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The MUSA model applied to luxury hotel customer satisfaction: A comparative survey of the top 10 European tourist cities

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A B S T R A C T

While analyzing customer satisfaction in luxury hotels through online reviews has become increasingly crucial, to our knowledge, many models still rely on questionnaires. Therefore, this paper aims to analyze customer satisfaction in luxury hotels using online reviews. Since Europe is a mature tourism and hospitality market, this paper conducts a comparative survey of luxury hotels in the top 10 European tourist cities by collecting customer reviews from TripAdvisor. This paper employs the Multicriteria Satisfaction Analysis (MUSA) model, a linear programming tool for customer satisfaction analysis, along with the refined Kano model to identify and compare areas for improvement in luxury hotels across various cities. The findings are presented through an interactive visualization application featuring a novel category-priority diagram to simplify comparison of criteria priorities. This application also provides automatic interpretations of the diagram for each city, allowing decision-makers to compare hotel performance, receive data-driven recommendations, and ensure analysis reproducibility.

1. Introduction

The hotel industry is a vital component of the tourism sector and has a direct impact on regional economic development (Bae, 2022; Achmad and Yulianah, 2022). In Europe, luxury hotels are often seen as symbols of economic vitality, attracting high-net-worth tourists and stimulating upscale consumption, thereby reinforcing municipal revenues (Prevolšek and Golja, 2024). For example, in Poland, the development of high-star hotels—mostly luxury properties—was significantly boosted by European Union funding during 2007–2013, particularly in the southeastern and central regions, positively affecting local employment and investment structures (Stawicki, 2016). In Spain, the number of starred hotels and the hotel price index have been identified as key determinants of tourism revenue in Andalusia, indirectly influencing regional economic growth (Nasir et al., 2016). In cities such as Barcelona and Madrid, luxury hotels have not only responded to evolving market demands through continuous service innovation but have also succeeded in increasing overnight stays and attracting affluent tourists willing to pay premium prices for unique, high-quality experiences. The demand for luxury tourism in these cities has continued to grow even during periods of economic crisis, largely due to the implementation of consistent and adaptive strategic approaches (Pie et al., 2019). In Tenerife, four-star and five-star hotels have significantly contributed to the local economy by promoting the consumption of locally sourced products and services (Santana-Talavera and González-Morales, 2024).

Building on this growing recognition of the economic and strategic importance of luxury hospitality, academic and industry attention has increasingly focused on understanding how these establishments deliver value and maintain competitiveness in dynamic markets. The increasing interest and significance of the luxury hotel industry among scholars and practitioners have been underscored in many studies (Sharma, 2016; Giglio et al., 2020; Shin and Jeong, 2022; Chang et al., 2023). The analysis of customer satisfaction is crucial for a luxury hotel to identify areas for improvement, thereby avoiding high customer dissatisfaction or customer loss. Luxury hotels place even greater emphasis on the experiences, feedback, and satisfaction of their guests (Choi and Kandampully, 2019; Cid-López et al., 2022; Chang et al., 2023).

Questionnaires are frequently employed to gather data for analyzing customer satisfaction. The models that can be used for analyzing customer satisfaction based on questionnaires include Importance-Performance Analysis (IPA), the Kano model, the MUlticriteria Satisfaction Analysis (MUSA) model, the SERVQUAL model, the SERVPERF

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model, among others. Each model offers unique advantages in identifying factors that drive customer satisfaction. This paper focuses on analyzing customer satisfaction in the luxury hotel sector, given the critical role luxury hotels play in the hospitality market. In the context of luxury hotels, researchers commonly resort to models such as IPA, the SERVQUAL model, and the SERVPERF model (Babic-Hodovic et al., 2019; Mohsin et al., 2019; Al-Shidhani and Tumati, 2021; Popovici et al., 2021; Wong, 2021; Chen et al., 2022a; Shu et al., 2023). Unlike these models, which primarily rely on perceptual gaps or performance-only measures, the MUSA model is grounded in multi-criteria decision analysis and linear programming. It incorporates both the importance and satisfaction levels assigned by customers to various attributes, allowing for the aggregation of individual preferences into collective satisfaction indices. This enables more precise prioritization in resource allocation and a deeper understanding of the key drivers of satisfaction. The approach also supports a more nuanced and quantitative evaluation of customer satisfaction, which can be particularly valuable in complex service environments, such as luxury hotels, where guest expectations are both multidimensional and highly individualized.

However, to the best of our knowledge, the MUSA model—a useful tool based on linear programming for analyzing satisfaction in areas like education (Glaveli et al., 2024; Zervoudakis et al., 2024), public policy (Karasmanaki et al., 2023), and healthcare (Ferreira et al., 2018; Al-Awlaqi and Aamer, 2020; Glaveli et al., 2021; Vieira et al., 2023)—has been used in luxury hospitality only once. This was by Glaveli et al. (2019), who applied it to assess job satisfaction in luxury resorts. In other words, the MUSA model has yet to be widely adopted in studies focusing on luxury hotel customer satisfaction, and it has not been integrated with either the traditional Kano model or its refined version. Accordingly, this paper wants to explore how the MUSA model can be applied to luxury hotel customer satisfaction and investigate its potential when combined with the Kano framework for a more comprehensive analysis.

Moreover, in light of the Internet's evolution, customers can directly engage and share their hotel experiences through social media dialogues and review sites. Online reviews have become essential references for customers (Ginting et al., 2023; Wu et al., 2024). They wield substantial influence on the reputation of hotels, with potential guests frequently depending on them to inform their decisions about accommodation choices. Social media and review sites serve as accessible information sources through which hotel establishments can understand their customers' requirements and gauge satisfaction (Ríos-Martín et al., 2020; Park, 2023). However, as far as we know, regardless of whether the satisfaction analysis pertains to luxury hotels or other fields, the majority of studies employing the MUSA model are questionnaire-based, thereby lacking analyses based on social media or online reviews.

Therefore, this paper aims to analyze customer satisfaction in luxury hotels using online reviews, with a focus on enabling broader cross-city comparisons. It applies both the MUSA model and the refined Kano model in an integrated approach known as ReK-M analysis. A key advantage of ReK-M analysis lies in the differentiated weights generated by the MUSA model, which supports the accurate classification of each criterion within the refined Kano model. This integration enables the identification of improvement priorities across various criteria, thereby enhancing the efficiency of resource allocation to boost customer satisfaction in luxury hotel settings. To the best of our knowledge, this combined approach has not been previously explored in the context of luxury hotels. This paper also introduces a category-priority diagram to facilitate the comparison of priorities among different criteria. This diagram not only aids in managerial decision-making but also contributes to theoretical development by clearly highlighting which criteria should be improved to avoid customer dissatisfaction and which should be enhanced to increase satisfaction and strengthen market competitiveness.

Regarding collecting data to validate the proposed approach, the sample for this paper was gathered from TripAdvisor, focusing on luxury hotels located in the top 10 European tourist cities as ranked by Euromonitor (2021). Europe was chosen due to its well-established and mature tourism and hospitality market. By including cities from various European countries, this paper adopts a broader geographic scope that enables meaningful cross-city comparisons. Such an approach offers valuable insights for hotel managers and city policymakers, supporting more informed decision-making. This comparative dimension represents one of the practical contributions of the paper. Finally, the construction of an interactive application for visualizing model results further enhances the practical contributions of the present paper. This application presents the key findings of the analysis and offers decision-makers automated and prescriptive interpretations of the results, enabling them to rapidly identify and compare areas for improvement in luxury hotels across different cities. Such a tool is particularly advantageous for decision-makers less familiar with the model yet in need of valuable insights for informed and prompt decision-making.

The rest of this paper is structured as follows. Section 2 presents an overview of studies related to the analysis of customer satisfaction in luxury hotels over the past five years. Section 3 introduces the fundamental concepts of the models underlying this paper. Section 4 presents the application of the proposed approach in a case study involving online reviews from ten European cities. Section 5 demonstrates the case study results through an interactive application developed in this paper. Section 6 discusses the theoretical and practical contributions of this paper and highlights potential limitations for further consideration and resolution. Section 7 summarizes the findings of this paper and proposes some future work.

2. Literature review and research objectives

Section 2.1 presents a systematic search conducted across the Web of Science, Scopus, and Google Scholar databases to identify studies analyzing customer satisfaction in luxury hotels between 2019 and 2023. This review aims to determine whether the MUSA model and the refined Kano model have been employed in such analysis. Section 2.2 then outlines the research objectives of this paper.

2.1. Related studies

The literature search used the following terms in the query: "customer satisfaction analysis," "customer satisfaction measurement," "luxury hotel," and their respective abbreviations and synonyms (e.g., "guest satisfaction analysis" for "customer satisfaction analysis," "5-star hotel" or "deluxe hotel" for "luxury hotel"). The search initially produced a total of 196 results from three databases. The literature scope was then narrowed down to 22 articles by applying a series of inclusion and exclusion criteria to identify relevant and valid papers, as shown in Fig. 1. Table 1 lists 22 articles related to the analysis of customer satisfaction in luxury hotels. Each entry provides information on the research object (e.g., analyzed place), along with details about the data source and methods employed in the respective study.

As illustrated in Table 1, many previous studies have relied on questionnaire surveys as their primary data collection method. Moreover, except for Chang et al. (2023), who conducted a sentiment analysis of online reviews from six European cities using data from Booking.com, most studies that have analyzed customer reviews from platforms such as TripAdvisor, Booking.com, or Google Travel have been limited to single cities (e.g., Sarajevo, Lisbon, Bucharest, Hong Kong, etc.), multiple cities within the same country, or limited regional samples. While these studies offer valuable localized insights, their geographic limitations reduce the generalizability of their findings. In terms of geographic scope and cross-city comparison, there remains a significant gap in the literature on luxury hotel customer satisfaction across major international cities. This paper addresses that gap by a comparative analysis of luxury hotel satisfaction across ten European cities.

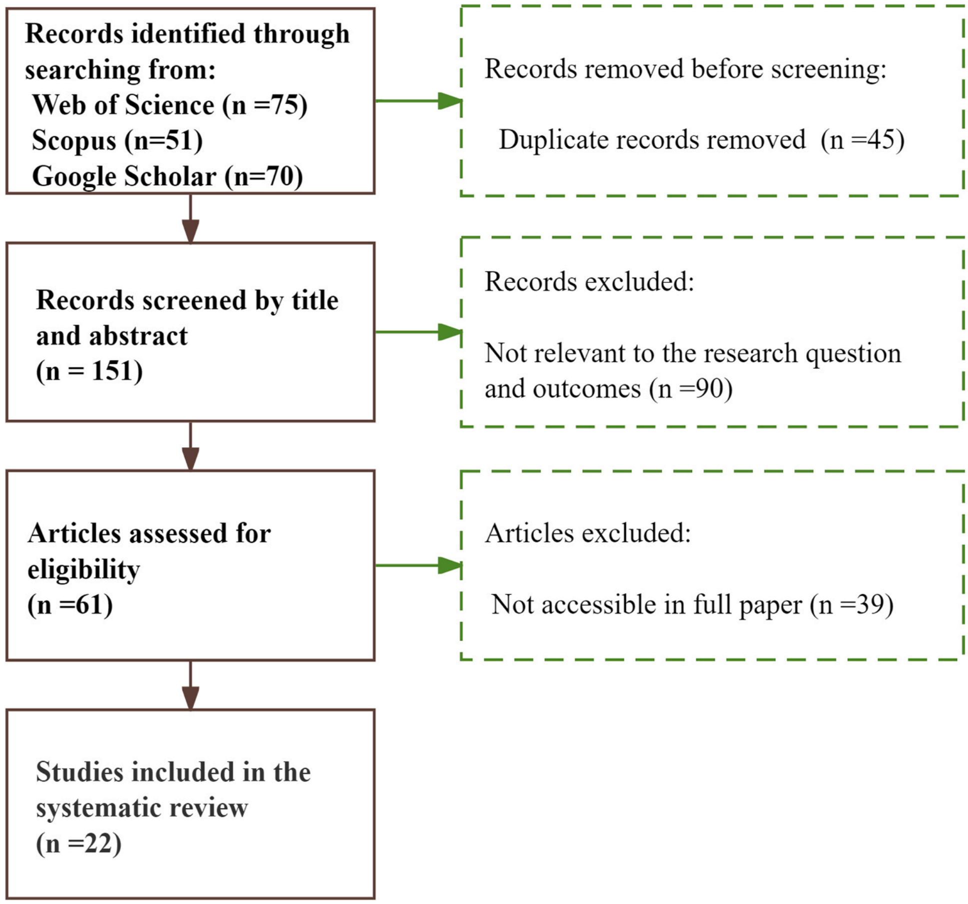

Fig. 1. Literature review process.

Various techniques have been applied in the study of luxury hotel customer satisfaction, including IPA, CFA, EFA, SERVQUAL, SERVPERF, regression analysis, text mining, and sensitivity analysis. For instance, Chen et al. (2022a) combined the Kano model with IPA and feature extraction methods to evaluate customer satisfaction in luxury hotels. With the rise of big data and artificial intelligence (AI) technologies, a range of advanced analytical approaches, such as natural language processing (NLP), machine learning, and sentiment analysis, have gained increasing attention in the field of customer satisfaction research. However, at the time of this paper, the integration of AI into academic research on luxury hotel satisfaction remained in its early stages, with few robust and validated methodologies available.

Furthermore, as summarized in Table 1, most existing studies—-whether based on questionnaire surveys or online review data—typically produce analytical outputs that are descriptive or diagnostic. While these methods are valuable for identifying trends and uncovering underlying factors, they often fall short of delivering actionable insights that directly support managerial decision-making. In other words, few studies to date employ structured analytical frameworks capable of generating prescriptive insights that recommend concrete actions based on data. This reveals a gap in the literature regarding the practical application of frameworks that can effectively support decision-making through prescriptive analysis. This paper addresses this limitation by a hybrid approach grounded in well-established theoretical models in the present study, to ensure both methodological rigor and practical applicability in guiding decision-making.

More concretely, this paper contributes to the literature by introducing a dual-model approach that combines the MUSA model with the refined Kano model (i.e., ReK-M analysis) to analyze online customer reviews in the context of luxury hotels. To the best of our knowledge, this is the first study to integrate these two models for customer satisfaction analysis within this sector. The MUSA model offers several important advantages, such as the ability to evaluate multiple satisfaction criteria simultaneously through linear programming, the incorporation of individual customer preferences using utility functions, and the automatic estimation of weights that reflect the relative importance of different criteria. Meanwhile, the refined Kano model advances the original two-dimensional framework by accounting for customers' perceived importance of specific service attributes, allowing for a more detailed classification of quality factors.

In the ReK-M analysis, the MUSA model is used to generate overall weights for each service criterion, as well as weights derived from satisfied and dissatisfied customer segments. These weights are then compared to determine the refined Kano category of each criterion, enabling a deeper understanding of customer satisfaction drivers and supporting more targeted and data-informed improvement strategies in the luxury hotel sector. Additionally, most previous research using the MUSA model has relied on structured questionnaire data, which is often time-consuming, expensive, and limited by small sample sizes and response bias. In contrast, this paper takes an innovative approach by applying both the MUSA and refined Kano models to online reviews, showing how these methods can generate useful, data-driven insights from large-scale review data.

Moreover, to the best of our knowledge, no existing studies on customer satisfaction analysis in the luxury hotel sector have implemented an interactive application to present the results of such methods in a user-friendly format. From a business perspective, there is a growing demand for analytical solutions that not only produce results but also translate them into accessible and intuitive visual insights, particularly for stakeholders without technical expertise. This paper addresses that

Table 1
Articles related to customer satisfaction in luxury hotels over the last five years.

Author (s) (year)	Geographic scope (Analyzed place)	Data source (data collection tool, if available)	Analytical and technical techniques	Visualization techniques	Analytical output types for decision-making support
Babic-Hodovic et al. (2019)	Single city (Sarajevo, Bosnia and Herzegovina)	Respondents (questionnaires)	IPA, SERVPERF model, Confirmatory factor analysis (CFA)	Tables	Descriptive
Gunasekar and Sudhakar, (2019)	Multi-city (Andaman and Nicobar Islands, India)	TripAdvisor (web crawling program)	Sentiment analysis, Text mining	Tables, word clouds, and bar charts	Descriptive
Mohsin et al. (2019)	Single city (Lisbon, Portugal)	Respondents (questionnaires)	IPA, Descriptive analysis, Exploratory factor analysis (EFA), CFA, multivariate ANOVA	Tables and Importance–performance mapping	Diagnostic
Li et al. (2020)	Multi-city (Five Chinese cities: Sanya, Beijing, Guangzhou, Shanghai, Hangzhou)	TripAdvisor	Regression analysis	Tables and line charts	Descriptive and diagnostic
Lo and Yeung (2020)	Single city (Hong Kong, China)	Respondents (questionnaires)	Modified IPA, CFA, EFA	Tables and IPA plot	Diagnostic
Nunkoo et al. (2020)	Multi-region (Three provinces of South Africa: Western Cape, Kwazulu-Natal, and Gauteng)	Respondents (questionnaires)	Partial least square structural equation modeling (PLS-SEM), Multi-group analysis (MGA), Importance-performance map analysis (IPMA)	Tables and Importance-performance map	Diagnostic
Padma and Ahn (2020)	Single country (Malaysia)	TripAdvisor	Content analysis, Critical incident technique (CIT), Word frequency analysis	Tables	Descriptive
Ríos-Martín et al. (2020)	Single country (Spain)	TripAdvisor	Content analysis, NVivo10 program (for qualitative analysis)	Tables	Diagnostic
Le et al. (2021)	Single city (Nha Trang, Vietnam)	Respondents (questionnaires)	PLS-SEM, SmartPLS 3.2.9 software, Redundancy Analysis (RDA)	Tables and relationship diagram	Diagnostic
Popovici et al. (2021)	Single city (Bucharest, Romania)	Respondents (questionnaires)	SERVQUAL model	Tables and bar charts	Descriptive
Wong (2021)	Single city (Hong Kong, China)	Respondents (questionnaires)	SERVQUAL model	Tables	Diagnostic
Chen et al. (2022a)	Single city (London, United Kingdom)	TripAdvisor	IPA, Kano model, Feature extraction techniques (TF-IDF and Word2Vec), PolarityRank algorithm	Tables, line charts, and IPA plots	Descriptive and diagnostic
Handani et al. (2022)	Single country (Singapore)	Google Travel (SCTM 3.0: a web-crawling program)	Text mining, Descriptive analysis, Linear regression	Tables and network visualization of most frequent keywords	Descriptive and diagnostic
Hien et al. (2022)	Multi-city (Six Vietnam cities: Hanoi, Da Nang, Da Lat, Nha Trang, Ho Chi Minh, Phu Quoc)	TripAdvisor (manually collected data)	Descriptive analysis, Inferential analysis	Tables	Descriptive
Jeganathan et al. (2022)	Single city (Pondicherry, India)	Luxury hotels in Pondicherry (questionnaires)	HOLSERV (new version of SERVQUAL), CFA, Structural equation modeling (SEM)	Tables	Diagnostic
Ma et al. (2022)	Single city (Sanya, China)	Qunar.com	Kernel density analysis, Grid analysis, Geographically weighted regression (GWR)	Tables, spatial diagrams, and kernel density map	Diagnostic
Perišić Prodan et al. (2022)	Single country (Croatia)	Respondents (questionnaires)	Factor analysis, Reliability analysis, Correlation analysis, Regression analysis	Tables	Diagnostic
Wibisono et al. (2022)	Single city (Bandung, Indonesia)	Guests of luxury hotels (questionnaires)	Regression analysis	Tables	Descriptive and diagnostic
Williady et al. (2022)	Single region (Bali, Indonesia)	Google Travel (SCTM 3.0: a web-crawling program)	Text mining, Factor analysis, Linear regression	Tables and Network graphs	Descriptive and diagnostic
Chang et al. (2023)	Cross-city (London, Amsterdam, Barcelona, Paris, Milan, Vienna)	Booking.com (public dataset on Kaggle.com)	Bag-of-Words (BOW) model, Sentiment analysis, Statistical analysis, Random Forest classification, Feature extraction techniques (TF-IDF and Word2Vec)	Tables, box plots, maps, word clouds, bar charts, and line charts	Descriptive
Roy (2023)	Single city (Darjeeling, India)	TripAdvisor (web scraping)	Aspect-based sentiment analysis (ASAM), Natural language processing Tool Kit (NLTK), TF-IDF, Regression analysis	Tables, word clouds, scatter plots, and line charts	Diagnostic
Wu et al. (2023)	Multi-city (Two Chinese cities: Beijing, Shanghai)	Ctrip.com (Octopus: a web scraping tool)	Link analysis, CBOW-KMeans algorithm, Kansei Engineering, Sentiment analysis	Tables, bar charts, and opportunity landscape map	Descriptive
This paper	Cross-city (Amsterdam, Barcelona, Paris, Berlin, London, Madrid, Rome, Munich, Vienna, Milan)	TripAdvisor (web scraping)	MUSA model, refined Kano model	Interactive application	Prescriptive

gap by developing an interactive application that features a novel category-priority diagram along with automated interpretations for each city, thereby enhancing transparency, reproducibility, and decision-making support.

To address the identified gaps in the literature, this paper employs web scraping to collect customer reviews of luxury hotels from TripAdvisor, focusing on the top 10 European tourist destinations. This broader geographic scope enables meaningful cross-city comparisons. The MUSA model is then applied in combination with the refined Kano model to analyze customer satisfaction and identify improvement priorities for each city. Finally, this paper develops an interactive application that presents the key findings and provides automated, user-friendly interpretations and prescriptive insights—offering concrete recommendations to support informed decision-making.

2.2. Research objectives

Building on the identified gaps in the literature regarding customer satisfaction analysis in luxury hotels (Section 2.1), this paper primarily aims to analyze customer satisfaction in luxury hotels using online reviews, with a focus on enabling broader cross-city comparisons. To achieve this, the specific objectives are:

1) To conduct a comparative analysis of customer satisfaction with luxury hotels across various European cities.
2) To gather online reviews from TripAdvisor to evaluate the effectiveness of the proposed model, instead of relying on traditional questionnaires.
3) To propose a novel hybrid framework based on established models, ensuring methodological rigor and practical relevance for customer satisfaction analysis.
4) To simplify comparing priorities among different criteria and identify aspects needing improvement to prevent customer dissatisfaction.
5) To develop an interactive visualization application that presents the results of the proposed model and automates their interpretation, facilitating broader accessibility and practical use by decision-makers without advanced technical expertise.
6) To offer hotel managers, policymakers, and stakeholders a prescriptive, user-friendly framework that generates data-driven insights for more targeted and effective decision-making to enhance customer satisfaction.

3. Theoretical framework

This section introduces the fundamental concepts of the models employed in this paper to assess and compare customer satisfaction with luxury hotels across 10 European tourist cities.

3.1. The MUlticriteria Satisfaction Analysis (MUSA) model

3.1.1. A brief overview of the MUSA model

The MUSA model was initially introduced by Grigoroudis and Siskos (2002). It is a preference disaggregation approach that follows the principles of ordinal regression analysis to evaluate a set of collective satisfaction functions. The primary advantage of the MUSA model lies in its consideration of the qualitative form of customer judgments and preferences (Grigoroudis and Siskos, 2002). This makes it particularly suitable for the luxury hotel sector, where customer preferences are often complex, multi-dimensional, and influenced by both tangible and intangible service attributes, requiring nuanced modeling of satisfaction drivers.

Regarding the methods used in customer satisfaction research within the luxury hotel sector, researchers have employed a wide range of approaches, including SEM (Jeganathan et al., 2022), the SERVQUAL model (Popovici et al., 2021; Wong, 2021), IPA (Babic-Hodovic et al., 2019; Mohsin et al., 2019; LoandYeung, 2020; Chen et al., 2022a), and the SERVPERF model (Babic-Hodovic et al., 2019). In contrast to these models, the MUSA model is grounded in multi-criteria decision analysis and linear programming. It incorporates both the importance and satisfaction levels assigned by customers to various attributes, allowing for the aggregation of individual preferences into collective satisfaction indices. The MUSA model allows for more accurate prioritization of resources and provides deeper insights into the key drivers of customer satisfaction. Moreover, this model facilitates a more nuanced and data-driven evaluation of satisfaction, making it particularly well-suited for the complex and experience-oriented nature of the luxury hotel industry.

The MUSA model and its extended version have been successfully employed in several studies analyzing satisfaction, such as healthcare services (Ferreira et al., 2018; Al-Awlaqi and Aamer, 2020; Glaveli et al., 2021; Vieira et al., 2023), e-Government services (Bournaris, 2020), supply chains (Tiganis et al., 2023), environmental management (Corrente et al., 2023), and so on. One extension of the MUSA model is the hierarchical MUSA model, typically applied when there are multiple subcriteria within each criterion. However, in the context of this paper, where each criterion does not contain any subcriteria, the original MUSA model is used. Section 3.1.2 introduces the fundamental concepts and notations of the MUSA model as applied in this paper.

Despite its broad applicability, existing studies that use the MUSA model to analyze customer satisfaction have primarily relied on questionnaire-based data. Within the luxury hospitality context, its application remains extremely limited. To date, it has only been used once—by Glaveli et al. (2019)—who applied the model to assess job satisfaction in luxury resorts. In other words, the MUSA model has yet to be widely adopted in studies focusing specifically on luxury hotel customer satisfaction, and it has not been integrated with either the traditional Kano model or its refined version. Accordingly, this paper explores how the MUSA model can be applied to luxury hotel customer satisfaction and investigate its potential when combined with the Kano framework for a more comprehensive and actionable analysis (see Section 3.2.2).

3.1.2. Fundamental elements and concepts of the MUSA model

In terms of the fundamental elements and concepts of the MUSA model, this paper uses the notation introduced by Ferreira et al. (2018) while making necessary adjustments to better suit the context of this paper. The notation is as follows:

1) $C = \{c_1, ..., c_j, ..., c_n\}$ is a set of criteria used to evaluate the object, n represents the total number of criteria;

2) c_j is the jth criterion of set C, with $j = 1, ..., n$;

3) E_j is the discrete scale of criterion c_j;

4) c_j^l, with $j = 1, ..., n$ and $l = 1, ..., L_j$, is the lth dissatisfaction/satisfaction level (hereafter referred to as satisfaction levels), i.e., $E_j = \{c_j^1, ..., c_j^l, ..., c_j^{L_j}\}$;

5) $c_j^1 < ... < c_j^l < ... < c_j^{L_j}$ denotes a total order for $c_j^l, j = 1, ..., n$ and $l = 1, ..., L_j$; symbols $<$ means "strictly less preferred than"; for example, the totally satisfied level $(l = L_j)$ is strictly more preferred than the totally dissatisfied level $(l = 1)$;

6) $E = \{c^1, ..., c^l, ..., c^L\}$ is a discrete scale associated with the overall satisfaction; as before, $c^1 < ... < c^l < ... < c^L$ denotes a total order for c^l, $l = 1, ..., L$;

7) $U = \{1, ..., q, ..., u\}$ represents a group of customers whose satisfaction with a hotel (or a group of hotels) is being evaluated; each customer $q \in \{1, ..., u\}$ will express their assessment of the hotel according to a single level of each scale E_j, for $j = 1, ..., n$ and E;

8) $x_j^{(q)} \in E_j$ represents the satisfaction level assigned by customer q with respect to the jth criterion c_j;

9) $x^{(q)} \in E$ represents the overall satisfaction level assigned by

customer q with respect to the whole hotel (or set of hotels);

10) $\widehat{x}^{(q)} \in E$ represents the overall satisfaction level;

11) $v(x^{(q)}) : E \longmapsto [0,1]$ is a monotone non-decreasing value function of its argument $x^{(q)} \in E$; $v(x^{(q)})$ is the value function associated with each overall satisfaction score, and $v(c^1) = 0 \leq \ldots \leq v(c^l) \leq \ldots \leq v(c^L) = 1$;

12) $v_j\left(x_j^{(q)}\right) : E_j \longmapsto [0,1]$ is a monotone non-decreasing value function associated with the partial satisfaction score j, with $v_j\left(c_j^1\right) = 0 \leq \ldots \leq v_j\left(c_j^l\right) \leq \ldots \leq v_j\left(c_j^{L_j}\right) = 1$;

13) $\alpha^{(q)}$ is a free error variable associated with customer $q \in \{1, \ldots, u\}$; $\alpha^{(q)+}$ and $\alpha^{(q)-}$ are two non-negative error variables decomposed by $\alpha^{(q)}$, with $\alpha^{(q)+}$representing overestimation error and $\alpha^{(q)-}$ representing underestimation error.

Since $x^{(q)} \in E$ represents the level assigned by customer q to describe the overall satisfaction with the hotel, the value of $\widehat{x}^{(q)}$ is denoted by $v(\widehat{x}^{(q)})$. If an additive model can be used for aggregating partial values, then:

$$v(x^{(q)}) = \sum_{j=1}^{n} v_j\left(x_j^{(q)}\right) \tag{1}$$

where $x_j^{(q)} \in E_j$ represents the satisfaction level assigned by customer q regarding the criterion c_j. The overall satisfaction level of a customer q should be identical to the aggregating results; therefore, there should be no difference between $\widehat{x}^{(q)}$ and $x^{(q)}$, denoted as $\widehat{x}^{(q)} \sim x^{(q)}$, which means:

$$v(\widehat{x}^{(q)}) = v(x^{(q)}) \tag{2}$$

Given that errors are frequently present, a free error variable $\alpha^{(q)}$ is introduced into Eq. 2 as follows:

$$v(\widehat{x}^{(q)}) = \sum_{j=1}^{n} v_j\left(x_j^{(q)}\right) + \alpha^{(q)} = \sum_{j=1}^{n} v_j\left(x_j^{(q)}\right) - \alpha^{(q)+} + \alpha^{(q)-} \tag{3}$$

where $\alpha^{(q)+}$ and $\alpha^{(q)-}$ are two non-negative error variables decomposed by $\alpha^{(q)}$, with $\alpha^{(q)+}$representing overestimation error and $\alpha^{(q)-}$ representing underestimation error.

Observing Eq. 3, similarities between the MUSA method and the principles of goal programming modeling and ordinal regression analysis can be found. The problem of evaluating customer satisfaction in luxury hotels can be formulated as an optimization problem by using goal programming. The estimation model can be represented with a linear programming formulation as follows (Ferreira et al., 2018):

$$\min z = \sum_{q=1}^{u} \left(\alpha^{(q)+} + \alpha^{(q)-}\right) \tag{4a}$$

subject to:

$$v(c^L) - v(x^{(q)}) = \left(\sum_{j=1}^{n} v_j\left(c_j^{L_j}\right) - v_j\left(x_j^{(q)}\right)\right) - \alpha^{(q)+} + \alpha^{(q)-}, \quad q = 1, \ldots, u \tag{4b}$$

$$v(c^l) - v(c^{l-1}) \geq 0, \quad l = 2, \ldots, L \tag{4c}$$

$$v_j\left(c_j^l\right) - v_j\left(c_j^{l-1}\right) \geq 0, \quad j = 1, \ldots, n, \quad l = 2, \ldots, L_j \tag{4d}$$

$$v(c^L) = 1 \tag{4e}$$

$$v(c^1) = 0 \tag{4f}$$

$$\sum_{j=1}^{n} v_j\left(c_j^{L_j}\right) = 1 \tag{4g}$$

$$v_j\left(c_j^1\right) = 0, \quad j = 1, \ldots, n \tag{4h}$$

$$v(c^l) \geq 0, \quad l = 2, \ldots, L-1 \tag{4i}$$

$$v_j\left(c_j^l\right) \geq 0, \quad j = 1, \ldots, n, \quad l = 2, \ldots, L_j \tag{4j}$$

$$\alpha^{(q)+}, \quad \alpha^{(q)-} \geq 0, \quad q = 1, \ldots, u \tag{4k}$$

The following provides a brief description of each equation of the previous model.

(4a) It is an objective function that involves minimizing the sum of the non-negative error variables, $\alpha^{(q)+}$ and $\alpha^{(q)-}$, for all $q \in \{1, \ldots, u\}$ (Grigoroudis and Siskos, 2002). This objective function strives to reduce the deviation (inconsistency) between customers' overall and partial judgments. A well-known concept in linear programming is that both deviations cannot be positive simultaneously. If the value of the objective function is zero, it signifies that all the information provided by the customers at the comprehensive level and the per-criterion levels is consistent. If not, some inconsistencies may arise.

(4b) It models the indifference relation between the overall satisfaction and the conjoint aggregation of the partial or the per-criterion satisfactions. The gap between the values of the highest satisfaction level and the overall qth judgment must equal the gap between the aggregated results, plus an error term (Ferreira et al., 2018).

(4c) It demonstrates that the value function $v(\bullet)$ is a non-decreasing monotonic function.

(4d) It demonstrates that the value function $v_j(\bullet)$ is a non-decreasing monotonic function.

(4e) It assumes that the value of the best performance is unitary, meaning that no satisfaction level is better than the highest one.

(4f) It assumes that the worst satisfaction level has a value of zero, which means that there is no satisfaction level worse than the lowest one, $l = 1$. Constraints (4e) and (4f) establish that the overall satisfaction value is limited to the range of [0, 1].

(4g) It indicates that the cumulative value of the best performance in all criteria equals the best performance's value in overall judgments.

(4h) It assumes that the partial value of the worst performance in each subcriterion is zero. Similarly, the cumulative value of the lowest satisfaction level in all subcriteria must be null.

(4i) Constraints (4i)–(4k) establish the non-negativity of the variables to be optimized.

3.2. The Kano model and its adapted version applied to the MUSA model

3.2.1. A brief overview of the Kano model

Introduced by Kano et al. (1984), the Kano model is a two-dimensional model that elucidates the asymmetric and nonlinear relationship between product/service performance and customer satisfaction. The Kano model is a valuable tool for identifying priority areas for improvement to rectify under-performance in the product's features, thereby increasing customer satisfaction. It has been applied across diverse fields, such as environment (Dace et al., 2019; Batwara et al., 2022; Chen et al., 2022b), banking and finance (Suzianti et al., 2021; Paul et al., 2022), tourism and hospitality (Shen et al., 2021; Pandey et al., 2022; Yılmaz Kaya, 2022; Wang et al., 2023; Zhao et al., 2023; Zhou and Yao, 2023), and healthcare (Ferreira et al., 2018; Materla et al., 2019; Chen et al., 2020; de Vasconcelos et al., 2023; Wachinger et al., 2023), to improve understanding and optimize the design and development of products and services.

The Kano model categorizes product/service features into five types (Kano et al., 1984): must-be/ basic qualities, one-dimensional/

performance qualities, attractive/ excitement qualities, indifferent qualities, and reverse qualities. The descriptions of these five categories are as follows:

(1) **Must-be qualities:** these are the requirements that customers expect and take for granted. When these requirements are fulfilled, customers remain neutral as they consider them granted; however, when they are not met, customers become very dissatisfied.
(2) **One-dimensional qualities:** these are the requirements that have a positive linear relationship with customer satisfaction. In other words, when these requirements are fulfilled, customer satisfaction increases, and vice versa.
(3) **Attractive qualities:** these are the requirements that contribute to customer satisfaction when present, but do not cause dissatisfaction when absent.
(4) **Indifferent qualities:** these are the requirements for which the presence or absence results in neither satisfaction nor dissatisfaction.
(5) **Reverse qualities:** these are the requirements that have a negative and linear relationship with customer satisfaction, leading to customer dissatisfaction whenever present and vice versa. While infrequent, they can happen on occasion.

In Yang's (2005) enhancement of the Kano model, known as the refined Kano model, he added customers' attention to specific quality factors and integrated the original two-dimensional model with an assessment of the perceived importance of each quality factor. The refined Kano model categorizes quality elements into eight distinct categories, as shown in Fig. 2. Table 2 outlines the eight categories in the refined Kano model, highlighting their relationships with the categories of the original Kano model, as well as their corresponding importance.

The Kano model's categories adhere to a hierarchical rule for establishing the order of improvement priority: must-be qualities> one-dimensional qualities> attractive qualities> indifferent qualities (Wang et al., 2023). In correspondence with that order, the improvement priority for refined categories in the refined Kano model is as follows: critical qualities> necessary qualities> high value-added qualities> low value-added qualities> highly attractive qualities>less attractive qualities> potential qualities >care-free qualities. Analyzing the refined category to which each criterion belongs enables the identification of the corresponding priority for improvement. This facilitates efficient resource management to improve customer satisfaction. This paper utilizes the MUSA model in conjunction with the refined Kano model to achieve this process. Further details can be found in Section 3.2.2.

3.2.2. *Refined Kano-MUSA (ReK-M) analysis*

The ReK-M analysis involves using the MUSA model to generate overall weights for each criterion, as well as weights associated with

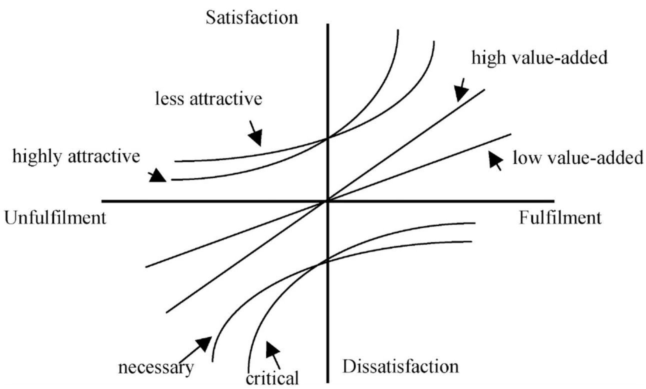

Fig. 2. Eight categories in the refined Kano model (Yang, 2005).

Table 2
Refined categories description and comparison.

Categories in the Kano model	Refined Kano model		
	Refined categories	**Description**	**Importance**
Must-be	critical qualities	They must be sufficiently provided due to their high importance to customers.	high
	necessary qualities	They must be provided with a specific standard of service to prevent customer dissatisfaction, although they are not deemed critical.	low
One-dimensional	high value-added qualities	They should be committed to providing to customers as they can generate high customer satisfaction.	high
	low value-added qualities	They contribute less to customer satisfaction, but should be provided to prevent customer dissatisfaction.	low
Attractive	highly attractive qualities	They could be provided as strategic qualities to attract more customers, thereby enhancing customer satisfaction and market competitiveness.	high
	less attractive qualities	They could not be provided if the company had cost considerations, given their limited ability to attract customers.	low
Indifferent	potential qualities	They might be provided when there is potential to attract customers, although it is also necessary to consider the company's costs and the level of attractiveness they might have.	high
	care-free qualities	They should not be provided if the company is mindful of cost considerations, aiming to effectively manage limited resources.	low

satisfied and dissatisfied customers, and then conducting weight comparisons to identify the refined category to which each criterion belongs. Fig. 3 shows the rules, as defined by Ferreira et al. (2018), for comparing these weights to identify the belonging category of each criterion.

As illustraed in Fig. 3, criterion c_j is considered "must-be critical" under the conditions $w_j^d > w_j^s$ and $w_j > \overline{w_j}$. If $w_j^d > w_j^s$ but $w_j < \overline{w_j}$, then this criterion is deemed "must-be necessary," and so forth. The notation included in Fig. 3 represents the following meanings:

1) c_j is the jth criterion of set C, with $j = 1, \ldots, n$ (see also Section 3.1.2);

2) w_j represents the overall weight for the jth criterion, $w_j = v_j\left(c_j^{L_j}\right)$;

3) $\overline{w_j}$ represents the average value of the overall weights associated with various criteria, $\overline{w_j} = \frac{\sum_{j=1}^{n} w_j}{n}$, n represents the total number of criteria, $\sum_{j=1}^{n} w_j = 1$;

4) w_j^s represents the weights associated with satisfied customers for the jth criterion, $w_j^s = v_j^s\left(c_j^{L_j}\right)$;

5) w_j^d represents the weights associated with dissatisfied customers for the jth criterion, $w_j^d = v_j^d\left(c_j^{L_j}\right)$.

As observed in the notation above, the computation of weights, whether for criterion overall weight or weights related to satisfied or dissatisfied customers for each criterion, follows the MUSA model's principles (refer to Section 3.1.2 for the model's equations). The main difference lies in the data used to calculate the weights. The data used to

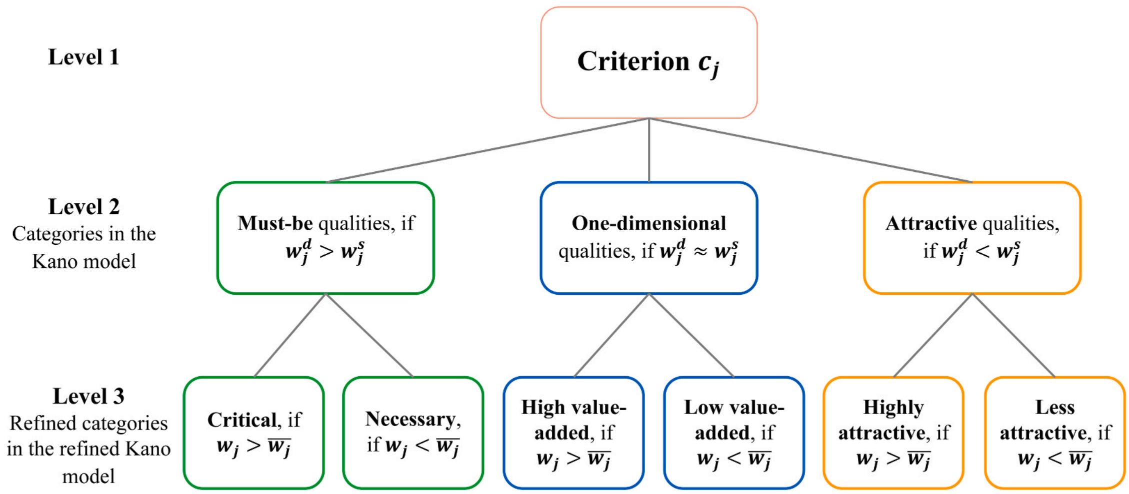

Fig. 3. Weight comparison rules for identifying criterion categories, adapted from (Ferreira et al., 2018).

calculate the overall weights is derived from the overall rating of customer reviews, without distinguishing whether those reviews express satisfaction or dissatisfaction. Nevertheless, when computing the weights related to satisfied or dissatisfied customers, it becomes essential to differentiate whether customer reviews express satisfaction or dissatisfaction. In the case study of this paper, customer reviews with an overall rating of 4 or 5 are considered satisfied, while those below are considered dissatisfied. Although there might be arguments about a rating of 3 representing a neutral level (neither satisfied nor dissatisfied), many studies have shown that an overall rating of 3 indicates service failure for most potential customers (Gunasekar and Sudhakar, 2019; Chen et al., 2022a). Consequently, customer reviews with a 3 overall rating also express customer dissatisfaction.

In addition, this paper creates a category-priority diagram to compare weights, providing a novel visual representation for ReK-M analysis results. This diagram simplifies the comparison of priority among different criteria, aiding understanding and interpretation of results. It provides a clear demonstration of the aspects that require improvement to prevent customer dissatisfaction, along with the identification of enhancements in specific aspects that can elevate customer

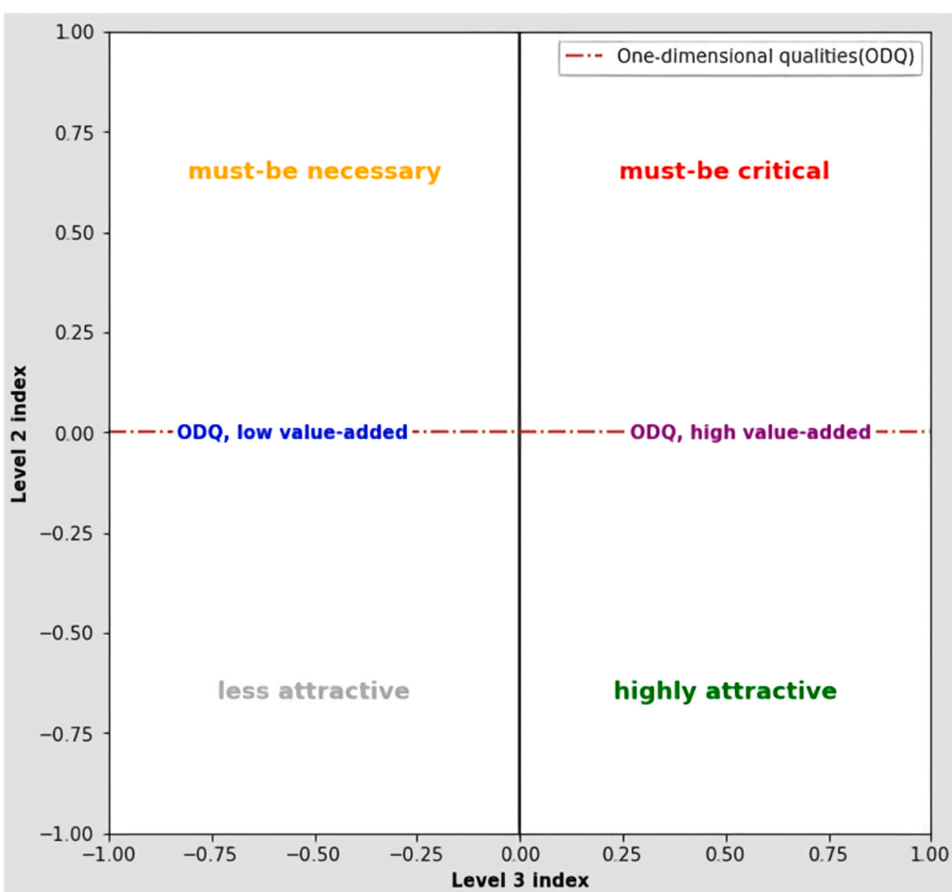

Fig. 4. Category-priority diagram.

satisfaction and contribute to gaining a competitive edge in the market. Fig. 4 displays the category-priority diagram, with the x-axis denoting level 2 index for determining Kano model categories and the y-axis representing level 3 index for determining refined categories. Level 2 index is obtained by subtracting w_j^s from w_j^d, if the resulting value is greater than 0, the category "Must-be" is assigned; if it is approximately 0, the category "One-dimensional" is assigned; and if it is less than 0, the category "Attractive" is assigned. Level 3 index is obtained by subtracting $\overline{w_j}$ from w_j, if the resulting value is positive, the refined category could be assigned as "critical," "highly attractive," or "high value-added," depending on the category assigned at Level 2; if not, the refined category could be assigned as "necessary," "less attractive," or "low value-added," depending on the category assigned at Level 2.

4. Case study

This section presents the application of ReK-M analysis to a case study involving online reviews, starting with data collection and selected criteria, and culminating in determining weights to identify priority improvement areas.

4.1. Data collection and selected criteria

A web-scarping using Python programming language was done to retrieve the data for satisfaction ratings (overall satisfaction, and satisfaction with eight criteria about the hotel: Location, Rooms, Cleanliness, Service, Check-in/front desk, Business service, Sleep quality, and Value). 745,062 customer reviews from the 457 luxury hotels were extracted from TripAdvisor in November 2022. However, fewer than one percent contained the sub-ratings of all eight criteria. In fact, on TripAdvisor, the overall rating is mandatory but sub-ratings are not. As shown in Table 3, "Check-in/front desk" and "Business service" are two criteria that are rarely rated. Only a few customers rated them (approximately 1 %).

Furthermore, although the number of reviews containing sub-ratings for "Value" is not insignificant, assessments of this criterion differ from other criteria as they also encompass customer overall satisfaction (i.e., overall rating), which could potentially diminish the significance of the model results. Zeithaml (1988) defined perceived value as “the customer’s overall assessment of the utility of a product based on perceptions of what is received and what is given.” Similarly, Bagnera (2017) described value as “the price paid for the room compared to the overall guest experience.” These definitions suggest that "Value” represents an aggregate judgment formed after customers evaluate specific aspects of their stay, making it conceptually similar to an overall rating. Moreover, based on the correlation analysis of the dataset collected in this paper, "Value" exhibits a strong positive correlation with "Overall rating" ($r = 0.746$), indicating a high degree of association that may introduce redundancy. Further analysis reveals notable multicollinearity with other criteria, as "Value" also shows strong correlations with "Rooms"(0.666), "Service" (0.664), "Cleanliness" (0.574), and "Sleep Quality" (0.581). This suggests that the information captured by "Value" significantly overlaps with these more specific indicators. Criteria such as "Rooms", "Service", and "Cleanliness" represent more concrete and distinguishable facets of customer experience; therefore, excluding "Value" is a reasonable step to reduce multicollinearity and mitigate potential impacts on the analysis results. Only customer reviews that contain an overall rating and all sub-ratings about five criteria (i.e., $C = \{c_1 = Service, c_2 = Cleanliness, c_3 = Location, c_4 = Rooms, c_5 = Sleep\ quality\}$) are analyzed, resulting in a total of 201,905 reviews from 355 luxury hotels. TripAdvisor employs a 5-point rating scale for both overall and sub-ratings, with the following descriptions: 1 ("Terrible"), 2 ("Poor"), 3 ("Average"), 4 ("Very Good"), and 5 ("Excellent").

Table 3
Coverage statistics for the overall rating of hotels and the sub-ratings of their eight criteria.

Criterion	Number of reviews	Coverage (%)
Overall rating	745,062	100
Service	488,698	65.6
Cleanliness	342,200	45.9
Value	341,389	45.8
Location	334,468	44.9
Rooms	331,659	44.5
Sleep Quality	303,244	40.7
Check in / front desk	8879	1.2
Business service	5821	0.8

4.2. Data validation

Using the MUSA model, it is essential to calculate the weights for each criterion based on the global evaluation (i.e., overall rating). If the overall rating of a customer review exactly matches the sub-ratings for all five criteria—meaning all scores are identical—it leads to redundancy in the MUSA model. Therefore, this paper eliminated customer reviews exhibiting such redundancy. Table 4 shows the distribution of the remaining 13,951 reviews across the 10 cities studied. These reviews were selected after eliminating those that would lead to redundancy in the MUSA model. This table also provides details on the number of luxury hotels in each city, their corresponding average overall ratings, and the ideal sample size calculated for each city at a 95 % confidence level.

The ideal sample size is determined using an approach that considers the proportion of a finite population; the equation for calculating the sample size can be found in Pereira et al. (2017). Since the number of reviews for each city varies, the ideal sample size differs for each city. The maximum ideal sample size from the 10 cities is utilized to maintain uniform sample sizes across these cities and to ensure that the error rate does not exceed 5 %. As shown in Table 4, this size is 335, and it is randomly selected from each city’s dataset for running the MUSA model.

4.3. Data classification

To achieve the goal of this paper, which is to compare customer satisfaction in the top 10 European tourist cities’ luxury hotels and identify priority areas for improvement in each city, it is necessary to assess whether customers are satisfied or not based on the overall rating of each review. As mentioned in Section 3.2.2, customer reviews are classified as satisfied if they have an overall rating of 4 or 5, whereas those with ratings below this threshold are considered dissatisfied. Fig. 5 shows the distribution of satisfied and dissatisfied customer reviews across the 10 cities studied.

The ideal sample size for both satisfied and dissatisfied reviews is determined following the equation mentioned in Section 4.2. The maximum ideal sample size for satisfied reviews across the 10 cities is 230, and for dissatisfied reviews, this size is 323. The sample to be used

Table 4
Distribution of hotel numbers and reviews.

City*	Number of luxury hotels	Number of reviews	Average overall rating	Ideal sample size
Paris	56	1585	2.7913	310
Amsterdam	19	1139	2.9236	288
Madrid	27	1382	2.9645	301
Rome	46	1616	2.8428	311
Berlin	23	1262	2.9794	295
London	78	2562	2.6854	335
Munich	7	873	2.9645	267
Barcelona	30	1749	2.8650	315
Vienna	15	1017	2.9921	279
Milan	19	766	3.1436	256

* The cities are sorted in accordance with the list of the top 10 European cities published by Euromonitor (2021).

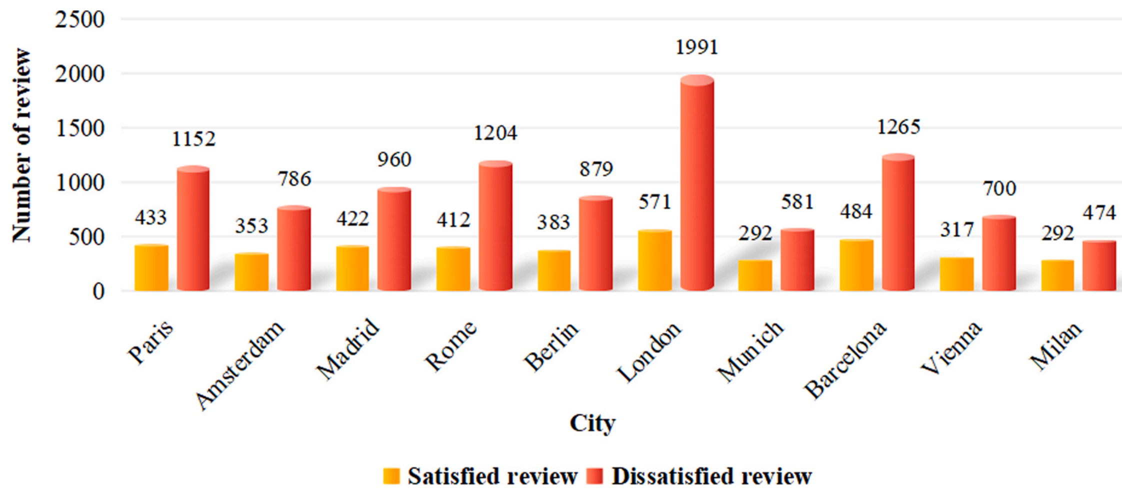

Fig. 5. Distribution of satisfied and dissatisfied customer reviews.

in running the MUSA model is randomly selected from the datasets of satisfied and dissatisfied reviews for each city, adhering to the size of the maximum ideal sample obtained.

4.4. Weights determination

The weights for each criterion are determined by calculating the average of the weight outputs obtained from 5000 runs of the MUSA model on random samples. These samples are drawn from three distinct datasets: overall customer reviews (for calculating overall weights, i.e., w_j), satisfied customer reviews (for calculating weights associated with satisfied customers, i.e., w_j^s), and dissatisfied customer reviews (for calculating weights associated with dissatisfied customers, i.e., w_j^d). Table 5 shows the diverse weights associated with various hotel criteria for each city.

As the five hotel criteria were studied in this paper, the average value of the overall weights associated with various criteria is calculated as $\overline{w_j} = \frac{\sum_{j=1}^{n} w_j}{n} = \frac{100\%}{5} = 20\%$. By adhering to the weight comparison rules illustrated in Fig. 3, the categories in the Kano model and those in the refined model can be assigned to each hotel criterion for every city. For example, in Parisian luxury hotels, both the "Rooms" and "Service" criteria are categorized as "Must-be" criteria, with "Rooms" labeled as "must-be critical" and "Services" identified as "must be necessary." This implies that, in Parisian luxury hotels, both Rooms and Services are essential requirements customers take for granted, which must be fulfilled to prevent customer dissatisfaction, with "Rooms" being more important than "Service". For further details on the assignment of categories to each hotel criterion in every city and the analysis of the results, refer to Section 5.

5. Results

This section introduces an interactive visualization application developed in this paper using the programming language Python (version 3.9). The application leverages several libraries, including *pandas*, *scikit-learn*, *numpy*, *panel*, and *matplotlib*, among others. This interactive visualization application is designed to simplify the presentation and automated interpretation of ReK-M analysis results, providing data-driven recommendations that guide decision-makers toward actions aimed at improving customer satisfaction, while also supporting the reproducibility of the experiment. Fig. 6 shows the three interfaces designed within this application. The first interface provides a brief introduction and explains what can be visualized in each interface.

The "Results Visualization" interface features two graphical elements to present the findings: (1) a bar chart that enables straightforward comparison of the weights assigned to each hotel criterion, including overall weights as well as those specific to satisfied and dissatisfied customers; and (2) a category-priority diagram for each city, which displays the refined category assigned to each criterion based on the comparison of these weights. This visualization facilitates a clearer understanding of criterion prioritization and aids in the rational allocation of resources to enhance customer satisfaction. Fig. 7 illustrates this interface using the cases of Rome and Berlin as examples.

As shown in Fig. 7, whether it is luxury hotels in Rome or Berlin, the "Service" criterion is considered an essential quality that customers take for granted. This criterion requires sufficient attention to avoid customer dissatisfaction. In the case of Berlin, however, the "Rooms" criterion emerges as even more critical than "Service." It should be prioritized for improvement and adequately provided to prevent significant customer dissatisfaction. In contrast, for luxury hotels in Rome, the "Rooms" criterion is identified as a highly attractive quality—one that can be

Table 5
Weights (%) of each hotel criterion for every city.

City	Rooms			Service			Cleanliness			Sleep Quality			Location		
	w_j	w_j^s	w_j^d	w_j	w_j^s	w_j^d	w_j	w_j^s	w_j^d	w_j	w_j^s	w_j^d	w_j	w_j^s	w_j^d
Paris	78.01	9.40	84.60	10.38	0.40	15.40	7.89	13.60	-	0.79	1.40	-	2.93	75.20	-
Amsterdam	47.12	46.00	30.50	14.93	22.20	69.50	5.24	1.20	-	1.05	2.60	-	31.66	28.00	-
Madrid	11.07	4.20	98.30	44.95	67.20	1.70	39.50	21.40	-	3.31	0.40	-	1.17	6.80	-
Rome	38.79	59.60	42.37	14.36	2.00	57.26	15.14	31.60	0.20	7.19	6.60	0.07	24.52	0.20	0.10
Berlin	25.90	24.80	46.50	0.10	2.00	50.90	24.00	14.40	-	0.20	-	0.20	49.80	58.80	2.40
London	46.16	11.80	96.20	22.40	-	3.40	7.07	20.60	-	1.34	-	0.40	23.03	67.60	-
Munich	8.86	8.40	36.97	18.83	5.00	62.96	49.21	74.80	-	14.15	7.00	0.07	8.95	4.80	-
Barcelona	35.76	43.60	23.10	35.80	2.60	76.80	14.57	49.00	0.10	6.27	0.40	-	7.60	4.40	-
Vienna	31.69	24.40	24.49	7.65	3.20	73.43	15.88	16.20	0.24	1.55	0.40	0.11	43.23	55.80	1.73
Milan	34.85	48.60	39.00	21.85	5.60	61.00	22.27	44.20	-	2.03	0.20	0.00	19.00	1.40	-

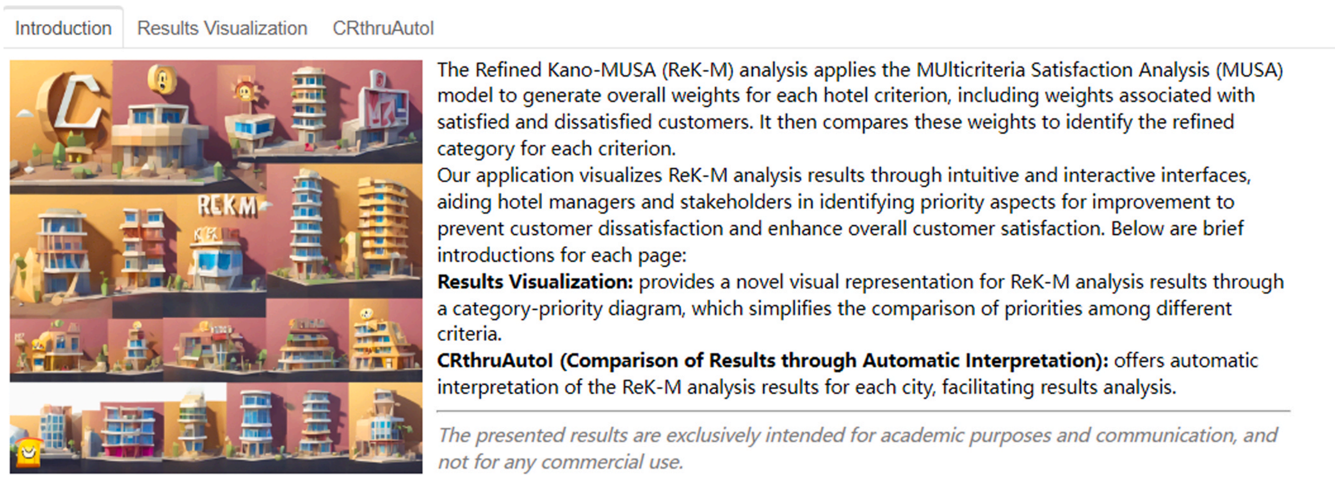

Fig. 6. Interfaces of the interactive visualization application.

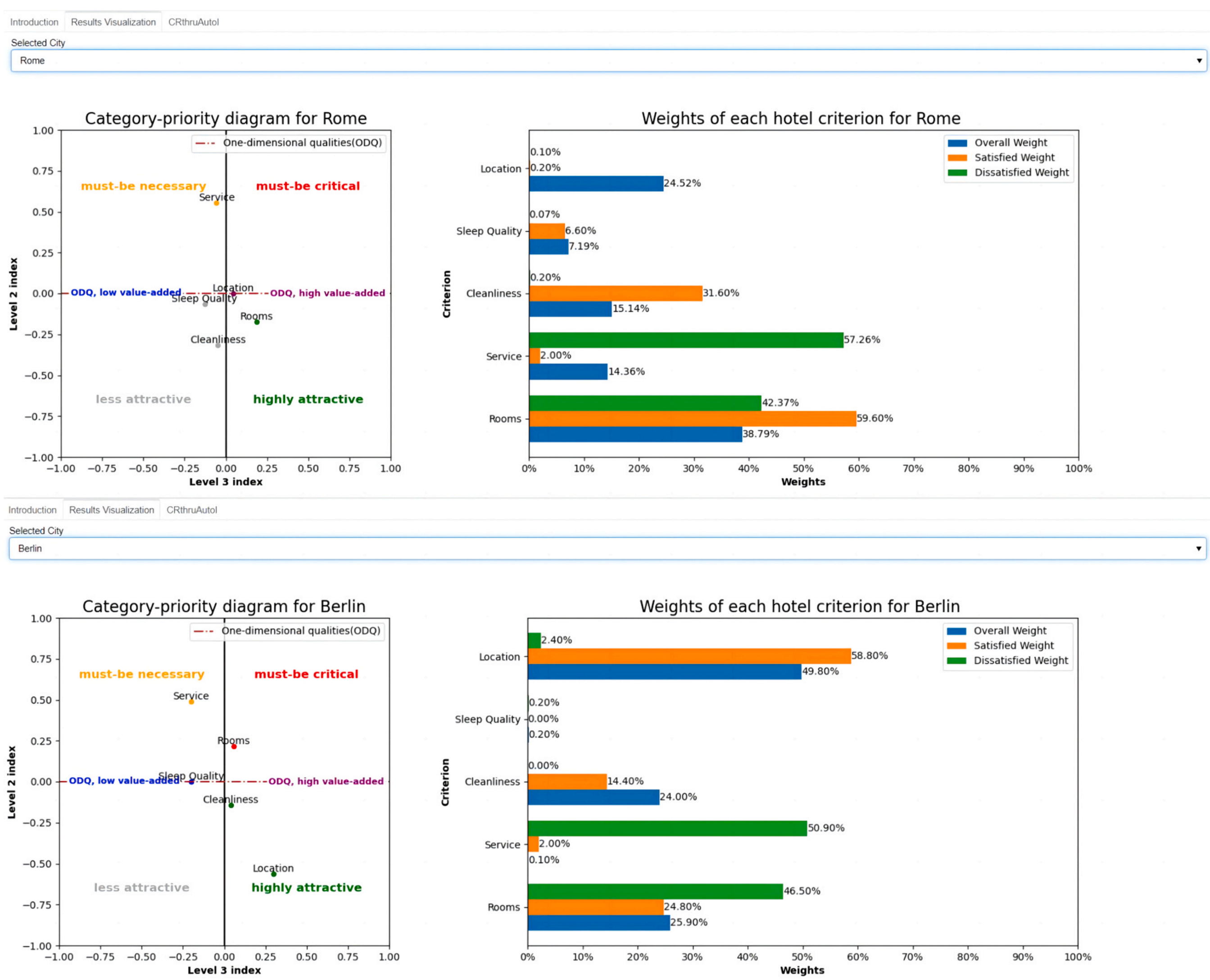

Fig. 7. Interfaces of the interactive visualization application.

strategically leveraged to enhance customer satisfaction and strengthen market competitiveness. Even so, compared to the "Service" criterion, the "Rooms" criterion does not require immediate attention for improvement in luxury hotels in Rome, as its absence does not lead to customer dissatisfaction.

The "CRthruAutoI" interface automates the interpretation of the category-priority diagram for each city and facilitates the comparison of ReK-M analysis results across selected cities, providing data-driven recommendations that guide decision-makers toward efficient actions aimed at improving customer satisfaction. In this interface, one or more cities can be chosen to compare the order of improvement priority for hotel criteria in each city, along with the automatic interpretation. Fig. 8 shows the automated interpretations generated by the interface when a single city is selected (e.g., Madrid) and when two cities are selected for comparison (e.g., Rome and Berlin).

As demonstrated in Fig. 8, in luxury hotels in Madrid, the highest priority for improvement is given to the "Rooms" criterion, which is considered essential to meet customer expectations and avoid dissatisfaction. For luxury hotels in Rome, by contrast, the "Service" criterion emerges as the most urgent area for improvement. Moreover, although the primary focus for improvement is on the "Rooms" criterion in luxury hotels in Madrid and Berlin, the hotel criterion with secondary priority for enhancement differs between them. In Madrid, the "Sleep Quality" criterion is the next most important criterion. Although it contributes less to increasing customer satisfaction, it should still be maintained to prevent customer dissatisfaction. In Berlin, however, the "Service" criterion holds the second highest priority. As an essential quality that customers take for granted, it must be adequately fulfilled to prevent customer dissatisfaction, although it is considered less critical than the must-be criterion (i.e., "Rooms").

These distinctions underscore the utility of the interface's automated interpretations. Not only do they clarify how criteria are prioritized within each city, but they also provide a structured and easily digestible comparison when examining cities side by side. The ability to distinguish between must-be, one-dimensional, and attractive qualities across multiple urban contexts enables hotel managers, policymakers, and stakeholders to align their strategies with the unique satisfaction drivers of each market, thereby guiding more targeted improvements. Furthermore, this interface supports cross-city comparisons, which is particularly valuable for hotel chains operating in multiple locations. It allows them to tailor service offerings and prioritize investments based on the specific needs and expectations of the target clientele, thereby enhancing both customer satisfaction and competitive positioning within the European luxury hotel market.

By comparing the analysis results across the top 10 European tourist cities—Paris, Amsterdam, Madrid, Rome, Berlin, London, Munich, Barcelona, Vienna, and Milan—it becomes clear that luxury hotels in these cities prioritize core service attributes differently depending on the specific market context. Overall, while criteria such as "Service" and "Rooms" are commonly regarded as must-be necessary or must-be critical qualities, their relative importance and influence on customer satisfaction vary from city to city. Similarly, attributes like "Location," "Cleanliness," and "Sleep Quality" show significant differences in perceived value. For instance, "Location" is considered a highly attractive quality in cities such as Vienna, Berlin, London, and Amsterdam, but is viewed as less important in markets like Madrid, Barcelona, Milan, and Munich. "Cleanliness" and "Sleep Quality" are generally seen as lower-priority areas; however, in cities like Berlin, Munich, and Milan, "Cleanliness" stands out as a highly attractive quality that warrants more attention.

6. Discussion

This section explores the theoretical and practical implications of this paper. It also discusses potential limitations that merit further attention.

In contrast to previous studies that typically apply either the MUSA model or the refined Kano model to analyze questionnaire data, this paper demonstrates the feasibility of using both models to analyze online customer reviews and extract actionable insights for decision-making. By collecting online reviews from TripAdvisor, a comparative survey of luxury hotel customer satisfaction is conducted across the top 10 European tourist cities. The ReK-M analysis—combining the MUSA model and the refined Kano model—is used to determine improvement priorities for various hotel service criteria.

This paper illustrates how to transform online reviews into a data

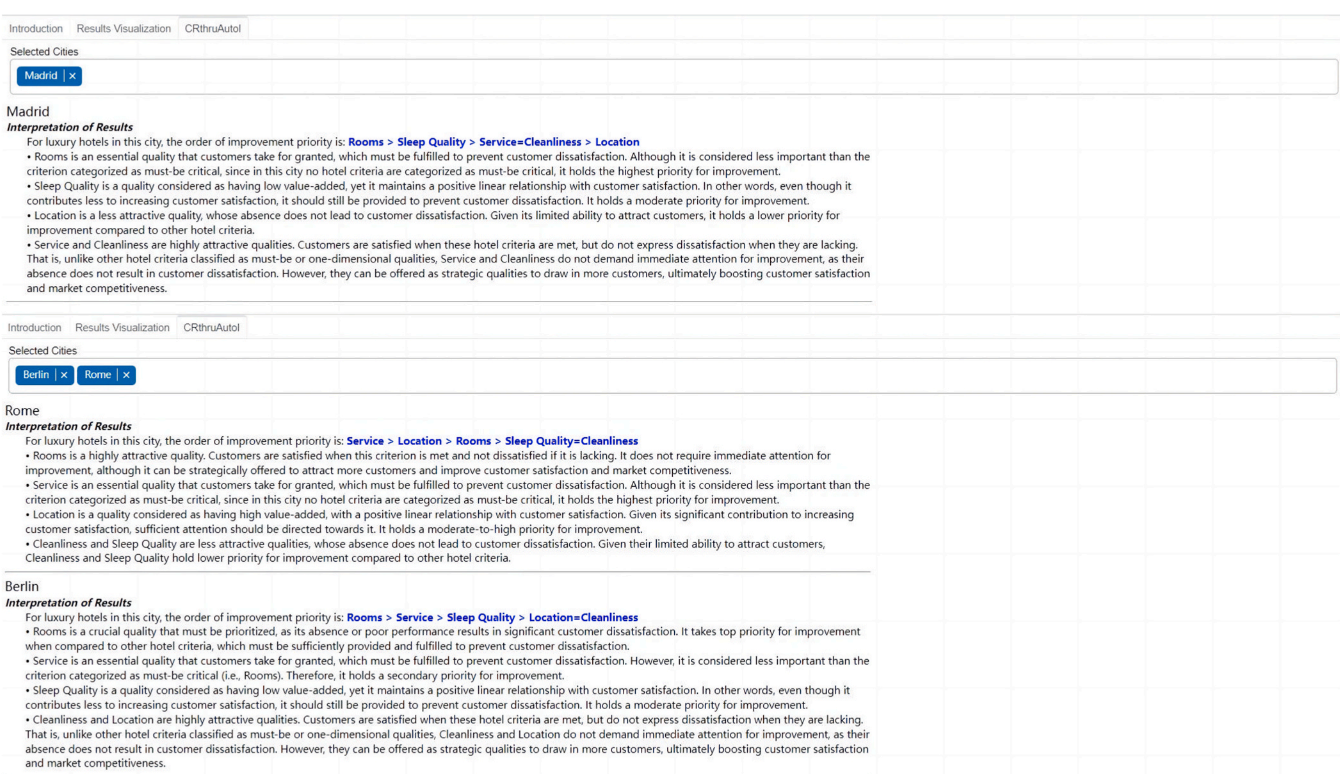

Fig. 8. Examples of the "CRthruAutoI" interface.

structure suitable for application in the MUSA model, enabling the calculation of overall weights as well as weights associated with satisfied and dissatisfied customers. These weights are then used to assign refined Kano categories to each hotel criterion, following predefined weight comparison rules (see Fig. 3). Additionally, a category-priority diagram is introduced to summarize the refined categories and visualize the relative importance of each hotel criterion more intuitively. To further support practical decision-making, an interactive visualization application is developed using Python. This application streamlines the presentation of results and automates the interpretation of the category-priority diagram for each city. It also facilitates comparisons of ReK-M analysis results across cities, offering data-driven recommendations that help decision-makers take effective actions to enhance customer satisfaction. These features collectively enhance the practical utility and interpretability of ReK-M analysis, making it a useful tool for real-world decision-making.

As discussed in Section 5, while criteria such as "Service" and "Rooms" are frequently identified as must-be necessary or must-be critical in luxury hotels across the 10 European cities analyzed in this paper, their relative importance and influence on customer satisfaction vary significantly from city to city. These differences can be attributed to several interrelated factors, including the primary purpose of travel (e.g., business vs. leisure), prevailing cultural expectations, socio-economic conditions, and the unique character of each city's tourism market. For example, in a historically rich city like Rome, where "Service" is regarded as a must-be necessary quality and "Location" as a high value-added quality, this likely reflects the preferences of luxury leisure travelers who prioritize seamless access to iconic cultural and historical landmarks. In such a context, an exceptional location significantly enhances the overall guest experience, even if other attributes meet only standard expectations.

Conversely, in Madrid, which functions as both a major business hub and a vibrant cultural destination, luxury hotel guests often hold dual expectations. They seek the efficiency and professionalism required for business travel, along with the warmth and personalized service that reflects Spanish hospitality. This is evident in the ReK-M results, where "Service" is categorized as a highly attractive quality, meaning that superior performance in this area significantly boosts guest satisfaction. Meanwhile, "Rooms" are classified as a must-be necessary quality, indicating that a certain level of comfort and functionality is expected as a baseline, with any shortfall likely to result in dissatisfaction. In Berlin, a city that blends creative innovation with a strong business ecosystem, luxury travelers show a clear preference for modern, high-functioning accommodations. Here, "Rooms" are identified as a must-be critical quality and "Service" as a must-be necessary quality, suggesting that comfort, contemporary design, and professional service are essential expectations. These preferences align with the city's reputation for progressive urban culture, technology, and design-conscious clientele.

To summarize, the main theoretical and practical contributions of this paper are as follows:

1) From a theoretical standpoint, this paper fills a gap in the literature by applying the MUSA model and examining its potential when integrated with the Kano framework to analyze customer satisfaction in luxury hotels using online reviews. In this context, this paper introduces the category-priority diagram, a novel tool designed to facilitate the comparison of different hotel criteria. In this diagram (see Fig. 4), the x-axis represents the difference in weights between satisfied and dissatisfied customers for each criterion—used to classify them according to Kano model categories (Kano et al., 1984; Berger et al., 1993)—while the y-axis compares the overall weight of each criterion to the average, thereby determining its refined category. Functioning similarly to a decision matrix, the category-priority diagram helps to visually and intuitively identify which criteria should be improved to avoid customer dissatisfaction, and which should be enhanced to boost satisfaction and strengthen market competitiveness.

2) From a practical standpoint, this paper presents a prescriptive analytical framework through an interactive visualization application that translates complex model outputs into accessible insights, while promoting reproducibility and transparency in the decision-making process. It is specifically designed to bridge the well-documented "analytics-to-action" gap, where complex data insights often fail to be implemented by managers due to a lack of technical expertise or accessible interfaces (Han and Schulz, 2023). By offering automated interpretation and a user-friendly visual format, the application empowers decision-makers (e.g., hotel managers, policymakers, and tourism stakeholders), particularly those without strong analytical backgrounds, to make informed, data-driven decisions. More than just identifying areas for improvement, this provides actionable guidance on how to take action, effectively transforming analysis into strategic decision-making. For instance, by highlighting "must-be critical" or "must-be necessary" criteria, managers can allocate resources more precisely to prevent customer dissatisfaction, thereby transforming analysis results into a forward-looking enhancement strategy.

Despite the above contributions, certain limitations of this paper need addressing. The order of priority improvement in criteria is limited to adhering to a hierarchical rule based on theory, without taking into account the business objectives of each organization. For example, for hotel managers, the order of improvement could be slightly different, depending on their goal—whether the focus is on enhancing customer satisfaction, increasing revenue, or promoting hotel sustainability. Recognizing these diverse objectives is crucial for effectively adjusting prioritization. Another limitation is that the timeliness of online reviews has not been considered when calculating the weights to determine the order of improvements. Older reviews may not accurately reflect the current level of satisfaction that customers have regarding distinct hotel criteria. Additionally, seasonal variations can have a significant impact on customer satisfaction. For example, a hotel might receive more dissatisfied reviews in off-peak seasons due to reduced services or amenities (e.g., no open swimming pool), even though it excels during peak times. In the category-priority diagram, one limitation exists in that debates may arise when a criterion's corresponding point lies very close to the boundary lines separating different zones. Although this issue can be resolved using the "CRthruAutoI" interface that offers automatic interpretation of each criterion category, the diagram's size limitation should be addressed to enhance clarity in categorization. Finally, although this paper collects a substantial volume of customer reviews from TripAdvisor, it does not exploit advanced big data analysis or machine learning techniques that could uncover latent patterns, trends, and sentiments embedded within the unstructured textual data, thereby limiting the depth of the insights.

7. Conclusions and future work

Analyzing customer satisfaction always involves gathering feedback, assessing experiences, and identifying areas for improvement to increase customer satisfaction. While traditional methods such as questionnaires, interviews, and focus groups remain relevant, the development of the Internet has made online reviews and social media platforms increasingly crucial for the analysis of customer satisfaction. This paper collects customer reviews from TripAdvisor—one of the leading online review platforms—to conduct a comparative analysis of luxury hotel customer satisfaction across the top 10 European tourist cities, enabling broader cross-city comparisons. To determine the priority for improvements in hotel criteria, the MUSA model and the refined Kano model (i.e., ReK-M analysis) are employed.

The findings of this comparative survey are presented through an interactive application, incorporating the category diagram developed in this paper to summarize the refined category of each hotel criterion, along with an automated interpretation of the category-priority diagram for each city. This interactive application serves as a useful tool for hotel managers, policymakers, or stakeholders to identify hotel criteria that require attention to prevent customer dissatisfaction, as well as those that can enhance customer satisfaction or contribute to gaining a competitive edge in the market. It also allows comparing the results between different cities to find out their similarity and differences in areas for improvement. For example, while the primary focus for improvement is on the "Rooms" criterion in luxury hotels in Madrid and Berlin, the secondary priority for enhancement differs between the two cities.

The main contributions of this paper, along with some limitations that need to be addressed, have been discussed in Section 6. The following outlines some future work planned to resolve the limitations of this paper:

1) A flexible prioritization framework, which considers not only theoretical hierarchies but also aligns with the specific business objectives of individual organizations to determine the order of priority improvement in criteria, could be developed. This might entail conducting thorough interviews or surveys with hotel managers to understand their diverse goals.

2) Adding a scaling feature to the application could allow users to dynamically adjust the diagram's scale, enhancing flexibility in representing results.

3) Temporal factors could be incorporated into the weighting system for determining the order of improvements in hotel criteria. Additionally, exploring sentiment analysis techniques designed to capture temporal nuances in online reviews could contribute to a more dynamic and accurate assessment of customer satisfaction.

4) Integrating more advanced techniques, such as NLP, sentiment analysis, and deep learning, could enable the extraction of richer and more nuanced insights from the large-scale unstructured textual data, thereby significantly enhancing the accuracy and interpretability of the satisfaction analysis.

CRediT authorship contribution statement

Ziwei Shu: Writing – review & editing, Writing – original draft, Visualization, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ramón Alberto Carrasco:** Writing – review & editing, Visualization, Supervision, Software, Resources, Methodology, Funding acquisition. **José Rui Figueira:** Validation, Supervision, Project administration, Methodology, Investigation. **Diogo Cunha Ferreira:** Writing – review & editing, Validation, Methodology, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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