	Glossy	Dynamic
Classical	Smooth	lovely	Warm
Serene	Solemn	Free	Flowery
Still	Formal	Friendly	Moist
Pretty	Reserved	Plain	Attractive
Conventional	Luxurious	Lustrous	Happy
Rounded	Gentle	Soft	Novel
Streamlined	Cultural	Having quality	Natural

Appendix D URL of Chinese ceramic teapot samples.

Number	Sample image	Shop Name	Chinese Ceramic Teapot Product Name	Data Collection URL
1		苏氏陶瓷京东自营旗舰店	苏氏陶瓷(SUSHI CERAMICS)茶壶羊脂玉中国白圆珠陶瓷功夫茶具泡茶壶德化猪油白亚光款礼盒装	https://item.jd.com/5148798.html#comment
2		钰铨龙门旗舰店	钰铨龙门白瓷茶壶 中国白羊脂玉素烧西施壶猪油白手工陶瓷泡茶壶功夫茶具 羊脂玉瓷西施壶(约200ml)	https://item.jd.com/71242518510.html#comment
3		MULTIPOTENT 京东自营旗舰店	元青茶壶(MULTIPOTENT)羊脂玉 中国白陶瓷功夫茶具泡茶壶单壶麒麟壶中秋佳节礼盒套装	https://item.jd.com/100025820266.html#comment
4		连山阁旗舰店	连山阁 陶瓷茶壶过滤家用泡茶器大号功夫茶具单壶带网隔内胆茶杯子套装中国风简便冲茶壶 方壶玉兰花陶瓷过滤单壶 380ml	https://item.jd.com/10042166563451.html#comment
5		宁不凡家居旗舰店	宁不凡(NINGBUFAN) 汝窑茶壶汝瓷泡茶器可开片汝窑茶具单茶壶小侧把壶(约 150ml)	https://item.jd.com/1421772305.html#comment
6		汇想旗舰店	汇想德化白瓷茶壶陶瓷 中国白玉瓷茶壶单壶西施壶象牙白功夫茶具蜂巢式密封过滤孔侧把手抓壶玉瓷侧把壶	https://item.jd.com/14588344427.html#comment
7		fw 家居旗舰店	fw 中国红色茶具龙凤双喜泡茶壶陶瓷水壶盖碗泡茶器结婚庆新人敬茶壶结婚礼品送人婚庆用品 富贵牡丹茶壶	https://item.jd.com/10022440237670.html#comment
8		唐舍官方旗舰店	唐舍中国风羊脂玉瓷户外旅行茶具套装快客杯一壶四杯德化白瓷陶瓷便携旅游办公家用泡茶壶 如意祥云-莲蓬	https://item.jd.com/10029922092486.html#comment
9		汉隶茶具旗舰店	汉隶 德化白瓷羊脂玉瓷茶壶茶具陶瓷中国白素烧纯白井栏壶功夫茶具泡茶壶茶家用办公泡茶工具高档礼盒装 祥瑞壶-大壶 300ml	https://item.jd.com/69503798137.html#comment
10		乾森茶具旗舰店	乾森茶壶中国白瓷泡茶壶茶具配件 青花白瓷茶壶	https://item.jd.com/10025871598558.html#comment

Appendix E URL of Japanese ceramic teapot samples.

Number	Sample image	Shop Name	Japanese Ceramic Teapot Product Name	Data Collection URL
1		爱陶旗舰店	爱陶(AITO)抚松庵濑户烧日本原产进口日式陶瓷功夫茶壶带滤网已停产 茶壶百子莲 11.0*10.6CM	https://item.jd.com/44281193891.html#comment
2		apous 旗舰店	Zero Japan 日本进口炫彩创意陶瓷彩色茶壶热水壶洌圆茶壶 墨绿-小	https://item.jd.com/10478719467.html#comment
3		陶趣居餐具专营店	日本进口 光锋 线唐草小蓝芽茶杯日式汤吞寿司茶杯陶瓷小杯泡茶杯子茶具套装茶壶一壶两杯礼盒装 线唐草 茶壶	https://item.jd.com/23329121883.html#comment
4		天佑厨具专营店	K-UNING 日本进口万古烧未来形急須茶壶陶瓷含漏网陶壶侧把壶功夫茶具泡茶壶普洱红茶单壶茶道 A7077 未来形急須 2 号黄 310ml	https://item.jd.com/31550233821.html#comment
5		美浓烧官方旗舰店	美浓烧 陶瓷茶壶万古窑紫泥茶壶 日本原装进口手工横手急需 送礼佳品	https://item.jd.com/10421814795.html#comment
6		吉奈海外自营旗舰店	吉奈常滑烧泡茶壶 日式功夫茶壶陶瓷茶具手工朱泥侧把壶日本进口养生壶过滤办公家用九宫壶 黑色梨皮 270ml	https://npcitem.jd.hk/100016983486.html#comment
7		天佑厨具专营店	K-UNING 日本进口万古烧急須自然派系列花吹雪陶壶功夫茶壶 日式侧把手泡茶壶陶瓷茶具 急須 1.5 号花吹雪 炎 310ml	https://item.jd.com/31553161014.html#comment
8		天佑厨具专营店	【K-UNING】日本原装进口茶壶带滤网复古手工泡茶壶大容量急须侧把壶富仙作 540ml	https://item.jd.com/10041846903098.html#comment
9		爱悦烧官方旗舰店	爱悦烧日本原装进口九谷烧花鸟茶壶茶杯陶瓷器茶具套装 九谷烧花鸟一壶两杯	https://item.jd.com/45444591885.html#comment
10		爱悦烧官方旗舰店	爱悦烧日本进口陶瓷九谷烧手绘日式和风茶壶茶杯茶具套装 绣眼鸟茶壶一只	https://item.jd.com/53149296676.html#comment

Appendix F Segmentation of consumer reviews on Chinese ceramic teapots and Japanese ceramic teapots (Part of the reviews).

Appendix F-1 Segmentation of consumer reviews on Chinese ceramic teapots (Part of the reviews).

中国陶瓷茶壶评论_分词后 - 记事本
文件(F) 编辑(E) 格式(O) 查看(V) 帮助(H)

小小 壶 子 非常 精致， 特别 喜欢 这种 哑 光风 格， 圆润 细腻 里里外外 摸 了 个 遍 没有 沙 点 突起 什么 的， 小 盖子 合 起来 的 时候 声音 清脆 整体 通透 让 人 爱不释手， 一下子 觉得 很 小 用 起来 刚刚 好 很 舒服， 真 怕 不 小心 给 摔 了， 泡茶 时水 不要 太 满会回 勾， 差不多 就 行， 好评！
木制 包装， 质量 很 好， 没有 纸袋 子， 包装 表面 不 是 很 干净， 磨砂 的， 不 是 很 大， 质地 很 好！
" 做工 品质： 很 上档次， 白瓷 的， 看 着 赏心悦目， 品质 是 没 问题， 也 没有 什么 瑕疵
包装 特点： 很 严实， 减震、 包裹 什么 的 很 到位， 没有 一丝 磕碰
容量 大小： 有点 小 了， 不过 专业 泡茶 都 这 容量 大小， 看 着 也 很 精致， 上传 照片 有 限 抽 纸 的 比较， 可以 估 一下 大小
清洗 难 易： 虽然 是 白色 的， 到 这个 材质 应该 很 容易 洗， 建议 用 来 泡 一 种 茶， 比如 专职 泡 红茶 什么 的， 不错
京东 物流 很 好"
" 首先 在此 先 说明， 我 手机 还有 我 不会 拍照， 所以 效果 不 是 很 好！
做工 品质： 做工 非常 好 的， 光滑 洁白， 基本 没 瑕疵， 看 着 就 感觉 到 舒服。 洁白 无瑕 的 壮 腿。 设计 简洁 而 不失 高雅
包装 特点： 大 木 盒 单独 包装， 非常 稳固
材质 特点： 材质 洁白， 无 杂质， 纯
出水 难 易： 出水 流畅， 有 凸起 隔 筛， 不怕 茶叶 堵塞
容量 大小： 个人 感觉 容量 够， 挺 好
清洗 难 易： 清洗 容易"
款式 简单 大方， 茶壶 出汤 快， 茶具 的 质感 也 非常 好，做工 精细， 在 灯光 下面 灯具 可以 透光 看见 莲花， 非常 喜欢。 一 套 茶具 有 盖碗， 茶杯， 茶漏， 还 搭配 了 一 个 茶壶， 够用 了。
做工 很 精致 出水 流畅 包装 还 行 材质 不错 容量 感觉 挚 好 清洗 简单。 京东 物流 贯 的 速度 快。 物品 也 很 完整 快递 服务 态度 好 不错 的
做工 细腻，手感 特 舒服，服务 态度 非常 好，放心 购买 吧
做工 细致， 出水 流畅， 包装 精美， 乳白色 非常 漂亮！ 容量 也 非常 合适， 壶口 适當， 特别 方便 清洗！ 润茶 是 密封 性 好， 茶 味 保留 完整， 值得 购买！
想 买 个 茶壶 京东 逛 了 好久 考虑 过 很多 材质 的 如 紫砂 感觉 太 脏 不 是 很 放心 正好 看到 这个 壶 而且 有 个 活动 价格 看上 去 很 合适 于是 就 确定 买 了 这个 到手 后 发现 的确 不错 做工 很 精致 没有 屏幕 上 写 的 那些 问题 这边 说一 下 啊 这 有 个 设计 我 很 喜欢 就是 出 水口 有 几 个 小孔 过滤 总之 性价比 不错 可以 考虑

第 1 行，第 1 列 100% Windows (CRLF) ANSI

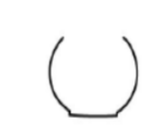
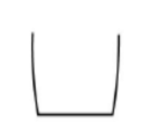
Appendix F-1 Segmentation of consumer reviews on Japanese ceramic teapots (Part of the reviews).

日本陶瓷茶壶评论_分词后 - 记事本
文件(F) 编辑(E) 格式(O) 查看(V) 帮助(H)

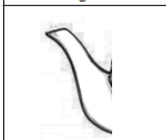
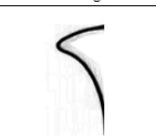
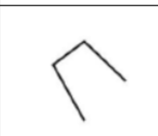
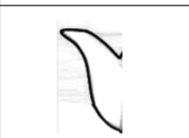
特别 棒 的 杯子， 杯 型 和 花纹 都 特别 的 满意， 颜色 比较 特别， 暗色 有些 旧 旧 的 感觉， 瓷器 比较 厚， 杯子 配有 过滤网， 还有 把手， 泡茶 方便 不会 烫 手。
在 网上 挑选 了 好久 才 下决心 买 的， 今天 终于 收到 了， 宝贝 太 漂亮 了， 包装 非常 用心， 商家 送 的 杯 垫 也 很 好看， 虽然 价钱 贵 些， 但 宝贝 做工 真的 很 精美， 物有所值， 推荐 哦！
茶壶 收到， 上 手感 很 好。 说实话 比 我 之前 买 的 贵 的 要死 的 紫砂壶 好 用 很多， 首先 身 筒 比较 高， 喝 小青 柑 不用 担心 盖子 盖 不严 的 问题， 口盖 还 很 大， 和 绿茶 不会 闷 到 叶子， 里面 还有 个 超大 的 茶 滤， 倒 茶 不用 单独 放 茶 滤 了。 各种 的 实用， 超 赞。
与 想象 中 的 一模一样， 色彩、 器 型、 大小、 都 很 适合。 拿来 泡 花茶、 红茶、 岩 茶、 白茶都 合适。 日本 的 东西 和 有 魅力， 吸引 人， 韵味 十足。 希望 它 陪 我们 开心 每 一天。
真心 觉得 好看， 是 俺 喜欢 的 类型， 高端 大气 上档次， 低调 的 奢华， 非常 好
非常 不错， 质量 很 好， 外观 也 很 漂亮， 包装 的 非常 牢固， 满意 的 购物 体验
质量 颜值 超级 好， 跟 店家 描述 的 一样 一样 滴！ 包装 上 更 是 没得说。 店家 送 的 水杯， 小 惊喜 啊？点 赞 点 赞？
做工 精致， 包装 完美， 非常 满意
质量 不错， 包装 完好， 很 漂亮！
很 可爱 的 一把 小 壶， 花样 和 款式 都 是非 常 喜欢 的。 里边 的 大 茶漏 让 茶叶 都 难 舒展 开来。 就是 有点 小 贵 啊。
整体 不错！ 花色 鲜艳 漂亮， 瓷 面 光滑， 没有 任何 异味， 出水 流畅， 两 个人 喝茶 很 不错。 壶内 底色 是 花 的， 乍 看 以为 脏 的， 咨询 客服 说 用 的 特殊 工艺， 白 茶 网 挡 着 也 看不 到。 好 用 好评
日本 的 东西 大多 粗 旷 的 样子， 但 手 的 触 感， 却 是 细腻 的， 光滑 的。 主要 它 设计 感 很 强。 而且 特色 鲜明， 一 看 就是 日本 风格。 这 是 第一次 买 美 浓 烧， 但 它 给 我 带来 的 喜悦感 是 无以 伦 比 的。
包装 完好， 杯子 大小 合适 图案 漂亮。
宝贝 到手 了， 爱 了 爱 了， 低调 不失 优雅， 朴实 且 细腻， 专 为 白 茶 所 选 Nice
真 好， 比 图片 还 漂亮， 颜色 自然 复古
图案 挺 漂亮！ 蛮 喜欢 的
没有 想象 中 的 好看， 脏兮兮 的 颜色
小小的， 也 挺 好 用 的。

Appendix G View feature lines of ceramic teapot

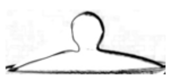
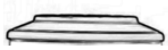
Appendix G-1 Front view feature lines of ceramic teapot body.

				
O_1	O_2	O_3	O_4	O_5
Straight line+Arc	Curve	Straight line+Arc	Straight line+Arc	Curve
				
O_6	O_7	O_8	O_9	O_{10}
Curve	Hyperbola+Straight line	Straight line+Curve	Curve	Curve
				
O_{11}	O_{12}	O_{13}	O_{14}	O_{15}
Straight line+Arc	Curve	Straight line+Curve	Straight line+Arc	Straight line
				
O_{16}	O_{17}	O_{18}	O_{19}	O_{20}
Straight line+Arc	Straight line+Curve	Straight line	Straight line+Arc	Straight line+Arc

Appendix G-2 Front view feature lines of ceramic teapot spout.

				
O_1	O_2	O_3	O_4	O_5
Curve	Curve	Curve	Straight line	Curve
				
O_6	O_7	O_8	O_9	O_{10}
Curve+Straight line	Curve	Curve	Straight line	Curve
				
O_{11}	O_{12}	O_{13}	O_{14}	O_{15}
Straight line	Curve+Straight line	Curve	Curve	Curve
				
O_{16}	O_{17}	O_{18}	O_{19}	O_{20}
Curve	Curve	Straight line	Curve	Curve

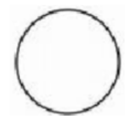
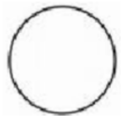
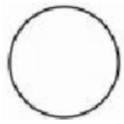
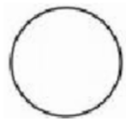
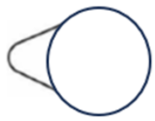
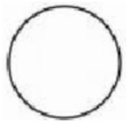
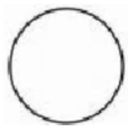
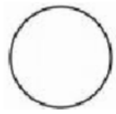
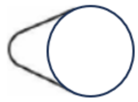
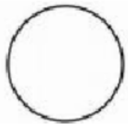
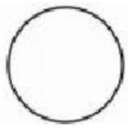
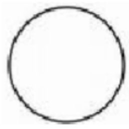
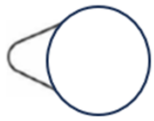
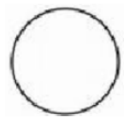
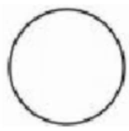
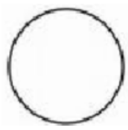
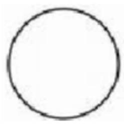
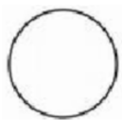
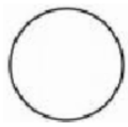
Appendix G-3 Front view feature lines of ceramic teapot lid.

				
O_1	O_2	O_3	O_4	O_5
Arc+Straight line	Straight line+Curve	Arc+Straight line	Arc+Straight line	Arc+Straight line
				
O_6	O_7	O_8	O_9	O_{10}
Arc+Straight line	Arc+Straight line	Arc+Straight line	Arc+Straight line	Straight line+Curve
				
O_{11}	O_{12}	O_{13}	O_{14}	O_{15}
Arc+Straight line	Arc+Straight line	Arc+Straight line	Arc+Straight line	Arc+Straight line
				
O_{16}	O_{17}	O_{18}	O_{19}	O_{20}
Arc+Straight line	Straight line	Arc+Straight line	Arc+Straight line	Arc+Straight line

Appendix G-4 Front view feature lines of ceramic teapot handle.

				
O_1	O_2	O_3	O_4	O_5
Arc	Arc	Curve + Arc	Straight line	Curve + Arc
				No handle
O_6	O_7	O_8	O_9	O_{10}
Arc	Curve + Arc	Arc	Straight line	No handle
				
O_{11}	O_{12}	O_{13}	O_{14}	O_{15}
Straight line	Straight line	Arc	Arc	Straight line
	No handle			
O_{16}	O_{17}	O_{18}	O_{19}	O_{20}
Curve + Arc	No handle	Straight line	Curve + Arc	Curve + Arc

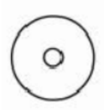
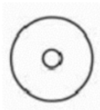
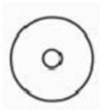
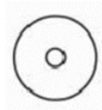
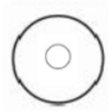
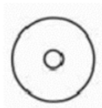
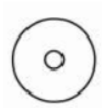
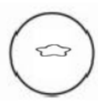
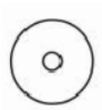
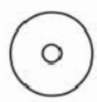
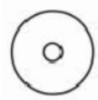
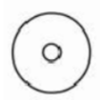
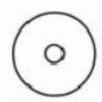
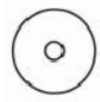
Appendix G-5 Top view feature lines of ceramic teapot body.

				
O_1	O_2	O_3	O_4	O_5
Circular	Circular	Circular	Circular	Circular+Straight line+Curve
				
O_6	O_7	O_8	O_9	O_{10}
Circular	Circular	Circular	Circular	Circular+Straight line+Curve
				
O_{11}	O_{12}	O_{13}	O_{14}	O_{15}
Circular	Circular	Circular	Circular+Straight line+Curve	Circular
				
O_{16}	O_{17}	O_{18}	O_{19}	O_{20}
Circular	Circular	Circular	Circular	Circular

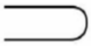
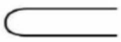
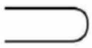
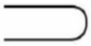
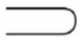
Appendix G-6 Top view feature lines of ceramic teapot spout.

				
O_1	O_2	O_3	O_4	O_5
Curve	Straight line+Curve	Curve	Curve	Curve
				
O_6	O_7	O_8	O_9	O_{10}
Curve	Straight line+Curve	Curve	Straight line+Curve	Straight line+Curve
				
O_{11}	O_{12}	O_{13}	O_{14}	O_{15}
Curve	Curve	Curve	Straight line+Curve	Straight line+Curve
				
O_{16}	O_{17}	O_{18}	O_{19}	O_{20}
Curve	Curve	Straight line+Curve	Straight line+Curve	Straight line+Curve

Appendix G-7 Top view outline of ceramic teapot lid.

				
O_1	O_2	O_3	O_4	O_5
Circular	Circular	Circular	Circular	Circular
				
O_6	O_7	O_8	O_9	O_{10}
Circular	Circular+Curve	Circular	Circular	Circular +Curve
				
O_{11}	O_{12}	O_{13}	O_{14}	O_{15}
Circular	Circular	Circular	Circular +Straight line+Curve	Circular
				
O_{16}	O_{17}	O_{18}	O_{19}	O_{20}
Circular	Circular	Circular	Circular	Circular

Appendix G-8 Top view feature lines of ceramic teapot handle.

				
O_1	O_2	O_3	O_4	O_5
Straight line+Curve	Straight line+Curve	Straight line+Curve	Arc+Straight line	Straight line
				No handle
O_6	O_7	O_8	O_9	O_{10}
Straight line+Curve	Straight line+Curve	Straight line+Curve	Arc+Straight line	No handle
				
O_{11}	O_{12}	O_{13}	O_{14}	O_{15}
Arc+Straight line	Arc+Straight line	Straight line+Curve	Straight line	Arc+Straight line
	No handle			
O_{16}	O_{17}	O_{18}	O_{19}	O_{20}
Straight line+Curve	No handle	Arc+Straight line	Straight line+Curve	Straight line