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How consumers' perceptions differ towards the design features of mobile live streaming shopping platform: A mixed-method investigation of respondents from Taobao Live

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ABSTRACT

Mobile Live Streaming Shopping (MLSS) has become the most rapidly growing e-commerce business. However, there is a dearth of theoretical concern on the MLSS platform designing issue - the key factor affecting business success. Based on the axiomatic design theory, a systematic view of design features of MLSS platform is given, and a three-layer model including thirteen design features is built. The perceived differences of consumers across design features and individual characteristics, as well as the prioritization strategies of MLSS platform are derived with a mixed-method schema. The study provides fine-grained insights for enhancing the differentiated consumer experience by optimizing and improving the design of MLSS platforms.

1. Introduction

The dramatic evolution of digital technology, Internet and communication technology has spawned the rise of the live streaming shopping paradigm (Guo et al., 2022). The real-time experience created facilitates consumers' understanding and interest in products, spreads brand value, and enhances consumer stickiness (Yin, 2020). Currently, an increasing number of consumers use their phones to shop on live streaming through mobile apps (Raphaeli et al., 2017; Kim et al., 2019; Omar et al., 2021), and MLSS platform has become the new gathering hub for consumers shopping online. The deliberate design of e-commerce platforms has been addressed to contribute to a reciprocal buyer-seller relationship, consumer loyalty, and commitment (Xiao et al., 2022; Lin et al., 2020). Therefore, the design of MLSS platform, the new type of e-commerce platform, is expected to exert considerable impacts on facilitating consumer-streamer interaction, improving consumer experience, and promoting sales conversion.

However, in terms of consumer research on the live streaming shopping field, extant literature mainly focused on consumer engagement motivations (Liu et al., 2021a; Busalim and Ghabban, 2021; Hu and Chaudhry, 2020), psychological antecedents of continuous use or purchase intentions (Zhang et al., 2020; Ko and Chen, 2020; Sun et al., 2018), or industry operations suggestions (Chen et al., 2019; Liu, 2020; Liu et al., 2020a). Most of these studies stopped at exploring impact factors on psychological levels, or policies from a macro perspective, and lacked an in-depth investigation on the genetic standpoint of platform design. Since consumers interact directly with streamers and other consumers through the interface afforded by the MLSS platform, the disregard of design aspects is not conducive to deriving actionable platform optimization strategies, especially within such a limited sized interaction interface of smartphones, which may further lead to poor user experience and even consumer churn.

The MLSS platform is downloaded and installed by the consumer as a holistic app, and during use, the consumer interacts with the MLSS platform through an array of design features. Design features are elements of a system that provide specific rules or functions (DeSanctis and Poole, 1994), the elegant design of which can convey positive hints to consumers and affect their attitudes and behavioral intentions (Hasan, 2016; Ashraf et al., 2019; Wu et al., 2022). As such, understanding consumers' perceptions toward these design features from a microscopic and multifaceted perspective would be beneficial to platform design to derive enlightening and constructive insights.

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Previous behavioral and psychological studies of consumers have focused on consumer perceptions of products, merchants, and e-services (Yang & Jun 2008; Sarkar and Bhuniya, 2022), and measured the perceptions in terms of dimensions such as perceived quality, perceived performance, perceived importance, and perceived satisfaction (Xiao, 2021). Literature on information products suggested a possible non-linear and asymmetric relationship between product/service performance and consumer perception (Kano et al., 1984; Tseng, 2020; Liu et al., 2021b; Mahapatra et al., 2022), however, in the context of live streaming e-commerce, the relationships between individual MLSS platform design features and consumer perceptions, the differences amongst consumer groups (e.g., consumers of different genders, ages, and live streaming shopping experiences), and further the effective design strategies for MLSS platforms, have not yet been clarified in the extant literature. Thus, the current study addresses the following three research questions (RQs) to bridge these identified gaps.

RQ1: What are the differences in consumer perceptions toward different design features of MLSS platform?
RQ2: For the same design features, what are the differences in the perceptions of consumers with different individual characteristics?
RQ3: Within the limited interaction and service resources, how should MLSS platform managers and designers develop effective prioritization strategies?

To answer the above questions, on the basis of the analysis of the current leading MLSS platforms (e.g., Taobao Live, Tiktok, Pinduoduo and Kwai), we select Taobao Live, the world's largest MLSS platform, to conduct a survey and make our unique contributions. First, based on the axiomatic design theory, the current study provides a systematic and comprehensive overview of the design features of MLSS platform, which goes beyond the one-sided focus in past studies and comprehensively describes the hierarchical relationships among design features. Second, utilizing the Kano model based on dummy variables regression, MLSS platform design features are identified as four different categories according to the relationship between their performance and consumer satisfaction, which facilitates the deriving of subsequent differentiated design, presentation, and management strategies for different categories of design features. Third, correspondence analysis is employed to capture the preferences of different consumer groups, which provides an in-depth understanding of which design features are of interest to each consumer group. Finally, in regard to the effective optimization of MLSS platform design within limitations in terms of screen size and interaction timing, importance-satisfaction analysis is conducted to inform platform designers the customized design strategies to elevate consumer experience and deliver positive outcome through streamlined pathways.

2. Literature review

2.1. Live streaming shopping

In the wake of the development and integration of streaming media and e-commerce technologies, the new business model, live streaming shopping, i.e., "live streaming + online shopping", has emerged (Li et al., 2021). Live streaming shopping is characterized by authenticity, visibility, interactivity, and entertainment (Hu and Chaudhry, 2020). In traditional online shopping contexts, consumers make purchase decisions by viewing edited and modified text, images, videos and other one-way information, while in live streaming shopping scenarios, consumers can visualize products in real time through video streams, interact with streamers to get purchase suggestions, and place orders for products directly in the live interface (Sun et al., 2019; Lu and Chen, 2021).

Currently, studies on live streaming shopping focus on three main topics. First, consumers' motivations for engagement in live streaming shopping, such as authenticity of the streamer (Liu et al., 2021a), social interactions (Busalim and Ghabban, 2021; Ma, 2021), and economic benefits (Hu and Chaudhry, 2020). Second, factors that influence consumers' continuous use or purchase intention, such as perceived ease of use (Yin, 2020), perceived certainty (Zhang et al., 2020), social interactions (Ko and Chen, 2020), customer engagement (Zheng et al., 2022), sex and humor appeals (Hou et al., 2020), guided shopping features (Sun et al., 2018), online celebrity and screen bullets (Meng et al., 2021), and the matchups between online celebrity and their live streaming content (Park and Lin, 2020). Third, the operation and development of the live streaming shopping industry, for example, Liu (2020) believed that the competitiveness of live streaming shopping would experience an evolutionary path of traffic dividends, refined operations and supply chain efficiency; Chen et al. (2019) found that the adoption of live streaming strategies in e-commerce led to an increase in online sales, while Liu et al. (2020a) studied the current status, methods, problems, and development strategies of brand marketing campaigns on the MLSS platform; Mao et al. (2022) investigated the pricing strategy of new products when they were launched in live streaming considering the consumer uncertainty and network externalities.

In general, research on live streaming shopping is still in its early stage, there is a lack of in-depth investigation into the design-related issues of live streaming shopping platforms. Past research in computer-mediated communication contexts has emphasized the significance of design factors (Xiao et al., 2022), but design as the psychological and behavioral genesis of users of live streaming e-commerce services has been overlooked. In particular, with the current popularity of mobile commerce, placing orders via smartphones has become the first choice for customers to participate in live streaming shopping (Lu et al., 2018). MLSS platform relies on such a small size but being carried around by consumers and frequently used smartphones, the consumer perception of its design and the deriving of optimization strategies should be duly concerned.

2.2. Design features of MLSS platform

MLSS platform is important medium for e-commerce company to maintain business relationships with customers, the designing of which affects consumers' shopping experience and loyalty (Fang et al., 2017; Gao and Li, 2019; Wijaya and Farida, 2018; Daassi & Debbabi,2021). Since such platform is recognized as critical factor for business success by information systems literature (Lu et al., 2020; Zhang et al., 2017, 2020), an exhaustive dissection is necessary. Taking a magnifying glass and looking from a microscopic view, an MLSS platform consists of many design features, which are defined as elements of a system that provide specific rules or functions (DeSanctis and Poole, 1994; Fu et al., 2017). Research by Hasan (2016) and Ashraf et al. (2019) suggests that meticulously designed features can convey positive implications to consumers, enhance shoppers' perceptions, and in turn change their attitudes and behavioral intentions.

Some specific design features of live streaming platforms have been studied out of the past, and the design features of interest are distributed in three main areas. The first one is the features associated with individual information of streamers or consumers. In the social commerce design model of Huang and Benyoucef (2013), individual layer refers to providing a sense of self identification and awareness that can be recognized by others, which includes design features such as personal, context and activity profiles. Lu et al. (2018) found that audiences concerned about the number of fans of streamers and favored the most popular or those with a large number of fans. The second group of studies focuses on social interaction-related features. Streamers can present product information to customers through social tools such as real-time chat rooms, so as to reduce purchase uncertainty, perceived risk, and purchase resistance (Chung et al., 2017). Virtual gifts giving from consumers is also a way to interact with the streamer, the way that not only attracts the streamer's attention but also gains social recognition from other customers (Lu et al., 2018; Li et al., 2018; Li et al., 2021).

Thirdly, in terms of transactional design features, discounts or coupons provided by streamers bridge the financial relationship between the stakeholders and thus strengthen consumers' willingness to continue watching (Hu and Chaudhry, 2020). When consumers are making a purchase, they can directly click on the embedded links presented in the live streaming interface to place orders and complete the deals (Liu et al., 2021a). In Table A1 in the Appendix we summarize the studies related to the design features of the MLSS platform, which reveals that design features in live streaming shopping platforms have been studied sporadically, but there is a lack of systematic framework on the variety of design features in live streaming shopping platforms, and a particular lack of attention to the design features of live streaming shopping platforms in mobile contexts.

Notably, in these fragmented studies of design features related to live streaming shopping platform, we observe some inconsistencies in the findings. Taking the social interaction design feature as an example, Hajli (2014) found that in online communities, consumers become increasingly willing to build positive relationships with other consumers and service providers as the use of interaction design features increased. However, the results of Lien et al. (2017) suggested that the effect of social interactions on consumer satisfaction was not significant. It is questionable, then, whether the high performance of the design features can lead to high satisfaction in turn. There are a few studies that have noted differences in the use of design features across populations. For instance, Li et al. (2018) indicated that gender made significant differences in the results when investigating the factors influencing the willingness to pay virtual gifts; Lu et al. (2019) demonstrated that gamification elements such as giving virtual gifts, fan badges, and rankings were beneficial in developing the stickiness of loyal fans, rather than general audiences. Since each design feature has its own intrinsic characteristics, consumers' perceptions of the quality of design feature will also vary with their personal characteristics (Bose & Chen, 2009, 2015), but in the context of live streaming shopping, what are the differences in consumer perceptions of the design features of MLSS platform was not well investigated in prior studies, and this study expects to fill the gap, thereby providing a more precise basis for the design of MLSS platform.

2.3. Kano model

Intuitively, the performance of a product or service attribute is approximately linearly related to consumer satisfaction (Tseng, 2020). In other words, the higher consumer's perceived quality of a product or service, the higher consumer satisfaction, and vice versa (Liu et al., 2020b). However, in their research on product quality management, Japanese scholar Kano discovered that improving the quality of certain product or service attributes might not bring an increase with consumer satisfaction, therefore, a model named as 'Kano model' was proposed to reveal different types of effects between product or service attributes and consumer satisfaction (Kano et al., 1984; Bi, 2012; Kreuzer et al., 2020). Considering such effects may be linear or nonlinear and may even be asymmetric, Kano et al. (1984) classified quality attributes into five categories, which are attractive quality, one-dimensional quality, must-be quality, indifferent quality and reverse quality. In the present, Kano model has been widely adopted for quality assessment of products or service in various fields, such as company consulting services (Huang, 2017), logistics and transportation services (Chen et al., 2021), restaurant services (Pai et al., 2018), food processing (Djekic et al., 2020), airline services (Wang and Fong, 2016), tourism services (Pandey et al., 2020), and fitness application design (Yin et al., 2022).

However, not all quality attributes of the same category are perceived as equally important from consumer's perspective. Although Kano model enables insight into the different influence relationships between attribute categories and consumer preferences, it fails to determine the relative importance of attributes within the same category (Bi, 2012; Dace et al., 2020). To compensate this deficiency, Berger et al. (1993) calculated Better-Worse coefficients basing on the traditional Kano model, by which the priority of attributes is determined. Despite this, Berge's approach as well as the traditional Kano model employs two-way questionnaires with one functional and one non-functional question for each attribute, and respondents' answers are mapped to the Kano assessment scale to determine the quality category of attributes (Madzík and Pelantová, 2018; Dace et al., 2020). Such a survey method will lead to long and tedious questionnaires (Matzler et al., 2004), resulting in unconvincing data and biased findings. Compared to the previous two methods, Kano model based on dummy variables regression has the advantage of simplifying data collection and process (Brandt, 1988; Violante and Vezzetti, 2017). More importantly, for MLSS platform design features of interest to this study, this method allows the determination of quality categories by regression coefficients, and further calculates the importance of design features, while by substituting sample data from different consumer groups into the regression model, preferences differences across consumers for design features can also be captured. In view of its high compatibility with the focus of this study, we utilize Kano model based on dummy variables regression to conduct our investigation.

3. Research methods

A four-stage framework is proposed in this paper in response to the addressed research questions (see Fig. 1). We first systematically summarize the representative design features of MLSS platforms, on which we adopt Kano model based on dummy variables regression to classify design features, so that the nonlinear relationship between design feature performance and consumer satisfaction can be identified. Then, correspondence analysis is conducted to visualize the asymmetric perception of different consumer groups for each design feature. Finally, importance-satisfaction analysis is carried out, so as to reveal design features' intrinsic characteristics implied by perceived importance and perceived satisfaction, which assists in developing optimization and management strategies for design features.

3.1. Scoping of MLSS design features

This study systematically summarizes design features of MLSS platform based on axiomatic design theory. Axiomatic design theory is developed to identify customer requirements and map them step-by-step into functional design of a system (Suh, 1998). Drawing upon its ideas, we progressively dissect design process of the MLSS platform into consumer domain, functional domain, physical domain, and process domains. In particular, consumer domain contains consumer requirements, functional domain covers functional requirements, physical domain is components or called design features that implement functions, and process domain includes subroutines, machine code, or compilers that implement system functions. Referring to Huang and Benyoucef's (2013) taxonomy of design features in a social commerce scenario, we separate consumer domain of MLSS platform into individual, community, and commerce layers, and then work downward to identify functional domains and their design features contained in each layer. The principles identified are derived from both literature and top MLSS platforms such as Taobao Live, Tiktok, Pinduoduo and Kwai. A summary of domain layers and design feature set of the MLSS platform is shown in Table 1, and the detailed explanations can be found in Table A2 in the Appendix.

3.2. Classification of Kano quality

For capturing the nonlinear quality perception of consumers across design features, we construct the following dummy variables regression model:

$$CS_i = \alpha_j + \beta_{1j} D_{1ij} + \beta_{2j} D_{2ij} \quad (1)$$

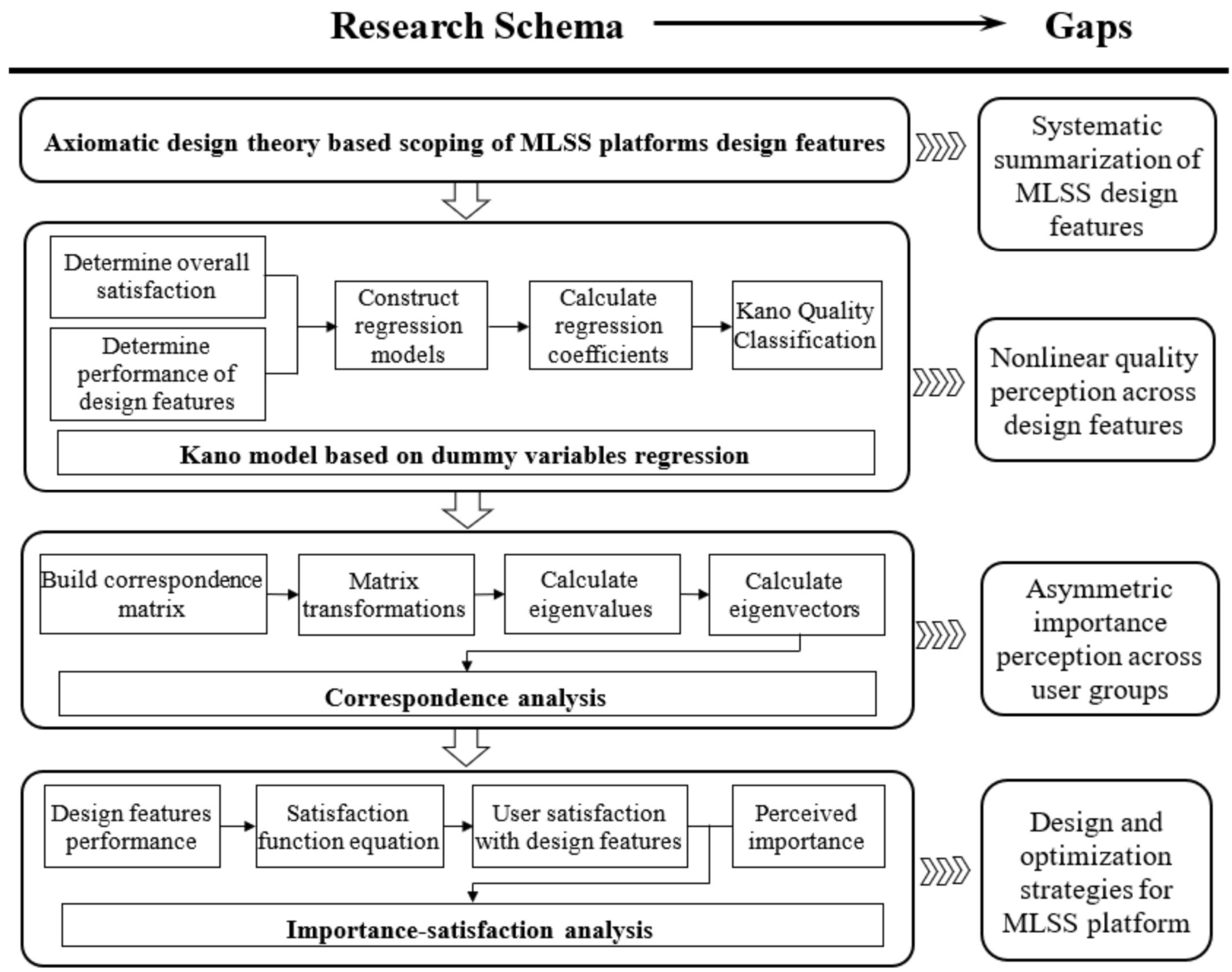

Fig. 1. Research framework.

Table 1
Domain layers and design feature set of MLSS platform.

Consumer domains	Functional domains	Design features	Symbols
Individual	Streamer Profile	Streamer Information	SI
		Live Streaming Videos	LV
	Live Streaming Channel	Channel List	CL
		Live Streaming Logs	LL
	Promotion	Event Information	EI
	Reminder and	Reminder	RM
	Recommendation	Recommendation	RD
Community	Social Interaction	Interaction Tools	IT
	Information Sharing	Sharing Tools	ST
	Consumer Participation	Participation Utilities	PU
Commerce	Reciprocity	Preferential Mechanism	PM
	Identification	Commerce Cues	CC
	Transaction	Transaction Suites	TS

where CS_i represents the overall satisfaction of the ith consumer with the MLSS platform. Let x_{ij} be the rating of performance of the jth design feature by the ith consumer, dummy variable D_{1ij} indicates the low performance level of the jth design feature by the ith consumer, and dummy variable D_{2ij} expresses the high performance level of the jth design feature by the ith consumer. Suppose $[\overline{x}_j]$ denotes to the average performance of the jth design feature rounded to the nearest integer, if $x_{ij} < [\overline{x}_j]$, then $D_{1ij} = 1$, otherwise $D_{1ij} = 0$. If $x_{ij} > [\overline{x}_j]$, then $D_{2ij} = 1$, otherwise $D_{2ij} = 0$. In addition, the constant term α_j denotes the mean of all reference groups regarding overall satisfaction, β_{1j} represents an incremental decrease associated with low satisfaction, while β_{2j} indicates an incremental increase associated with high satisfaction, and these two regression coefficients assess the impacts of design feature's performance on consumer dissatisfaction and satisfaction. The quality classification principle based on dummy variables regression is shown in Table 2.

Table 2
Quality classification principle based on dummy variables regression.

Regression Coefficients		Quality Categories
β_{1j}	β_{2j}	
Non-significant	(+) Significant	Attractive quality
(−) Significant	(+) Significant	One-dimensional quality
(−) Significant	Non-significant	Must-be quality
Non-significant	Non-significant	Indifferent quality

Notes: (+) indicates the coefficient is positive; (−) indicates the coefficient is negative.

3.3. Correspondence analysis

As a multivariate statistical technique, correspondence analysis is applied to explore bivariate associations between multiple categorical variables and similarities among individuals (Audigier et al., 2017; Jung and Suh, 2019). The essence of this method is to convert the cross-tabulation of row and column variables into a scatter plot, characterizing the strength of association between variables in terms of spatial distance of each scatter (Jalayer and Zhou, 2016; Tekaia, 2016). In order to investigate the asymmetric perceptions of design features of MLSS platform across consumers with different characteristics, this study develops correspondence analysis based on perceived importance of design features by grouped consumers. First we obtain consumer's perceived importance of the jth design feature by regression coefficients β_{1j} and β_{2j} as:

$$w_j = \frac{|\beta_{1j}| + |\beta_{2j}|}{2} \tag{2}$$

Then we use this calculated perceived importance as basis, and utilize equation (3) to calculate the importance frequencies of each design feature for different groups of consumers, i.e., the number of consumers who consider a design feature important, which is also a reflection of consumers' preference for design features. Subsequently, the importance frequencies were transformed by equation (4) for the subsequent correspondence analysis (Maiti et al., 2014).

$$x_{ij} = \left[\left(w_{ij} \Big/ \sum_{i=1}^{m} \sum_{j=1}^{n} w_{ij} \right) \cdot S \right] \tag{3}$$

$$z_{ij} = \frac{x_{ij} - x_{i\cdot} \cdot x_{\cdot j} \Big/ \sum_{i=1}^{m} \sum_{j=1}^{n} x_{ij}}{\sqrt{x_{i\cdot} \cdot x_{\cdot j}}} (i = 1, 2, \cdots, m; j = 1, 2, \cdots, n) \tag{4}$$

where x_{ij} denotes the importance frequency for the jth design feature by the ith group of consumers, z_{ij} indicates the value after corresponding transformation of x_{ij}, m refers to the number of consumer groups, n indicates the total number of design features, and S means the sample size. For R-type factors we calculate $Z'Z$, while for Q-type factors we calculate ZZ'. After such an eigen decomposition process, the dominant eigen values associated with corresponding eigenvectors are used to draw the two-dimensional correspondence analysis diagram.

3.4. Importance-satisfaction analysis

Importance-performance analysis is a method proposed by Martilla and James (1977), which analyzes perceived performance as well as perceived importance of a product or service, so as to identify priority of indicators and provide reference for improvement strategies (Cohen et al., 2016; Izadi et al., 2017). The analysis results are typically presented in a two-dimensional coordinate plot, with the horizontal axis representing consumer's measurement of attribute performance and the vertical axis indicating the consumer's perceived importance for attributes. Four target-oriented improvement strategies can be obtained based on the four quadrants divided. However, it is observed that the impact mechanism of design features on consumer satisfaction varies with quality category, as evidenced by the previous Kano model analysis in this study. For example, while one attribute is attractive quality and the other is must-be quality, even though they perform similarly, consumer's perceived satisfaction may be a far cry from each other. Indeed, what should receive more attention is the relationship between consumers' perceived satisfaction and perceived importance, which is the importance-satisfaction analysis suggested (Wang, 2016). Hence, this study conducts an importance-satisfaction analysis to acquire management and optimization strategies for the MLSS platform design features.

Consumer's perceived importance of design features is calculated as equation (2). Since consumer's performance evaluation of design features is investigated in Kano analysis, a curve fitting is implemented to access consumer's satisfaction with design features. The functional relationship between the performance of design feature j and consumer satisfaction is defined as:

$$y = f_j(p), \quad (j = 1, 2, \cdots, n) \tag{5}$$

where y indicates consumer satisfaction with the design feature and p refers to consumer's performance rating of the design feature, which takes values in range of $[-1, 1]$.

Considering the characteristics of satisfaction curves for different quality categories in Kano model, we set the satisfaction curve fitting function of attractive quality (A) as an exponential function: $y = a_1 e^p + b_1$, the satisfaction curve fitting function of one-dimensional quality (O) and indifferent quality (I) as a linear function: $y = a_2 p + b_2$, and the satisfaction curve fitting function of must-be quality (M) as an exponential function: $y = a_3(-e^{-p}) + b_3$. Via the results of the calculations in Section 3.2, the coordinates of the points $(1, \beta_{2j})$ and $(-1, \beta_{1j})$ can be determined, which are substituted into equation (5) to solve for the specific functional expressions, thus the functional equation for each Kano quality category is obtained:

$$y = \begin{cases} \dfrac{e(\beta_{2j} - \beta_{1j})}{e^2 - 1} e^p + \dfrac{e^2 \beta_{1j} - \beta_{2j}}{e^2 - 1} & , j \in A \\ \dfrac{\beta_{2j} - \beta_{1j}}{2} p + \dfrac{\beta_{2j} + \beta_{1j}}{2} & , j \in \{O, I\} \\ -\dfrac{e(\beta_{2j} - \beta_{1j})}{e^2 - 1} e^{-p} + \dfrac{e^2 \beta_{2j} - \beta_{1j}}{e^2 - 1} & , j \in M \end{cases} \tag{6}$$

Moreover, consumer's perceived satisfaction with a design feature can be calculated by substituting the performance of the design feature based on quality category into equation (6). Then the importance-satisfaction analysis can be carried out by drawing a floor plan based on the calculated perceived importance and perceived satisfaction of design features.

4. Evaluation case: Taobao Live

4.1. Data collection

China is one of the global leaders in live streaming shopping recently, and Taobao Live has the top market share of live streaming shopping market in China, with its share of 48.3%, followed by Kwai (24.2%) and Tiktok (9.7%) (Ecommerce China, 2020; Ecdataway, 2020). Therefore, this study takes Taobao live platform as the research object and adopts questionnaire survey on Taobao live users. We collect demographic characteristics, consumers' live streaming shopping participation-related information, consumers' overall satisfaction with Taobao live platform, and consumers' performance ratings on each design feature of Taobao live platform. For excluding non-Taobao Live consumers from filling out the questionnaire and avoiding significant bias in the data collection process, we select the paid sample service of Questionnaire Star (wjx.com), the largest online questionnaire platform in China, to ensure that all the respondents are Taobao Live users. After excluding invalid questionnaires due to incomplete information, careless filling or identical responses, 237 questionnaires are retained for formal analysis. The demographic characteristics of respondents are shown in Table 3.

4.2. Performance of design features

We aggregated respondents' performance ratings on the 13 design features of MLSS platform. As shown in Table 4, the overall average performance rating of the 13 design features is 3.78, where the high-performance design features include "Preferential Mechanism (PM)" and "Transaction Suites (TS)", while the low-performance design

Table 3
Demographic characteristics of respondents.

Respondents' characteristics	Statistical description (%)
Gender	Male (46.0%), Female (54.0%)
Age	18 years and younger (3.4%), 19–24 years (27.8%), 25–30 years (26.6%), 31–35 years (21.5%), 36–40 years (10.1%), 41–50 years (8.0%), 51 years and older (2.5%)
Years of live streaming shopping	Within 3 months (13.1%), 3–6 months (excluding) (12.7%), 6 months-1 year (excluding) (25.3%), 1–2 years (excluding) (24.1%), 2–3 years (excluding) (10.1%), 3 years and above (14.8%)
Average frequency of live streaming shopping per month	Less than 1 time (18.1%), 1–3 times (excluding) (43.5%), 3–6 times (excluding) (28.3%), 6–10 times (excluding) (8.4%), 10 times and above (1.7%)
Average consumption amount of live streaming shopping per month	200 yuan and below (27.4%), 201–500 yuan (30.8%), 501–1000 yuan (25.3%), 1001–2000 yuan (12.7%), 2001 yuan and above (3.8%)
Average length of time spent watching each live streaming session	Less than 10 min (11.4%), 10–30 min (excluding) (39.2%), 30–60 min (excluding) (40.5%), 60–120 min (excluding) (7.6%), 2 h and above (1.3%)
Frequently purchased product categories	Clothing (74.7%), shoes, hats and bags (39.7%), jewelry and accessories (13.1%), food and beverages (66.2%), make-up and skin care (47.3%), daily necessities (61.2%), appliances (15.2%), electronic products (30.0%), others (2.5%)

features include "Commerce Cues (CC)", "Participation Utilities (PU)", "Interaction Tools (IT)" and "Recommendation (RD)", especially, "Commerce Cues (CC)" has the lowest performance rating of 3.34. It is clear that differences in perceived performance exist across design features. To explore the perceived performance differences across consumers, we group consumers by characteristics such as gender, age, years of live streaming shopping (years), average frequency of live streaming shopping per month (frequency), and measure the perceived performance of design features by each group. An F-test is conducted to examine the differences between different sample groups for the average of the performance ratings for each design feature. As indicated in Table 4, the ratings of design features have differences between groups, for example, respondents live streaming shopping 3 times or more per month rate the performance of "Streamer Information (SI)" at 4.05, those with frequency of 1–3 times (excluding three) give it a rating of 3.87, while those live streaming shopping less than once per month assess it at 3.28 only, with a maximum difference among groups of 0.77.

Considerable differences are also observed in the performance ratings of "Preferential Mechanism (PM)" across years groups, "Recommendation (RD)" among ages groups, and "Commerce Cues (CC") between genders groups, etc., which supports our proposition of differences in perceived quality across design features and across consumer groups.

4.3. Quality classification of design features

Quality classification results of design features according to Kano model based on dummy variables regression are presented in Table 5. As the overall results show, "Commerce Cues (CC)" is attractive quality, "Streamer Information (SI)", "Channel List (CL)", "Live Streaming Logs (LL)", "Event Information (EI)", "Reminder (RM)", "Recommendation (RD)", "Interaction Tools (IT)" and "Participation Utilities (PU)" are identified as must-be quality, while "Live Streaming Videos (LV)", "Sharing Tools (ST)", "Preferential Mechanism (PM)" and "Transaction Suites (TS)" are one-dimensional quality. Meanwhile, different classification results appear in different respondent groups in terms of several design features. For instance, males regard "Streamer Information (SI)" as indifferent quality, while females consider it to be must-be quality; respondents who live streaming shop less than once per month view "Transaction Suites (TS)" as must-be quality, those with frequency of 1–3 times regard it as one-dimensional quality, while those live streaming shop 3 times and above per month consider it as attractive.

4.4. Results of correspondence analysis

For the category of gender, the chi-square test for correspondence analysis fails, so correspondence analysis regarding three other sets of respondent characteristics (i.e., age, year, frequency) are conducted. The results of correspondence analysis between design features and age groups are shown in Fig. 2. It can be observed that respondents 24 years old and younger are more concerned about "Live Streaming Logs (LL)", "Participation Utilities (PU)", "Recommendation (RM)", and "Channel List (CL)"; respondents 25–35 years old consider "Preferential Mechanism (PM)" and "Transaction Suites (TS)" more valuable; respondents 36 years old and older favor design features such as "Event Information (EI)", "Commerce Cues (CC)", and "Interaction Tools (IT)".

It could be seen the results of correspondence analysis over design features and years groups in Fig. 3. Respondents with less than 6 months of experience pay more attention to "Live Streaming Logs (LL)", "Live Streaming Videos (LV)", "Sharing Tools (ST)", "Reminder (RM)", etc.; those with 6 months-2 years of experience are more interested in "Participation Utilities (PU)", "Transaction Suites (TS)", "Recommendation (RM)", "Event Information (EI)", etc.; while those with 2 years

Table 4
Average performance ratings of design features for all sample groups.

Design features	All	Gender			Age				Years				Frequency			
		Male	Female	Sig.	24 and below	25–35	36 and above	Sig.	Within 6 months	6 months −2 years (excluding)	2 years and above	Sig.	Less than one time	1-3 times (excluding)	3 times or more	Sig.
SI	3.84	3.88	3.8	ns	3.58	3.96	3.92	**	3.61	3.86	4.02	*	3.28	3.87	4.05	***
LV	3.92	4.02	3.84	ns	3.82	4.02	3.86	ns	3.8	3.96	3.98	ns	3.42	4	4.08	***
CL	3.87	3.89	3.86	ns	3.74	3.97	3.84	ns	3.61	3.97	3.97	*	3.44	3.89	4.05	***
LL	3.73	3.72	3.74	ns	3.54	3.83	3.8	*	3.48	3.79	3.88	*	3.23	3.83	3.86	***
EI	3.85	3.91	3.8	ns	3.69	3.95	3.88	ns	3.59	3.94	3.95	*	3.3	3.93	4.02	***
RM	3.84	3.8	3.88	ns	3.76	3.9	3.82	ns	3.72	3.82	4	ns	3.49	3.82	4.03	**
RD	3.65	3.64	3.65	ns	3.38	3.88	3.51	***	3.44	3.72	3.71	ns	3.28	3.57	3.9	***
IT	3.6	3.72	3.5	ns	3.39	3.67	3.76	ns	3.52	3.59	3.69	ns	3.4	3.6	3.69	ns
ST	3.8	3.79	3.81	ns	3.68	3.92	3.71	ns	3.66	3.87	3.81	ns	3.4	3.77	4.03	***
PU	3.6	3.63	3.57	ns	3.36	3.75	3.61	*	3.52	3.67	3.54	ns	3.16	3.58	3.82	**
PM	4.07	4.08	4.06	ns	3.86	4.21	4.06	*	3.82	4.11	4.25	*	3.6	4.03	4.34	***
CC	3.34	3.49	3.21	*	3.15	3.41	3.45	ns	3.18	3.31	3.56	ns	3.21	3.29	3.45	ns
TS	4.04	4.03	4.05	ns	3.99	4.11	3.98	ns	3.8	4.17	4.03	*	3.67	4.05	4.21	**

Notes: Significance: * ($p < 0.05$), ** ($p < 0.01$), *** ($p < 0.001$), ns (not significant).

Table 5
Quality classification results of design features for all sample groups.

Design features	All			Gender						Age								
				Male			Female			24 and below			25–35			36 and above		
	β1	β2	Category	β1	β2	Category	β1	β2	Category	β1	β2	Category	β1	β2	Category	β1	β2	Category
SI	−0.52**	0.13	M	−0.21	0.22	I	−0.76**	0.07	M	−0.51**	0.16	M	−0.39**	0.07	M	−0.7**	0.26	M
LV	−0.48**	0.3**	O	−0.41**	0.24	M	−0.53**	0.39**	O	−0.51**	0.23	M	−0.13	0.31**	A	−0.9**	0.34	M
CL	−0.55**	0.17	M	−0.44**	0.32*	O	−0.65**	0.04	M	−0.59**	0.23	M	−0.24	0.13	I	−0.91**	0.18	M
LL	−0.44**	0.15	M	−0.48**	−0.07	M	−0.39**	0.34*	O	−0.4**	0.5*	O	−0.22	0.06	I	−0.86**	0.04	M
EI	−0.44**	0.11	M	−0.49**	0.06	M	−0.4**	0.15	M	−0.3	0.29	I	−0.25*	0.1	M	−0.87**	−0.1	M
RM	−0.36**	0.09	M	−0.3*	−0.11	M	−0.47**	0.25	M	−0.02	0.52**	A	−0.29*	−0.09	M	−0.81**	−0.03	M
RD	−0.35**	0.17	M	−0.37**	0.15	M	−0.34**	0.18	M	−0.36	0.23	I	−0.32**	0.02	M	−0.51*	0.19	M
IT	−0.34**	0.19	M	−0.31*	0.12	M	−0.37**	0.3	M	−0.03	0.4*	A	−0.16	0.08	I	−0.79**	0.35	M
ST	−0.32**	0.29**	O	−0.27*	0.33*	O	−0.36**	0.27	M	−0.21	0.46*	A	−0.25*	0.19	M	−0.66**	0.31	M
PU	−0.43**	0.11	M	−0.45**	0.0	M	−0.4**	0.2	M	−0.4	0.23	I	−0.42**	0.02	M	−0.61**	0.07	M
PM	−0.45**	0.27**	O	−0.35*	0.26*	O	−0.54**	0.28*	O	−0.25	0.38*	A	−0.52**	0.1	M	−0.56*	0.49*	O
CC	−0.18	0.23*	A	−0.04	0.17	I	−0.24	0.29*	A	−0.13	0.28	I	−0.14	0.09	I	−0.48	0.43	I
TS	−0.44**	0.41**	O	−0.47**	0.4**	O	−0.42**	0.42**	O	−0.22	0.44*	A	−0.45**	0.3**	O	−0.82**	0.61**	O

Design features	Years									Frequency								
	Within 6 months			6 months −2 years (excluding)			2 years and above			Less than one time			1-3 times (excluding)			3 times or more		
	β1	β2	Category	β1	β2	Category	β1	β2	Category	β1	β2	Category	β1	β2	Category	β1	β2	Category
SI	−0.44*	−0.01	M	−0.38**	0.1	M	−0.97**	0.19	M	0.07	0.68**	A	−0.32*	0.22	M	−0.43**	−0.02	M
LV	−0.75**	0.36	M	−0.24*	0.32*	O	−0.69**	0.2	M	−0.56	0.6*	A	−0.46**	0.32*	O	−0.1	0.23	I
CL	−0.68**	0.2	M	−0.36**	0.1	M	−0.74**	0.34	M	0.05	0.8**	A	−0.43**	0.07	M	−0.26	0.21	I
LL	0.34	0.6**	A	−0.33**	0.08	M	−0.55*	0.14	M	−0.43	0.62*	A	−0.45**	0.16	M	−0.08	0.06	I
EI	−0.51**	0.21	M	−0.52**	−0.02	M	−0.16	0.28	I	−0.86*	0.2	M	−0.43**	0.03	M	−0.31*	−0.01	M
RM	−0.52**	0.18	M	−0.2	0.0	I	−0.54*	0.15	M	−0.65	0.36	I	−0.36**	0.09	M	0.01	−0.01	I
RD	0.08	0.35	I	−0.33**	0.14	M	−0.4	0.27	I	−0.45	0.41	I	−0.38**	0.06	M	−0.06	0.22	I
IT	−0.48**	0.04	M	−0.19	0.18	I	−0.56**	0.17	M	−0.0	0.86**	A	−0.3*	0.21	M	−0.13	0.07	I
ST	−0.53**	0.3	M	−0.16	0.18	I	−0.37	0.44*	A	−0.39	0.65**	A	−0.12	0.44**	A	−0.2	0.11	I
PU	−0.28	0.19	I	−0.45**	0.08	M	−0.54**	0.07	M	−0.42	0.5	I	−0.26*	0.1	M	−0.34**	0.06	M
PM	−0.32	0.4	I	−0.38**	0.19	M	−0.82**	0.18	M	−0.52*	0.6*	O	−0.17	0.37**	A	−0.58**	−0.0	M
CC	−0.19	0.13	I	−0.16	0.18	I	−0.38	0.21	I	−0.51	0.3	I	−0.11	0.2	I	−0.03	0.14	I
TS	−0.35	0.61*	A	−0.44**	0.33**	O	−0.58**	0.45*	O	−0.79**	0.41	M	−0.36*	0.45**	O	−0.16	0.29**	A

Notes: (1) Significance: *$p < 0.05$ **$p < 0.01$ ***$p < 0.001$.
(2) Category: A- Attractive, O- One-dimensional, M- Must-be, I- Indifferent.

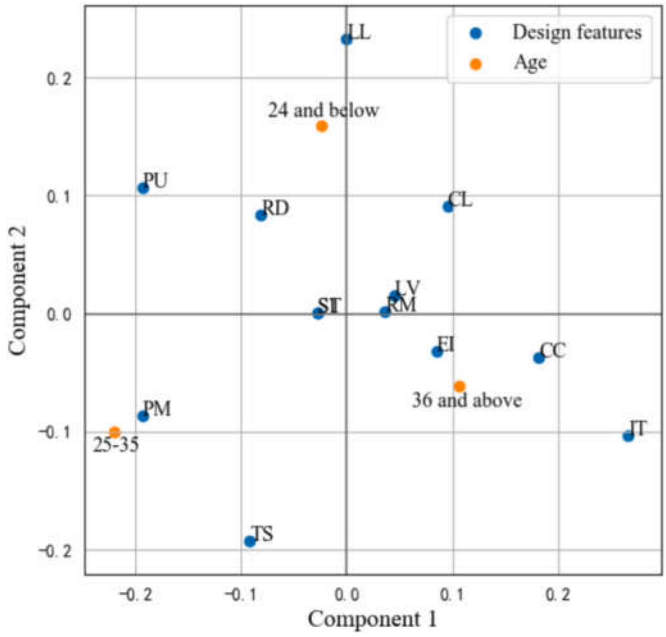

Fig. 2. Correspondence analysis of design features and age groups.

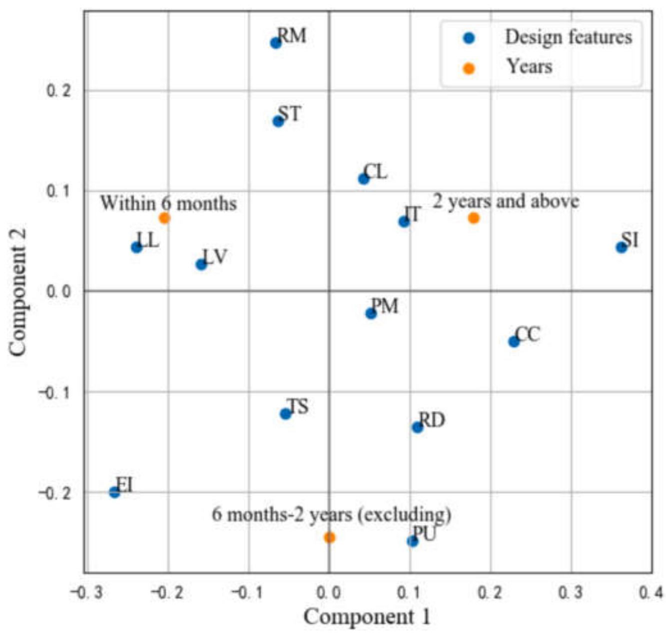

Fig. 3. Correspondence analysis of design features and years groups.

and above favor "Channel List (CL)", "Interaction Tools (IT)", "Preferential Mechanism (PM)", "Streamer Information (SI)", "Commerce Cues (CC)", etc.

As Fig. 4 regarding design features and shopping frequencies, respondents who live streaming shop less than once per month are more concerned about design features such as "Event Information (EI)", "Recommendation (RM)", "Participation Utilities (PU)" and "Commerce Cues (CC)"; those with frequency of 1–3 times focus more on "Live Streaming Videos (LV)", "Transaction Suites (TS)", "Sharing Tools (ST)", "Live Streaming Logs (LL)" and "Interaction Tools (IT)"; while those live streaming shopping 3 times and above per month prefer "Streamer Information (SI)", "Channel List (CL)" and "Preferential Mechanism (PM)".

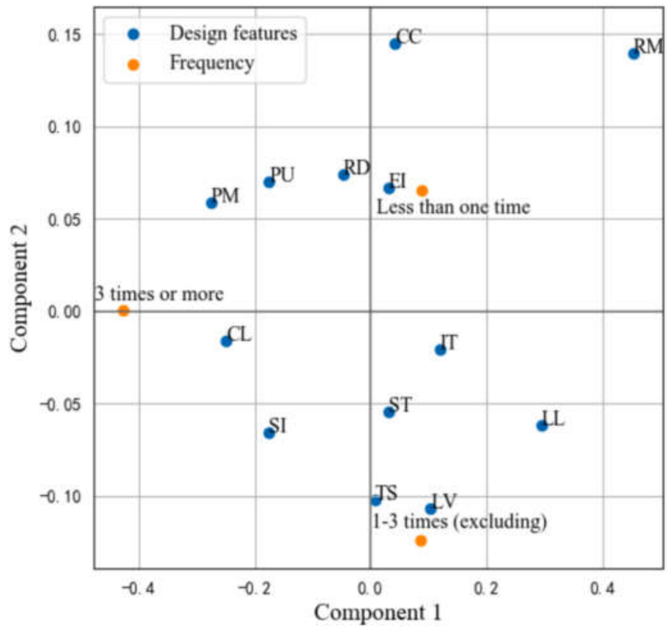

Fig. 4. Correspondence analysis of design features and frequency groups.

4.5. Results of importance-satisfaction analysis

The fitting function between performance and satisfaction, the reported performance and calculated satisfaction and importance are presented in Table 6 and importance-satisfaction analysis is performed, with the results shown in Fig. 5. As indicated, the perceived importance of "Transaction Suites (TS)", "Live Streaming Videos (LV)", "Channel List (CL)", "Preferential Mechanism (PM)" and "Sharing Tools (ST)" stands at a high level, and respondents are satisfied with their performance, thus located in the "Keep up the good work" quadrant. While "Commerce Cues (CC)", "Reminder (RM)", "Participation Utilities (PU)", "Event Information (EI)" and "Live Streaming Logs (LL)" have low satisfaction as well as perceived importance, which are design

Table 6
Customer satisfaction and importance of design features in the overall samples.

Design features	$y = f(p)$	Performance	Satisfaction	Importance
SI	$y = -0.2773e^{-p} + 0.2337$	0.42	0.05	0.33
LV	$y = 0.3915p - 0.0897$	0.46	0.09	0.39
CL	$y = -0.3081e^{-p} + 0.2835$	0.44	0.08	0.36
LL	$y = -0.2511e^{-p} + 0.2465$	0.37	0.07	0.3
EI	$y = -0.2319e^{-p} + 0.1903$	0.43	0.04	0.27
RM	$y = -0.1924e^{-p} + 0.1582$	0.42	0.03	0.23
RD	$y = -0.2218e^{-p} + 0.2479$	0.32	0.09	0.26
IT	$y = -0.2280e^{-p} + 0.2757$	0.3	0.11	0.27
ST	$y = 0.3067p - 0.0138$	0.4	0.11	0.31
PU	$y = -0.2298e^{-p} + 0.1937$	0.3	0.02	0.27
PM	$y = 0.3628p - 0.0915$	0.54	0.1	0.36
CC	$y = 0.1755e^{p} - 0.2475$	0.17	−0.04	0.21
TS	$y = 0.4275p - 0.0170$	0.52	0.21	0.43

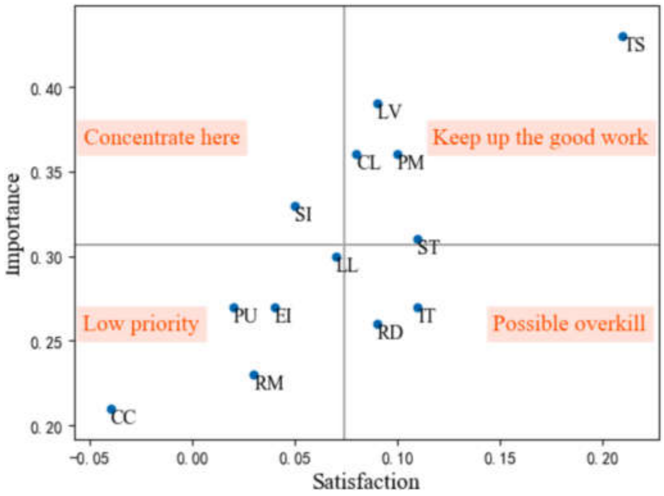

Fig. 5. Importance-satisfaction analysis of the overall samples.

features with low priority. Respondents appreciate "Streamer Information (SI)", but are disappointed with its current performance, which is a design feature that requires to be focused on. In addition, "Recommendation (RM)" and "Interaction Tools (IT)" have high respondent satisfaction but low perceived importance, possibly with some degree of "overkill".

Furthermore, in order to educe optimal design strategies for different consumer groups, we also apply importance-satisfaction analysis on grouped samples, with the overall results shown in Table 7, and the details of importance and satisfaction values are provided in Table A3 and Table A4 in the Appendix. It can be found that there exist significant differences in distribution of design features across various sample groups. For example, "Event Information (EI)" is low priority for female consumers, but it is necessary to focus on requirements of male consumers in this aspect. In terms of "Channel List (CL)" design feature, it performs well for respondents of 24 years old and younger, but there is an over-optimization condition for those of 25–35 years old, while it is a design feature worthy of attention for those of 36 years old and older.

Table 7
Results of importance-satisfaction analysis for all sample groups.

	Keep up the good work	Low priority	Concentrate here	Possible overkill
All	TS, LV, CL, PM, ST	CC, RM, PU, EI, LL	SI	RD, IT
Male	TS, LV, CL, PM, ST	LL, RM, PU	EI	RD, IT, SI, CC
Female	LV, TS, LL, RM	CC, EI	SI, PM, CL	IT, ST, PU, RD
24 and below	LL, CL, LV, TS	RD, CC	SI, ST, PU, PM	EI, IT, RM
25–35	TS, PM, LV, ST	RM, RD, LL, IT, CC	PU, SI	CL, EI
36 and above	TS, LV, IT, PM	EI, RM, LL, CC, PU, RD	CL	SI, ST
Within 6 months	LV, LL, ST, PM	IT, SI, PU, CC	CL, TS, EI, RM	RD
6 months -2 years (excluding)	TS, PM, LV, RD	CL, LL, IT, CC, RM	EI, PU, SI	ST
2 years and above	CL, TS, PM, LV	PU, CC, LL, RD, IT, RM	SI, ST	EI
Less than one time	TS, PM	PU, CC, RD	LV, LL, EI, ST, RM	IT, CL, SI
1–3 times (excluding)	TS, LV, ST, SI, PM	CL, EI, RD, RM, PU, CC	LL	IT
3 times or more	ST, CL, TS, LV	IT, LL, RM	PM, PU, SI, EI	CC, RD

Similar distribution differences over quadrants are also found in different year groups and different frequency groups. In summary, the results of importance-satisfaction analysis on different consumer groups in this paper provides a detailed reference for the fine-grained prioritization of the MLSS platform design features.

5. Discussion and implication

5.1. Discussion

In line with our proposed framework, a survey covering 13 representative design features of the MLSS platform provides insightful findings compared to prior studies. First, with preliminary statistics of the collected data, it is noted that there exist considerable differences in consumer's perceived performance towards the design features of Taobao Live platform. Among all the design features, the highest performance rating is 4.07 (for Preferential Mechanism), the lowest performance rating is only 3.34 (for Commerce Cues), as for the average performance rating to be 3.78, indicating that consumers don't have a high opinion regarding the performance of the design features of MLSS platform. Alongside this finding, we also realize that perceived differences in performance do exist across consumer subgroups of gender, age, years of live streaming shopping, and frequency of live streaming shopping. It is revealed that males rate the performance of "Commerce Cues (CC)" higher than females, which may be due to the fact that males don't participate in online live streaming shopping as often as females do, and have incomplete information about streamers, products and shopping process, leading them to observe or follow other consumers' behaviors to assist their own purchase decisions. Moreover, as the frequency of live streaming shopping increases, consumers establish a stronger familiarity and intimacy with each design feature (Liu et al., 2021a), which makes consumer experience better and higher perceived performance ratings as feedback.

Secondly, in classifying design features of the MLSS platform, the results of Kano model based on dummy variables regression indicate that design features are distributed in multiple quality categories. "Commerce Cues (CC)" is identified as attractive attribute, whereby consumer satisfaction will not be significantly reduced when the live streaming shopping platform don't offer it, whereas consumers are much more satisfied if an improvement is achieved in its design; "Streamer Information (SI)", "Channel List (CL)", "Live Streaming Logs (LL)", "Event Information (EI)", "Reminder (RM)", "Recommendation (RD)", "Interaction Tools (IT)" and "Participation Utilities (PU)" belong to must-be quality, whose performance improvement doesn't deliver consumer satisfaction, but in case of unreasonable design, it will dramatically reduce consumer satisfaction. "Live Streaming Videos (LV)", "Sharing Tools (ST)", "Preferential Mechanism (PM)" and "Transaction Suites (TS)" are one-dimensional quality, such design features generate consumer satisfaction approximately linearly correlated with performance. With an overview of the manifestations across consumer groups, we find asymmetry in perceived quality of design features. For example, "Streamer Information (SI)" is deemed as indifferent for males but must-be for females, which suggests that females care more about "Streamer Information (SI)" compared to males as a basis for continued watching or purchase decisions, also reflecting females' herd mentality (Yin, 2020). As for "Preferential Mechanism (PM)", it is attractive for consumers aged 24 and below, must-be for those aged 25–35, and one-dimensional for those aged 36 and above, which is an interesting finding that the perception differs across the three groups. This may be due to the fact that consumers aged 24 and below are pleasantly surprised at preferential features offered by the MLSS platform, while those aged 25–35 are accustomed to features such as bonus packages, coupons, and consider them indispensable, in contrast to those aged 36 and above relatively rational and interested in economic utility (Hu and Chaudhry, 2020), whereby preferential items and offer intensity affects their satisfaction.

Thirdly, correspondence analysis captures differences in perceived importance of the MLSS platform design features from consumers with different characteristics. Consumers aged 36 and older prefer design features such as “Event Information (EI)”, “Commerce Cues (CC)” and “Interaction Tools (IT)”, indicating that this type of consumers is passionate about social interaction and tends to make purchase decisions guided by external information and the opinions or behaviors of other consumers (Yin, 2020). Consumers who have been live streaming shopping for 6 months or less are more concerned about “Live Streaming Logs (LL)”, “Live Streaming Videos (LV)”, “Sharing Tools (ST)” and “Reminder (RM)”, signifying that these consumers weigh the quality of marketing content, highlight effective information and is open to receiving information shared by others or sharing useful information with others (Molinillo et al., 2020). Consumers live streaming shopping 1–3 times per month attach more importance to “Live Streaming Videos (LV)”, “Live Streaming Logs (LL)”, “Transaction Suites (TS)”, “Sharing Tools (ST)”, “Interaction Tools (IT)”, etc., which suggests that such consumers may comprehensively consider the suitability of live streaming style, product category, content quality and their own needs before entering live room, actively interact with the streamer or other consumers after entering, are pleased to share interesting or useful information to others, and have a strong willingness to purchase. Consumers who live streaming shop 3 times and above per month favor “Streamer Information (SI)”, “Channel List (CL)” and “Preferential Mechanism (PM)”, which signals that this category of consumers values the attractiveness of streamers and is keen on low prices, full discounts, grouping and other offers.

Finally, the results of importance-satisfaction analysis demonstrate different combinations of importance and satisfaction levels and, more importantly, present the path of prioritization of design features. As is found, of the 13 MLSS platform design features, only “Transaction Suites (TS)”, “Live Streaming Videos (LV)”, “Channel List (CL)”, “Preferential Mechanism (PM)” and “Sharing Tools (ST)” are in an ideal state. Conversely, “Commerce Cues (CC)”, “Reminder (RM)”, “Participation Utilities (PU)”, “Event Information (EI)” and “Live Streaming Logs (LL)” are in “Low priority” quadrant, whose improvement may be on hold with limited technical resources (e.g., screen size or computing power), or even allow consumers to remove these features from the platform. Regarding “Streamer Information (SI)” located in “Concentrate here” quadrant, it is a feature that consumers value but are not satisfied with, so its performance needs to be enhanced as a priority in the future. “Recommendation (RD)” and “Interaction Tools (IT)” are overkill in our results, which may be over-optimized. Another possibility is that consumers don’t yet perceive these two design features as important enough for live streaming shopping, once their importance is recognized, they will shift to “Keep up the good work” quadrant. The importance-satisfaction analysis for grouping samples gives more detailed improvement strategies, which provide the basis for the MLSS platform to create personalized and customized interfaces for different consumer groups, so as to more accurately meet the needs of kinds of consumers.

5.2. Implication

It has become a hot new form of e-commerce worldwide that using smartphones to shop while watching live streaming videos, but relevant academic research lags behind practice at present, which in turn causes blindness in application development and deficiency of consumer experience. In this study, we explore consumer perceptions of MLSS platform and differences in depth from the perspective of design features, with its uniqueness and insights.

Theoretically, this paper begins by mapping the design of the MLSS platform into consumer domain, functional domain, physical domain and process domain based on the axiomatic design theory, and follows this process route to filter representative design features layer by layer. To the best of our knowledge, it is one of the first studies to systematically sort out the design feature set of the MLSS platform, which may provide a global view for subsequent research on live streaming shopping behavior and design. Secondly, compared to previous studies that examine consumer engagement regarding live streaming shopping platforms as a whole, the current study notes the differences between design features and achieves quality classification of design features by utilizing Kano model based on dummy variables regression. The distribution of design features across quality categories we identified alerts future researchers to the nonlinear relationship between design features performance and consumer perceptions, and it may be misleading to consider platforms as a whole or ignore functional differences. Thirdly, the study complements the existing literature by exploring the relationship between consumer characteristics and platform use by identifying consumers’ asymmetric preferences for MLSS design features, which also extends correspondence analysis to the MLSS contexts. Fourthly, to address the needs of MLSS platform design, we expand the traditional importance-performance analysis to importance-satisfaction analysis, which enables to derive more accurate optimization paths for MLSS platform design on the basis of capturing the impact of real consumer satisfaction, both overall and in terms of consumer groups. Finally and in general, we propose a framework for a detailed multi-perspective review of MLSS design elements in this study, which is also applicable to a comprehensive diagnosis of other products or services. And from the methodological point of view, we start from the idea of Kano’s quality asymmetry, overcome the shortcomings of the traditional Kano model two-way questionnaire, and combine methods of dummy variables regression, correspondence analysis and importance-satisfaction analysis to form an overall mixed-methods technical system to support the implementation of the proposed comprehensive diagnosis framework.

At the same time, this study provides rich practical implications for MLSS platform designers and operators. Currently, the scattered theoretical research on MLSS platform design and the fragmented relationship between design features pose obstacles to designing well-functioning and good-experienced mobile apps. This study starts with dissecting the MLSS platform and establishing a hierarchical set of design features guided by the axiomatic design theory, which provides a design baseline for the optimization and operation of the MLSS platform. On this basis, the results of Kano quality classification based on dummy variables regression suggest that designers should treat different design features distinctively to fulfill consumers’ requirements more efficiently, for instance, design features of must-be quality must be displayed prominently, such as “Streamer Information (SI)”, “Reminder (RM)” and “Interaction Tools (IT)”, which should be easy to operate by consumers. As for design features of attractive category such as “Commerce Cues (CC)”, we should also think about how to layout them in a more appropriate way to bring unexpected surprises for consumers, which may be the key for the platform to win over competitors through differentiation. In further, the preference differences in design features of consumer groups with different characteristics captured by correspondence analysis will facilitate platform operators to provide more personalized and customized services for consumers with different characteristics. For example, the MLSS platform can first provide an initial interaction interface for consumers based on the characteristics they have already learned (e.g., a simplified interface for elders), and for more professional consumers, provide more open customizable capabilities to allow them to assemble the design features of the MLSS platform like building blocks to enhance their live shopping experience. This customized consumer interface enables consumers to feel the care and empathy from the platform, which in turn enhances psychological recognition and leads to transactions. More particularly, the results of importance-satisfaction analysis can serve as a reliable foundation for platform operators to decide on the allocation of technical and service resources, and point the way for platform designers to optimize and upgrade design features. It is worth mentioning that the research framework and methodology proposed in this paper have strong operability and interpretability for the optimization and operation of MLSS platform.

6. Conclusion

Live streaming shopping is currently the high-profile new economic form. At present, research related to this area is far less prosperous than practice, and there is a particular lack of focus on MLSS platform design. However, the platform design directly affects consumers' shopping experience and in turn impacts consumer's subsequent purchase behavior, of which there may be differences in perceptions of consumers and influence mechanism involved. It is crucial to identify the differences in consumers' perceptions towards the design of MLSS platform to meet their differentiated information needs through the platform and thus enhance their usage satisfaction and shopping experience. To gain a detailed knowledge in this regard, this study is conducted from the perspective of design features. We systematically sort out the design features of MLSS platforms, analyze them with respect to consumers' perceived performance, perceived quality and preferences, then further explore strategies for platform optimization based on consumers' preferences and satisfaction. In terms of methodology, dummy variables regression, Kano model, correspondence analysis and importance-satisfaction analysis are integrated in a unified framework that together serves to understand various differences in consumer perceptions of MLSS platform design features with micro lens.

Although this paper fills some gaps in existing theoretical research and practice, there are still several deficiencies which can guide the future thinking and direction in this field. First, we collect data on Taobao Live, the largest MLSS platform in China, but it remains to be further verified that the findings obtained can be generalized to other platforms. Secondly, although our method has significant improvements over the traditional Kano two-way questionnaire in terms of question design and compatibility with external methods, it is still influenced to some extent by subjectivity of respondents. In future, it is achievable to analyze acquired objective data by means of text analysis, data mining, machine learning, etc., and we believe that our approach can be effectively combined with these methods. Moreover, this study only considered consumers' characteristics such as gender, age, years of live streaming shopping and average frequency of live streaming shopping per month, whereas more unique characteristics such as consumers' personality and risk preferences can be included in future studies to obtain more valuable conclusions. Further, the mechanisms explaining how these consumer characteristics affect consumers' perceptions of quality, purchase intentions, and behaviors on the MLSS platform are also expected to be explored going forward.

Author contributions

Quan Xiao: Conceptualization, Methodology, Writing- Reviewing and Editing; Shanshan Wan: Writing- Original draft preparation, Data curation; Xing Zhang: Conceptualization, Writing- Reviewing and Editing; Mikko Siponen: Writing- Reviewing and Editing; Lu Qu: Conceptualization. Xia Li: Validation.

Declarations of competing interest

None.

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Appendix

Table A1
Studies related to design features of MLSS platform

Context	Design features	Findings/Propositions	Source
online shopping	emotional design	Website design features play a significant role in developing online trust.	Pengnate and Sarathy (2017)
social commerce	social tools	Social tools such as real-time chat rooms can reduce purchase uncertainty, perceived risk, and purchase resistance.	Chung et al. (2017)
live streaming	number of followers	Consumers favor streamers with large numbers of followers.	Lu et al. (2018)
live streaming	gifting, danmaku	The social interaction of danmaku has a significant impact on paid gifting in the virtual world.	Zhou et al. (2019)
outdoor livestreaming	gifting, danmaku, fan badges	Gifting, danmaku, fan badges, and are important for building engagement and increasing paimian with dedicated viewers.	Lu et al. (2019)
live streaming	virtual gifting	Virtual gifting stimulates streamers' content generation and viewer-streamer interactions.	Li et al. (2021)
e-commerce live streaming	discounts or coupons	Discounts or coupons strengthen consumers' willingness to continue watching.	Hu and Chaudhry (2020)
eCommerce streaming	embedding links	Consumers click on an embedded link provided in the video and then check out.	Liu et al. (2021a)

Table A2
Explanations of the design features of the MLSS platform

Design feature & Description	Screenshot	Design feature & Description	Screenshot
Streamer Information (SI) SI allows users to view the profile of the streamers, including information such as avatar, nickname, number of fans, number of favorites, area of expertise, ranking, number of contents, number of likes, etc.		**Interaction Tools (IT)** IT encourages users to communicate and interact with the streamers or other users, and the interaction tools include chatting, liking, rewarding, and connecting.	

(continued on next page)

Table A2 (*continued*)

Design feature & Description	Screenshot	Design feature & Description	Screenshot
			
Live Streaming Videos (LV) LV provides users with the view of the streamer's current and historical live streaming videos, including the video's status, number of viewers, title, number of hot products, recommended products, preview, etc.		**Sharing Tools (ST)** ST supports sharing interesting live streams to other users, which includes friends within the same live e-commerce platform, as well as external links to other social apps.	
Channel List (CL) CL enables users to view all live channels of the live e-commerce platform, which includes information such as the title of the live streaming, the number of views, the nickname of the streamer, and the recommended products.		**Participation Utilities (PU)** PU supports users to increase the popularity of the streamers and bring them closer to the streamers by completing tasks on the platform, such as intimacy enhancement and joining the fan list, etc.	
Live Streaming Logs (LL) LL is available for users to view live content profiles and key information that has been published in the live streaming, such as live streaming overviews and live streaming imprints.		**Preferential Mechanism (PM)** PM provides participating users with ways to earn monetary or non-monetary rewards, including earning credits, newcomer bonuses, discount coupons, and group buying.	
Event Information (EI) EI highlights the content of specific thematic events for users to view and participate in, such as celebrity tips, lifestyle festivals, origin direct supply, night markets.		**Commerce Cues (CC)** CC provides clues to user behavior in the live streaming channel, such as information like "XXX is here", "XXX is following the streamer", "XXX has paid ", etc.	

(*continued on next page*)

Table A2 (*continued*)

Design feature & Description	Screenshot	Design feature & Description	Screenshot
			
Reminder (RM) RM reminds users to follow the streaming in time, or pay attention to the start time of the live streaming, which includes following reminder and starting reminder.		**Transaction Suites (TS)** TS supports users to add products to the shopping cart or place orders immediately. The design features include links to products in the shopping cart, “grab now button”, links to products on the product shelf, etc.	
Recommendation (RD) RD can push live streaming that may be of interest to the users, or similar live streaming to those that the users have watched, which includes guess the favorite live streaming and similar live streaming recommendations.			

Table A3
Importance of design features of subgroup samples

Design features	Gender		Age			Years			Frequency		
	Male	Female	24 and below	25–35	36 and above	Within 6 months	6 months –2 years (excluding)	2 years and above	Less than one time	1-3 times (excluding)	3 times or more
SI	0.22	0.42	0.34	0.23	0.48	0.23	0.24	0.58	0.38	0.27	0.22
LV	0.33	0.46	0.37	0.22	0.62	0.56	0.28	0.45	0.58	0.39	0.16
CL	0.38	0.35	0.41	0.19	0.54	0.44	0.23	0.54	0.43	0.25	0.23
LL	0.27	0.36	0.45	0.14	0.45	0.47	0.21	0.34	0.52	0.31	0.07
EI	0.28	0.27	0.3	0.18	0.48	0.36	0.27	0.22	0.53	0.23	0.16
RM	0.21	0.36	0.27	0.19	0.42	0.35	0.1	0.35	0.51	0.22	0.01
RD	0.26	0.26	0.29	0.17	0.35	0.21	0.24	0.34	0.43	0.22	0.14
IT	0.22	0.34	0.22	0.12	0.57	0.26	0.18	0.36	0.43	0.25	0.1
ST	0.3	0.31	0.33	0.22	0.48	0.41	0.17	0.41	0.52	0.28	0.16
PU	0.23	0.3	0.32	0.22	0.34	0.23	0.27	0.3	0.46	0.18	0.2
PM	0.31	0.41	0.32	0.31	0.52	0.36	0.29	0.5	0.56	0.27	0.29
CC	0.11	0.27	0.2	0.11	0.45	0.16	0.17	0.3	0.41	0.16	0.08
TS	0.43	0.42	0.33	0.37	0.72	0.48	0.38	0.51	0.6	0.41	0.22

Table A4
Satisfaction of design features of subgroup samples

Design features	Gender		Age			Years			Frequency		
	Male	Female	24 and below	25–35	36 and above	Within 6 months	6 months −2 years (excluding)	2 years and above	Less than one time	1-3 times (excluding)	3 times or more
SI	0.1	−0.03	0.05	0.02	0.15	−0.08	0.04	0.08	0.28	0.16	−0.06
LV	0.17	0.13	0.14	0.11	0.19	0.22	0.17	0.11	−0.13	0.13	0.15
CL	0.11	−0.04	0.12	0.04	0.05	0.06	0.05	0.23	0.33	0.02	0.1
LL	−0.13	0.11	0.17	−0.02	−0.08	0.44	0.03	0.05	−0.1	0.08	0.02
EI	0	0.08	0.1	0.06	−0.19	0.09	−0.08	0.16	−0.02	−0.02	−0.04
RM	−0.14	0.16	0.23	−0.12	−0.13	0.08	−0.06	0.08	−0.02	0.03	−0.01
RD	0.07	0.1	−0.01	−0.02	0.07	0.24	0.07	0.06	0.04	−0.02	0.15
IT	0.06	0.19	0.13	0	0.2	−0.05	0.05	0.07	0.31	0.12	0
ST	0.15	0.19	0.08	0.14	0.17	0.17	0.08	0.02	−0.01	0.14	0.04
PU	−0.07	0.1	−0.03	−0.04	−0.04	0.02	0	−0.03	0.07	0.04	0.01
PM	0.12	0.09	0.06	0.06	0.24	0.19	0.14	0.11	0.21	0.13	−0.04
CC	0.09	−0.07	0.09	0	0.07	−0.01	0.04	−0.01	−0.07	0.07	0.08
TS	0.19	0.22	0.14	0.13	0.25	0.11	0.17	0.2	0.24	0.26	0.12

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