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Digital VoC analysis for product/service quality tracking in the era of Quality 4.0

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Abstract

Purpose – This study aims to explore how organizations can leverage digital voice-of-customer (VoC) data to effectively monitor and enhance the quality of products and services. Specifically, it investigates the application of the KA (key attribute) VoC Map, a novel analytical framework designed to systematically extract insights from digital customer feedback, categorize key product and service attributes and support continuous quality improvement in line with Quality 4.0 principles.

Design/methodology/approach – The KA-VoC Map leverages topic modeling algorithms to analyze customer feedback from digital platforms, identifying key attributes and categorizing them based on their frequency of discussion (mean topical prevalence) and associated sentiment (mean rating proportion). A case study involving smartwatch feedback collected from 2021 to 2024 demonstrates the practical implementation of the methodology.

Findings – The results reveal the utility of the KA-VoC Map in identifying and prioritizing key quality attributes, monitoring their evolution over time, and supporting continuous quality improvement.

Originality/value – This study introduces a novel methodological enhancement of the KA-VoC Map, demonstrating its use for dynamic quality tracking over time. This approach enables continuous monitoring of customer sentiment evolution, providing actionable insights for proactive quality management in the era of Quality 4.0.

Keywords Quality 4.0, Digital voice-of-customer, KA-VoC Map, Quality tracking, Customer satisfaction

Paper type Research article

List of abbreviations

Acronym	Definition
BERT	Bidirectional Encoder Representations from Transformers
KA	Key Attribute
LDA	Latent Dirichlet Allocation
MRP	Mean Rating Proportion
MTP	Mean Topical Prevalence
NLP	Natural Language Processing
PDCA	Plan-Do-Check-Act
STM	Structural Topic Model
TP	Topical Prevalence
VoC	Voice-of-Customer

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1. Introduction

Quality management is a strategic priority in today's competitive market (Dias *et al.*, 2022). Consumer expectations are constantly evolving. This evolution is driven by rapid technological advancements, greater access to information, and the proliferation of digital platforms (Bolton *et al.*, 2018; Broday, 2022). Furthermore, the increasing integration of physical product and service components stimulates further challenges (Barravecchia *et al.*, 2021). It is therefore necessary to develop specialized tools for quality design and management in order to effectively address these new complexities (Barravecchia *et al.*, 2020a, b, c).

Delivering high-quality products and services is a key market differentiator that can significantly influence organization's market position and long-term success (Mandal, 2020). To navigate this scenario, organizations must develop a deep understanding of customer needs and preferences (Ostrom *et al.*, 2021). This involves collecting and interpreting feedback and acting on it in a timely and effective manner (Escobar *et al.*, 2021; Bilal *et al.*, 2022). Traditional methods of gathering customer perceptions, such as surveys and focus groups, while valuable, often fall short in capturing the full spectrum of customer experiences and sentiments, particularly in the digital age where consumer voices are more fragmented and dispersed across various online platforms (Bi *et al.*, 2019; Mastrogiacomo *et al.*, 2021).

This raises a critical research question: *How can organizations effectively track and improve product and service quality by leveraging the insights embedded in the Digital Voice-of-Customer data?*

To address this challenge, a viable approach is the adoption of advanced tools, such as the KA-VoC Map. This tool is specifically designed to analyze Digital Voice-of-Customer (VoC) data—comprising insights derived from customer reviews, social media posts, forums, and other online interactions—and systematically categorize the key attributes (KAs) of products and services based on their frequency and associated sentiment (Barravecchia *et al.*, 2022b).

In addition to its traditional use for classifying key attributes, this study proposes an enhanced version of the KA-VoC Map that allows for dynamic tracking of quality perceptions over time. While prior research has largely emphasized static analyses of customer feedback, this approach offers a longitudinal perspective. This capability supports organizations in identifying emerging issues, assessing the impact of improvement actions, and making more informed, proactive decisions aligned with the Quality 4.0 paradigm (Broday, 2022; Dias *et al.*, 2022).

The remainder of the paper is structured as follows. Section 2 examines the challenges of analyzing digital VoC and the methodologies that can be used for this purpose. Section 3 introduces the KA-VoC map and the process for its development. Section 4 presents details on how the KA-VoC map can be applied to track quality over time. This is followed, in Section 5, by a practical case study. Section 6 contains the discussion, while the final section summarizes the key findings and offers suggestions for future research.

2. Literature review

2.1 Digital Voice of Customer (VoC) and its role in quality 4.0

Traditional methods for tracking product and service quality typically involve structured data collection techniques such as surveys, interviews, and focus groups (Lepistö *et al.*, 2024). These methods have provided valuable insights, enabling companies to measure customer satisfaction, identify areas of improvement, and monitor performance over time (Brits and du Plessis, 2007). Nevertheless, traditional approaches have significant limitations, including high costs, limited sample sizes, potential respondent biases, and the perception of intrusiveness, often resulting in delayed or insufficiently detailed feedback.

With the advent of Quality 4.0, organizations have increasingly shifted towards leveraging Digital Voice of Customer (digital VoC) data. Digital VoC refers to unsolicited customer feedback published online, such as product reviews on e-commerce sites, comments on social media, blogs, forums, and review aggregators (Barravecchia *et al.*, 2023). The rapid growth of digital platforms has made vast amounts of customer-generated content freely available, creating a rich source of real-time, spontaneous, and diverse customer feedback (Bi *et al.*, 2019; Özdağoğlu *et al.*, 2018).

Digital VoC offers several key advantages over traditional methods. First, it enables continuous monitoring of customer perceptions, providing organizations with immediate insights into emerging quality issues. Second, digital VoC covers a wider customer base, capturing diverse opinions across various demographic and geographic segments, often uncovering latent quality determinants that traditional surveys might not identify (Barravecchia *et al.*, 2023). Moreover, the costs associated with analyzing digital VoC data are generally lower than traditional survey-based methods since the data already exist online, eliminating the expenses associated with data collection (Bi *et al.*, 2019).

Digital VoC data is characterized by several features that make it a rich source for customer understanding (Subhashini *et al.*, 2021): (1) *large quantity*: Digital VoC records are generated in vast amounts from various online platforms such as e-commerce websites, social media, and forums; (2) *unstructured text*: the data primarily consists of unstructured text, including reviews, comments, and social media posts; and (3) *presence of metadata*: alongside the text, digital VoC data often includes metadata such as ratings (numerical or symbolic evaluations given by customers reflecting different satisfaction levels) and dates (the time when feedback was provided). For example, a digital VoC record related to a smartwatch might look like this: (1) Review title "*Good product*"; (2) Review Text "*The battery life of this smartwatch is fantastic! It lasts for days without needing a charge, which is perfect for my busy schedule*"; (3) Rating "*5 stars"; (4)* Date "*October 8, 2024*"; (5) Author "*Lorence B.*"; (6) Nationality "*Italian*"; (7) Source "e-commerce website".

2.2 Analytical approaches for digital VoC analysis

Leveraging digital VoC data also introduces several challenges. The primary issue is the unstructured nature of the data, characterized by variability in format, content, and quality, complicating automatic analysis (Özdağoğlu *et al.*, 2018). The massive volume of digital VoC data further complicates analysis, requiring data mining techniques to ensure interpretation and actionable insights (Barravecchia *et al.*, 2023).

To address these challenges, analytical techniques such as text mining and topic modeling become essential. Text mining encompasses a wide range of computational methods to extract meaningful patterns and trends from large textual datasets (Blei *et al.*, 2003). Topic modeling algorithms identify latent themes or "topics" within unstructured textual data (Blei *et al.*, 2003). Several algorithms can be employed for topic modeling, with Latent Dirichlet Allocation (LDA) (Blei *et al.*, 2003) and Structural Topic Model (STM) (Roberts *et al.*, 2014) being among the most popular.

Topic modeling algorithms provides two main outputs (Blei *et al.*, 2003). The first is *Topical Content* (*TC*), which refers to the specific words that compose each identified topic within the analyzed digital VoC data. For instance, when analyzing reviews of Bluetooth headphones, a common topic might be related to battery life. This topic would typically be described by a set of representative keywords such as battery, charge, life, hours, and duration. The second output is *Topical Prevalence* (*TP*), which measures how frequently each topic is discussed across all documents. For each review, the algorithm assigns a multinomial distribution of probabilities that reflect the extent to which each topic is present. For example, if five topics are identified and a given review discusses topic 1 and topic 2 equally, the resulting probability distribution might be (0.5; 0.5; 0; 0; 0). This indicates that the content is evenly divided between the first two topics, with no mention of the others.

When topic modeling algorithms are applied to digital VoC data, the identified topics can be interpreted as key attributes of the product or service (Mastrogiacomo *et al.*, 2021). These key attributes are the elements that customers most frequently evoke to describe their overall experience, and thus they are the most significantly influential factors in determining customer satisfaction.

The application of topic modeling techniques to digital Voice of Customer (VoC) data has been successfully implemented across a variety of sectors. Examples are hospitality services (Amat-Lefort *et al.*, 2022; Ding *et al.*, 2020), technological products (Barravecchia *et al.*, 2020a, b, c, 2022b; Ha *et al.*, 2017), sharing mobility (Barravecchia *et al.*, 2020a, b, c; Barravecchia *et al.*, 2025; Jeong *et al.*, 2019).

Large Language Models, such as BERT (Catelli *et al.*, 2022; Devlin *et al.*, 2018) and GPT (Shahin *et al.*, 2024), have shown the potential to achieve similar results with improved performance in analyzing digital VoC. However, these models still need to be tested to validate their effectiveness and reliability.

Despite these advances, current research in digital VoC quality tracking reveals several unsolved issues and methodological gaps. A significant gap is the lack of standardized approaches for consistently collecting, processing, and analyzing digital VoC data, which often leads to inconsistent outcomes across studies and complicates comparisons and validations (Dahiya *et al.*, 2021). Another notable limitation is the incomplete application of longitudinal analytical approaches. Most existing studies have conducted static analyses, failing to adequately capture the dynamic nature of customer perceptions over time (Majumder *et al.*, 2022). Consequently, there is a need for methods that effectively track changes in quality determinants, capturing temporal trends and detecting significant shifts or anomalies promptly.

The Key Attribute Voice-of-Customer (KA-VoC) Map methodology can address these gaps. The KA-VoC Map approach was originally developed to identify product/service quality attributes and to associate them with actionable categories (see Section 3) (Barravecchia *et al.*, 2022a, b). This paper proposes a dynamic use of KA-VoC Map. This enables organizations to understand not only which attributes are most critical to customers but also how customer perceptions of these attributes evolve over time. Implementing the KA-VoC Map methodology can also support proactive quality management, allowing organizations to respond to emerging customer concerns.

2.3 Conceptual background

The development of the KA-VoC Map are rooted in several foundational theories from quality management, product/service design, and customer satisfaction research. These conceptual roots help frame the model not only as a technical tool but also as a structured approach for interpreting customer perceptions and guiding strategic quality decisions.

First, the KA-VoC Map conceptually builds on the Kano Model (Kano *et al.*, 1984), a framework able to classify product and service attributes based on their impact on customer satisfaction. Kano distinguishes between *must-be* (basic), *one-dimensional* (performance), and *attractive* (excitement) qualities, each eliciting different emotional responses when present or absent. Similarly, the KA-VoC Map categorizes product/service attributes on the basis of digital VoC data. The KA-VoC Map thus offers a data-driven operationalization of the Kano model, allowing organizations to dynamically detect which features act as satisfiers or dissatisfiers over time. Unlike traditional Kano questionnaires, which require manual customer input, this model leverages naturally occurring feedback from digital sources, increasing scalability and real-world relevance.

Second, the KA-VoC Map aligns with established methods in product/service design, particularly Quality Function Deployment (QFD). QFD is a structured methodology used to systematically translate customer requirements into specific engineering characteristics and design attributes (Franceschini, 2001; Franceschini *et al.*, 2015). By integrating customer feedback directly into the product/service development process, QFD helps prioritize engineering features based on their relative importance to customer satisfaction (Maisano *et al.*, 2024; Franceschini and Maisano, 2018). Similarly, the KA-VoC Map operationalizes this customer-centric approach by systematically identifying and categorizing customer perceptions drawn from digital feedback, allowing organizations to continuously prioritize quality improvements according to real-time customer feedback (Barravecchia *et al.*, 2020a, b, c).

Third, the model reflects the ongoing evolution in quality management thought, from classical frameworks such as Deming's Plan-Do-Check-Act (PDCA) cycle and Juran's quality trilogy—which emphasized internal process control and defect reduction—towards the paradigm of Quality 4.0 (Broday, 2022; Dias *et al.*, 2022). Quality 4.0 represents the convergence of quality principles with digital transformation, advanced analytics, and real-time feedback integration. It shifts the focus from compliance-based quality assurance to customer-driven, predictive quality systems (Oliveira *et al.*, 2025). The KA-VoC Map embodies this transformation by fusing unstructured data analytics (e.g. topic modeling, sentiment analysis) with strategic quality monitoring and continuous improvement logic.

Taken together, these three conceptual perspectives, provide a comprehensive foundation for understanding the relevance of the KA-VoC Map.

3. KA-VoC Map

Unlike traditional VoC analysis approaches that focus either on topic frequency or sentiment alone, the KA-VoC Map introduces an integrated framework that combines these two dimensions. By jointly considering the Mean Topical Prevalence (MTP) and the Mean Rating Proportion (MRP), the method enables a structured classification of key product/service attributes based on both customer attention and satisfaction.

The methodological workflow adopted in this study (Figure 1) consists of four sequential steps. First, digital VoC data is collected from online platforms and preprocessed (Mastrogiacomo *et al.*, 2021). Second, a topic modeling algorithm (e.g. STM*)* is applied to identify latent topics, which are interpreted as key product/service attributes. Third, for each attribute, two indicators are computed: *Mean Topical Prevalence* (*MTP*), capturing how frequently it is discussed, and *Mean Rating Proportion* (*MRP*), capturing the associated sentiment. Finally, attributes are positioned within the KA-VoC Map, which classifies them into six strategic categories to guide quality improvement efforts.

3.1 Mean Topical Prevalence (MTP)

The *Mean Topical Prevalence* (MTP) measures how frequently a key attribute is discussed within the digital VoC (Mastrogiacomo *et al.*, 2021). The MTP indicator can be calculated as follows:

$$MTP_d = \frac{\sum_{j=1}^{N} TP_{j,d}}{N}$$

Where, N represents the total number of Digital VoC records analyzed, and $TP_{j,d}$ is the topical prevalence corresponding to the d -th key attribute in the j-th Digital VoC record.

By way of illustration, consider a scenario in which 10 Digital VoC records ($N = 10$) are analyzed, and the topic modeling algorithm identifies three key attributes: "Material Quality," "Usability," and "Customer Service." Table 1 presents a summarized content for each Digital VoC record, accompanied by the related rating expressed on a 5-level ordinal scale and the topical prevalence ($TP_{j,d}$) associated with the three key attributes.

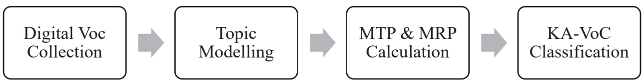

Figure 1. Overview of the methodological process adopted in this study. Source: Authors' own work

Table 1. Example of 10 Digital VoC Records and Topical Prevalence $TP_{j,d}$ related to the three key attributes ("Material Quality"; "Usability" and "Customer Service") identified by the topic modeling algorithm

j-th	Digital VoC record	Rating (k)	Material quality ($TP_{j,1}$)	Usability ($TP_{j,2}$)	Customer service ($TP_{j,3}$)
1	Extremely poor material quality and difficult to use	1	0.8	0	0.2
2	Broke quickly, difficult to use, slow customer response	2	0.4	0.3	0.3
3	Great usability and software, excellent customer service	5	0	0.8	0.2
4	Very solid construction, but tough to navigate the settings. Customer service responsive	3	0.3	0.3	0.4
5	Feels good, the interface is intuitive, very helpful customer service	4	0.3	0.4	0.3
6	Average quality build, I had a terrible customer service experience	2	0.4	0	0.6
7	Amazing support when I had issues with setup	3	0	0.2	0.8
8	Had a minor issue with a feature, but customer service was helpful in resolving it	4	0	0.5	0.5
9	Materials feel cheap and break easily, interface is complex	1	0.8	0.2	0
10	Excellent usability and materials and interface very simple, no service needed	5	0.2	0.7	0.1

Source(s): Authors' own work

The *MTP* indicator for a key attribute can calculated by summing all the topical prevalence values related to the key attribute and then dividing by 10, i.e. the total number of digital VoC records (N). This is expressed as follows:

$$MTP_1 = \frac{TP_{1,1} + TP_{2,1} + TP_{3,1} + TP_{4,1} + TP_{5,1} + TP_{6,1} + TP_{7,1} + TP_{8,1} + TP_{9,1} + TP_{10,1}}{N} =$$

$$= \frac{0,8 + 0,4 + 0 + 0,3 + 0,3 + 0,4 + 0 + 0 + 0,8 + 0,2}{10} = 0.32$$

$$MTP_2 = \frac{0 + 0,3 + 0,8 + 0,3 + 0,4 + 0 + 0,2 + 0,5 + 0,2 + 0,7}{10} = 0.34$$

$$MTP_3 = \frac{0,2 + 0,3 + 0,2 + 0,4 + 0,3 + 0,6 + 0,8 + 0,5 + 0 + 0,1}{10} = 0.34$$

A high *MTP* value indicates that the relater key attribute is a common subject of discussion. Attributes with *MTP* above the threshold (as a rule of thumb *1/D*, where *D* is the number of key attributes) are considered highly discussed, while those below are considered poorly discussed.

3.2 Mean rating proportion (MRP)

While *MTP* focuses on the frequency of discussion, it does not reflect how positively or negatively an attribute is perceived. To capture this sentiment dimension, the *Mean Rating Proportion* (*MRP*) indicator is introduced.

The *MRP* assesses the sentiment associated with a key attribute by examining the ratings given by customers (Barravecchia *et al.*, 2020a, b, c). The *MRP* indicator can be calculated as follows:

$$MRP_{d,k} = \frac{\sum_{j \in R_k} TP_{j,d}}{|R_k|}$$

Where d is the key attribute; k is the level of the rating scale; R_k is the subset of reviews associated to a rating level equal to k; $TP_{i,d}$ is the topical prevalence of the d-th key attribute in the j-th Digital VoC record; $|R_k|$ is the cardinality of R_k.

To illustrate the calculation of *MRP*, consider the 10 digital VoC records reported in Table 1. The *MRP* values for the key attribute "Material Quality" are calculated as follows:

$$MRP_{1,1} = \frac{TP_{1,1} + TP_{9,1}}{|R_1|} = \frac{0.8 + 0.8}{2} = 0,80$$

$$MRP_{1,2} = \frac{TP_{2,1} + TP_{6,1}}{|R_2|} = \frac{0,4 + 0.4}{2} = 0,40$$

$$MRP_{1,3} = \frac{TP_{4,1} + TP_{7,1}}{|R_3|} = \frac{0 + 0.30}{2} = 0,20$$

$$MRP_{1,4} = \frac{TP_{5,1} + TP_{8,1}}{|R_4|} = \frac{0.3 + 0}{2} = 0,15$$

$$MRP_{1,5} = \frac{TP_{3,1} + TP_{10,1}}{|R_5|} = \frac{0 + 0.2}{2} = 0,10$$

Each key attribute can be associated with an *MRP* profile, which represents the frequency with which the key attribute is discussed in digital VoC records associated with the different levels of ratings. The *MRP* profiles for the three exemplificative key attributes are as follows:

$$\begin{aligned} MRP\ Profile_1 &= (MRP_{1,1};\ MRP_{1,2};\ MRP_{1,3};\ MRP_{1,4};\ MRP_{1,5}) \\ &= (0.80;\ 0.40;\ 0.20;\ 0.15;\ 0.10) \end{aligned}$$

$$MRP\ Profile_2 = (0.10;\ 0.15;\ 0.30;\ 0.45;\ 0.75)$$

$$MRP\ Profile_3 = (0.10;\ 0.45;\ 0.50;\ 0.40;\ 0.15)$$

The analysis of *MRP* profiles allows for the categorization of the attribute's impact on customer satisfaction as follows: (a) *Positive MRP Profile*, the key attribute is more frequently discussed in high-rated reviews, indicating that it contributes positively to customer satisfaction; (b) *Neutral MRP Profile*: the key attribute is predominantly discussed in reviews with intermediate ratings, suggesting a neutral impact on customer satisfaction; (c) *Negative MRP Profile*, the key attribute is primarily mentioned in low-rated reviews, indicating that it contributes to customer dissatisfaction. One practical way to classify *MRP* profile into the three categories is by using the Spearman's rank correlation coefficient (negative if $q_S < -0.4$, neutral if $-0.4 \leq q_S \leq 0.4$, positive if $q_S > 0.4$) (Barravecchia *et al.*, 2022b). In cases where ratings are not available (e.g. in social media posts), sentiment analysis algorithms can be utilized to assess the sentiment associated with digital VoC records (Amat-Lefort *et al.*, 2022; Cambria *et al.*, 2013; Liu, 2012).

3.3 Attribute classification in the KA-VoC map

Considering *MTP* and *MRP* indicators, the KA-VoC map classifies attributes into six distinct categories (see Figure 2), each representing a different impact on customer satisfaction (Barravecchia *et al*., 2022b):

(1) *Obstacles*: these are highly discussed attributes (high *MTP*) that generate dissatisfaction (negative *MRP*). Obstacles are major sources of customer complaints and require immediate and radical changes to improve.

(2) *Frictions*: these attributes are less frequently discussed (low *MTP*) but still cause dissatisfaction (negative *MRP*). They represent minor issues that, while not as critical as obstacles, still need attention through incremental improvements.

(3) *Indifferents*: attributes that are rarely discussed (low *MTP*) and have a neutral impact on satisfaction (neutral *MRP*). Indifferents do not significantly affect customer satisfaction and can generally be deprioritized in quality improvement efforts.

(4) *Sleeping Beauties*: these are attributes that are highly discussed (high *MTP*) but have a neutral impact on satisfaction (neutral *MRP*). While they do not currently affect satisfaction, they are critical and must be monitored to prevent any potential negative shifts.

(5) *Promises*: attributes that are less frequently discussed (low *MTP*) but contribute to satisfaction (positive *MRP*). Promises are emerging attributes that should be preserved and improved to enhance customer satisfaction.

(6) *Delights*: these are highly discussed attributes (high *MTP*) that generate significant satisfaction (positive *MRP*). Delights are primary sources of customer satisfaction and should be preserved and highlighted in marketing strategies.

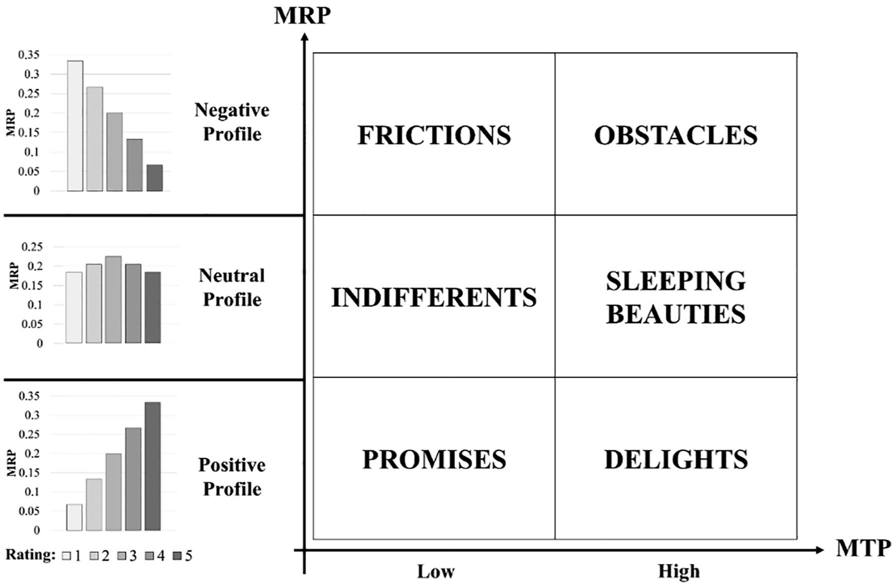

Figure 2. KA-VoC Map framework accompanied by examples of MRP profiles. Source: Authors' own work

4. KA-VoC Map for quality tracking

Building upon the presented classification framework, this section illustrates how the KA-VoC Map can be updated to monitor the evolution of customer perceptions over time. Key attributes can shift between KA-VoC categories due to changes in customer feedback, product improvements, market conditions, and emerging trends (Barravecchia *et al.*, 2023). For instance, an attribute initially classified as a "Delight" might provide significant satisfaction and be frequently discussed positively by customers. However, if this attribute's quality decreases or if competitors introduce superior alternatives, it could transition to the "Obstacle" category. This shift would indicate a severe issue that needs immediate attention. The drop from a highly praised attribute to a significant source of dissatisfaction is a clear signal that the product feature in question is not meeting customer expectations anymore.

To effectively use the KA-VoC Map for quality tracking, organizations should establish a routine for updating the map with new customer feedback data. This involves regularly collecting VoC data from digital sources and applying topic modeling tools to identify and categorize attributes. By doing so, organizations can observe trends, detect emerging issues, and react proactively.

For each key attribute, two general types of changes can typically occur within the KA-VoC Map. The first is a *vertical shift*, which reflects a change in the sentiment associated with a given attribute—essentially, a modification of its Mean Rating Proportion (MRP) profile. This kind of shift occurs when an attribute moves from one sentiment category to another, such as from positive to negative or vice versa. For instance, if an attribute transitions from being classified as a "Delight" to an "Obstacle," it indicates a significant deterioration in customer sentiment. Conversely, a shift from "Friction" to "Promise" highlights an improvement in perception. The second type is a *horizontal shift*, which captures a change in the level of discussion surrounding the attribute, as measured by Mean Topical Prevalence (MTP). This shift indicates whether customers are talking more or less frequently about a particular feature. For example, an attribute initially considered "Indifferent" might become a "Sleeping Beauty" if it begins to appear more frequently in customer feedback, suggesting a rise in customer interest. On the other hand, an attribute moving from "Delight" to "Promise" might signal that, while still viewed positively, it is being mentioned less often—perhaps because it is no longer a major point of differentiation.

Understanding these transitions helps organizations proactively manage product/service quality by identifying emerging issues and capitalizing on positive attributes. Continuous monitoring and updating of the KA-VoC Map ensure that organizations stay responsive to customer needs.

5. Case study: application of the KA-VoC Map for quality tracking of a smartwatch

5.1 Research design

This case study adopts a longitudinal single-case approach to assess the applicability of the KA-VoC Map in tracking customer perceptions over time. A smartwatch was selected due to its hybrid product-service nature and the abundance of digital feedback available. The analysis covers a four-year period (2021–2024) and follows the methodological steps outlined in Sections 3 and 4, with the aim of observing how key quality attributes evolve in terms of both customer attention and sentiment.

5.2 Data collection

For this case study, digital Voice-of-Customer (VoC) data related to a popular smartwatch was collected from multiple online platforms, including Amazon, Best Buy and Facebook. The dataset spans the period from 2021 to 2024 and includes a total of 23,000 customer-generated records. Each record has an average length of approximately 150 words and is written in English.

The connection between the smartwatch and the selected online platforms (Amazon, Best Buy and Facebook) lies in their function as primary digital spaces where customers spontaneously share product experiences. On e-commerce platforms such as Amazon and Best Buy, reviews are tied to verified purchases, ensuring that feedback refers explicitly to the smartwatch model under investigation. Facebook, by contrast, hosts user-generated discussions in groups and brand communities, where customers exchange opinions, report issues, and compare experiences with alternative devices.

The methodological choice of these platforms is justified by three elements: (1) relevance, they represent the most widely used channels for consumer feedback in the smartwatch market; (2) data richness, they provide both textual reviews and metadata (ratings, timestamps), crucial for the KA-VoC Map construction; (3) credibility, product-linked reviews from Amazon and Best Buy guarantee that the feedback originates from actual users.

To extract the data, a custom web-scraping tool was developed in Python, relying on the widely used BeautifulSoup and Selenium libraries for automated data collection. The tool is available upon request from the authors. It enabled the retrieval of customer reviews, social media posts, and forum discussions, including both textual content and associated metadata such as ratings (when available) and timestamps.

The data collection process was carried out in full compliance with the terms of service of each platform, ensuring that only publicly available customer feedback was retrieved. No direct authorization from companies was required, as the data were collected exclusively from openly accessible online sources. The study avoided any personal identifiers, focusing solely on product-related feedback to comply with ethical research practices.

For confidentiality reasons, the specific model of the smartwatch analyzed is not disclosed. Nevertheless, the smartwatch belongs to a widely commercialized and internationally distributed product line. This choice does not affect the methodological validity of the study, as the focus is on the applicability of the KA-VoC Map rather than on brand-specific or model-specific performance.

5.3 Data analysis – topic modeling analysis

Using a topic modeling algorithm, the Structural Topic Model (STM) (Roberts *et al.*, 2014, 2019), the digital VoC data is analyzed to identify key attributes discussed by customers. This approach follows the analysis method proposed by Mastrogiacomo *et al*. (2021), which combines topic modeling with quality management perspectives. Specifically, 10 product attributes are identified for the analyzed smartwatch (see Table 2)

5.4 Data analysis - KA-VoC map

In order to gain a comprehensive understanding of customer perceptions and quality issues, the digital Voice of Customer (VoC) was subjected to a comprehensive analysis. This provides an overview of the prevailing sentiment and the relative importance of each attribute over the entire period of study, spanning from 2021 to 2024. The categorization of key attributes is presented in Figure 3a.

Connectivity and *Battery Life* were marked as “obstacles”, indicating they are significant sources of customer dissatisfaction and require urgent improvement. *Customer Support* fell under “frictions”, showing less severe issues needing attention. *Notifications* and *Price/Value* were categorized as “indifferents”, suggesting these attributes have a neutral impact on customer satisfaction. *Build Quality* and *Fitness Tracking* were identified as “sleeping beauties”, frequently discussed but with a neutral sentiment and *App Compatibility* was categorized as a “promises”, generating customer satisfaction. *Display Quality* and *User Interface* were classified as “delights”, highly valued by customers and significantly enhancing satisfaction.

This analysis provides a broad view of customer perceptions and quality issues on the four-year interval covered. However, to gain a deeper understanding of Digital VoC, it is also

Table 2. Description of the ten key product attributes identified through topic. For each attribute, representative keywords are shown, corresponding to the most frequent terms within each topic cluster

Key attribute	Description	Keywords
Battery life	Discussions about battery longevity and charging time	battery, charge, life, duration, hours
Display quality	Comments on screen resolution, brightness, and touch sensitivity	screen, resolution, brightness, touch, quality
Fitness tracking	Feedback on fitness and health monitoring features, such as heart rate and step counters	fitness, health, heart rate, run, monitoring
User interface	User experiences with the smartwatch's operating system and ease of use	interface, update, system, ease, use
Build quality	Opinions on the durability and materials used in the smartwatch	durability, materials, build, quality, robust
Connectivity	Issues and praises related to Bluetooth, Wi-Fi, and GPS connectivity	Bluetooth, Wi-Fi, GPS, connectivity, signal
Notifications	Evaluation of how well the smartwatch handles notifications from smartphones	notifications, messages, alerts, handling, sync
Price/value	Perceptions of the smartwatch's cost versus its features and benefits	price, cost, value, features, benefits
Customer support	Experiences with the manufacturer's customer service and support	support, service, customer, help, response
App compatibility	Feedback on the availability and performance of third-party applications and connected devices	apps, compatibility, performance, scale, band

Source(s): Authors' own work

important to examine what happens within this timeframe. Are the key attributes consistently categorized in the same way, or do they shift between categories over time? Understanding these dynamics can reveal trends and changes in customer satisfaction, helping to identify whether improvements are having a lasting impact or if new issues are emerging. This period-by-period analysis can provide more insights, enabling more targeted and effective quality management strategies.

5.5 Data analysis - KA-VoC map for quality tracking

To track the evolution of Key Attributes customer perceptions, the analysis was sub-divided into four distinct periods, each covering one year: 2021, 2022, 2023, and 2024. Figure 3b separately illustrates the four KA-VoC Maps developed for each of the four periods. This breakdown allows to observe changes in the attribute categorizations over time.

It can be observed that some attributes demonstrated a consistent categorization. *Connectivity* and *Battery Life* remained in the "obstacles" category across all four years. This persistence indicates that these features were sources of dissatisfaction, underscoring the need for targeted and effective improvements in these areas to enhance overall customer satisfaction. *Display Quality* was consistently considered as a "delight", suggesting that this feature met or exceeded customer expectations, maintaining strong customer satisfaction. *Build Quality* stayed in the "sleeping beauties" category, suggesting that while it was frequently discussed, it had a neutral impact on customer satisfaction and did not strongly influence overall perceptions. *Notifications* remained consistently categorized as "indifferent" over the four years.

An examination of the shifts of other key attributes reveals a more dynamic change in customer perceptions. Figure 4 provides examples of key attributes that suffered changes in their KA-VoC category.

Fitness Tracking was in 2021 an "obstacle", reflecting significant customer dissatisfaction. By 2022 and 2023, this attribute shifted to a "sleeping beauty", indicating frequent discussions

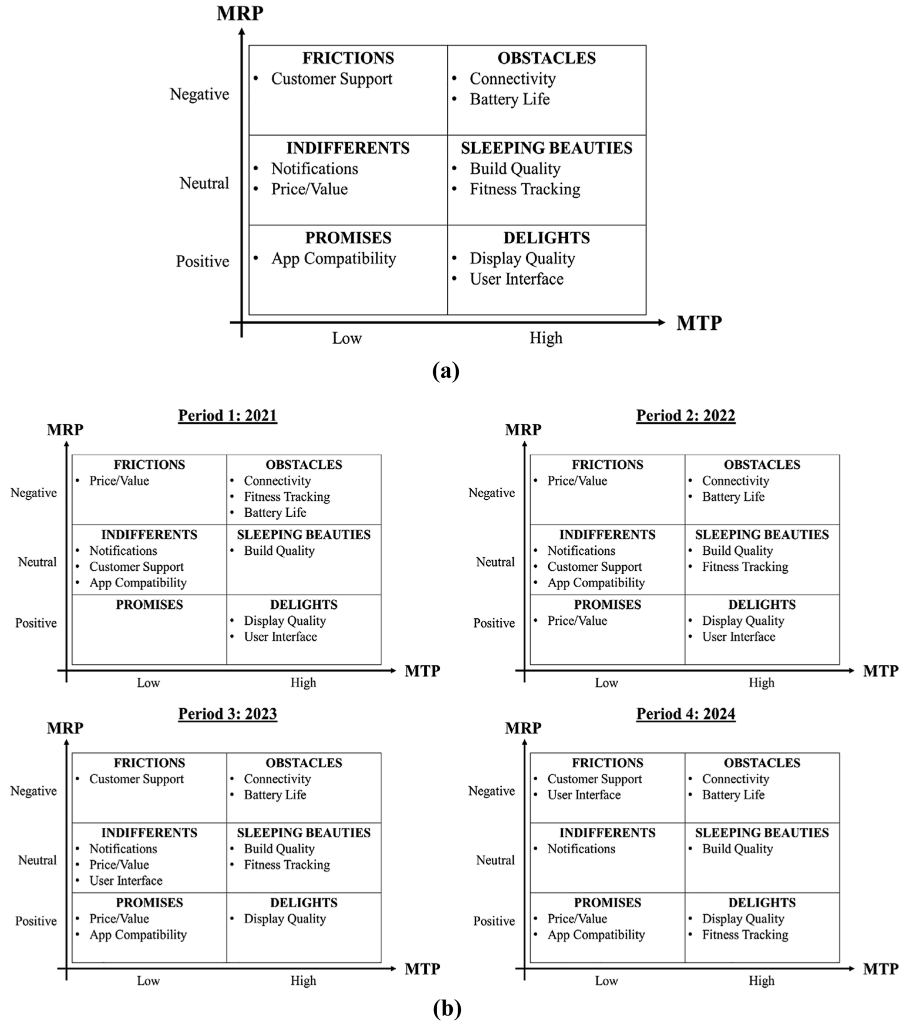

Figure 3. (a) Application of the KA-VoC Map for the smartwatch case study, considering all digital VoC records from 2021 to 2024. (b) Application of the KA-VoC Map for the smartwatch case study. Each KA-VoC Map refers distinctly to the 4 periods of analysis (year 2021, year 2022, year 2023 and year 2024). Source: Authors' own work

but a neutral sentiment, suggesting that some improvements had been made but were insufficient to turn the feature into a delight. However, by 2024, *Fitness Tracking* became a "delight", showing that enhancements were implemented, boosting customer satisfaction.

Price/Value was a "friction" in 2021 and 2022, indicating concerns about the cost relative to the smartwatch's features. However, in 2023, it moved to "indifferent", suggesting that the cost-benefit issue became less significant, possibly due to price adjustments. By 2024, *Price/Value* transitioned to a "promise", reflecting further improvements and a growing perception of good value for money.

App Compatibility began as an "indifferent" attribute in 2021 and 2022. Improvements were made by 2023, shifting it to a "promise", indicating increasing satisfaction with

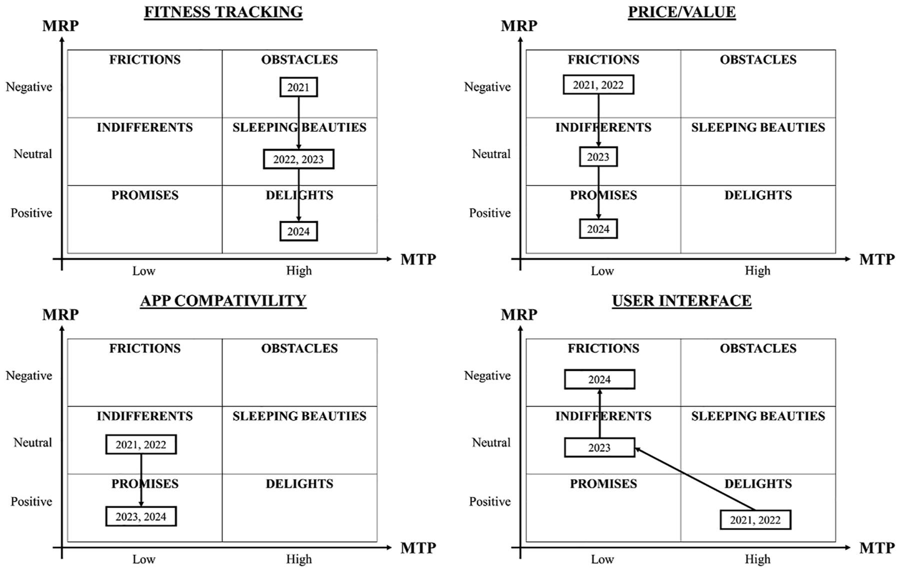

Figure 4. Examples of four key attributes of the smartwatch product (fitness tracking, price/value, app compatibility, user interface) demonstrating their shift across different categories of the KA-VoC Map over the four periods of analysis. The boxes within the KA-VoC Maps indicate the years during which each attribute was classified in the corresponding category. Source: Authors' own work

third-party app performance and availability. This positive trend continued into 2024, as *App Compatibility* remained a "promise".

The *User Interface* was a "delight" in 2021 and 2022, significantly enhancing customer satisfaction with its ease of use and functionality. However, in 2023, it dropped to "indifferent", suggesting that user experience issues emerged, or competitors' improvements overshadowed it. By 2024, it further declined to a "friction", indicating growing dissatisfaction and highlighting the need for usability enhancements to regain its former positive standing.

6. Discussion and conclusions

This study introduced the KA-VoC Map as a systematic framework for classifying and tracking the evolution of product and service quality attributes over time. By analyzing digital Voice-of-Customer (VoC) data, the proposed model supports organizations in identifying attributes that require urgent attention (e.g. obstacles and frictions) and those that significantly contribute to customer satisfaction (delights and promises). The longitudinal analysis of VoC data highlights how customer priorities shift over time, reflecting broader market dynamics and evolving expectations. These findings align with the principles of Quality 4.0, emphasizing the role of real-time feedback and advanced analytics in improving quality management strategies (Dias *et al.*, 2022; Özdağoğlu *et al.*, 2018). Furthermore, this study reinforces previous research on text mining and topic modeling (Mastrogiacomo *et al.*, 2021; Barravecchia *et al.*, 2022b) by demonstrating how unstructured customer feedback can be transformed into structured, actionable insights.

In positioning our contribution within the existing body of literature, it is important to highlight the connection between previous research and our empirical findings. Seminal studies in service and quality management (e.g. Bolton *et al.*, 2018; Ostrom *et al.*, 2021; Majumder *et al.*, 2022) have emphasized the challenges of capturing dynamic and fragmented customer voices in the digital era. However, these studies mainly adopt static approaches, without offering systematic tools for longitudinal quality tracking. Our empirical analysis addresses this gap by combining (1) a large-scale dataset, (2) advanced analytical techniques, and (3) longitudinal observation.

To enhance the robustness of the findings, the study integrates three complementary perspectives. Digital-VoC-records triangulation is ensured by combining topic modeling outputs with numerical ratings and by collecting data from diverse sources. Temporal triangulation is achieved through longitudinal analyses across distinct periods, enabling the detection of evolving patterns. This multi-perspective design strengthens both the methodological reliability of the KA-VoC Map and the practical relevance of its implications.

6.1 Managerial insights

The KA-VoC Map offers a practical and data-driven framework to support decision-making in quality management. By systematically classifying product and service attributes based on customer attention and sentiment, the method allows organizations to move beyond traditional, static feedback tools and embrace a more dynamic, real-time approach.

In operational terms, the KA-VoC Map can guide prioritization efforts by clearly identifying which features are causing dissatisfaction and therefore require immediate action. For example, attributes classified as Obstacles or Frictions highlight current pain points that can be targeted through corrective measures. At the same time, attributes categorized as Promises or Delights indicate competitive strengths that can be leveraged in product development and communication strategies.

The model also helps monitor improvement initiatives. A shift from negative to neutral or positive sentiment (e.g. from Obstacle to Sleeping Beauty or Delight) provides clear evidence that customers are recognizing recent product or service updates. In this sense, the KA-VoC Map acts as a feedback loop that links customer perception with quality performance, helping managers align resource allocation with emerging customer needs and expectations.

6.2 Educational and societal implications

Beyond its business-oriented applications, the KA-VoC Map has potential implications in educational and policy-making contexts.

In educational contexts, the KA-VoC Map offers a concrete, data-driven case for teaching topics such as quality management, customer experience, and text analytics. The methodology can be used in engineering and business courses to show how Natural Language Processing (NLP) and machine learning techniques can be applied to real-world feedback data. It also supports interdisciplinary teaching approaches that link quality, marketing, and data science.

From a societal and public policy perspective, the approach could be valuable for public sector organizations aiming to improve digital services and citizen engagement. By analyzing citizen-generated content—such as social media comments or feedback on public platforms—governments could better understand evolving needs, identify service gaps, and adapt policies more rapidly. This is particularly relevant in domains such as public transport, healthcare services, and digital administration, where the "Voice-of-the-Citizen" is becoming increasingly accessible but still underutilized.

6.3 Limitations and future research directions

The effectiveness of the KA-VoC Map depends on data availability and quality. Biased or incomplete datasets can affect insights. Additionally, rapidly evolving technological attributes demand frequent updates to maintain accuracy. The approach may also be sensitive to linguistic and cultural differences, requiring further research into cross-lingual VoC analysis.

Enhancing NLP (Natural Language Processing) capabilities with transformer-based models (e.g. BERT, GPT) could improve sentiment classification and trend detection. Comparative research against traditional quality tracking methods would further validate its effectiveness. Furthermore, the use of the KA-VoC Map could be augmented by the incorporation of predictive analytics, which would facilitate the anticipation of the progression of attributes within categories and the projection of future customer requirements.

References

Amat-Lefort, N., Barravecchia, F. and Mastrogiacomo, L. (2022), "Quality 4.0: big data analytics to explore service quality attributes and their relation to user sentiment in airbnb reviews", *International Journal of Quality and Reliability Management*, Vol. 40 No. 4, pp. 990-1008, doi: 10.1108/ijqrm-01-2022-0024.

Barravecchia, F., Mastrogiacomo, L, Casadesús Fa, M. and Franceschini, F. (2025), "MOBI-Qual: a common framework to manage the product-service system quality of shared mobility", *Flexible Services and Manufacturing Journal*, Vol. 36 No. 4, pp. 1359-1398, doi: 10.1007/s10696-023-09520-y.

Barravecchia, F., Mastrogiacomo, L. and Fiorenzo, F. (2020a), "Categorizing quality determinants in mining user-generated contents", *Sustainability*, Vol. 12 No. 23, pp. 1-12.

Barravecchia, F., Mastrogiacomo, L. and Franceschini, F. (2020b), "Identifying car-sharing quality determinants: a data-driven approach to improve engineering design", *4th International Conference on Quality Engineering and Management*, University of Minho, Portugal, pp. 125-140.

Barravecchia, Mastrogiacomo, L. and Franceschini, F. (2020c), "The player-interface method: an approach to support product-service systems concept generation and prioritization", *Journal of Engineering Design*, Vol. 31 No. 5, pp. 331-348, doi: 10.1080/09544828.2020.1743822.

Barravecchia, F., Mastrogiacomo, L., Franceschini, F. and Zaki, M. (2021), "Research on product-service systems: topic landscape and future trends", *Journal of Manufacturing Technology Management*, Vol. 32 No. 8, pp. 208-238, doi: 10.1108/jmtm-04-2020-0164.

Barravecchia, F., Mastrogiacomo, L. and Franceschini, F. (2022a), "Digital voice-of-customer processing by topic modelling algorithms: insights to validate empirical results", *International Journal of Quality and Reliability Management*, Vol. 39 No. 6, pp. 1453-1470, doi: 10.1108/ijqrm-07-2021-0217.

Barravecchia, F., Mastrogiacomo, L. and Franceschini, F. (2022b), "KA-VoC map: classifying product key-attributes from digital voice-of-customer", *Quality Engineering*, Vol. 34 No. 3, pp. 344-358, doi: 10.1080/08982112.2022.2057805.

Barravecchia, F., Mastrogiacomo, L. and Franceschini, F. (2023), "Product quality tracking based on digital voice-of-customers", *Total Quality Management and Business Excellence*, Vol. 34 Nos 11-12, pp. 1386-1409, doi: 10.1080/14783363.2023.2177147.

Bi, J.-W., Liu, Y., Fan, Z.-P. and Cambria, E. (2019), "Modelling customer satisfaction from online reviews using ensemble neural network and effect-based Kano model", *International Journal of Production Research*, Vol. 57 No. 22, pp. 7068-7088, doi: 10.1080/00207543.2019.1574989.

Bilal, M., Akram, U., Rasool, H., Yang, X. and Tanveer, Y. (2022), "Social commerce isn't the cherry on the cake, its the new cake! how consumers' attitudes and eWOM influence online purchase intention in China", *International Journal of Quality and Service Sciences*, Vol. 14 No. 2, pp. 180-196, doi: 10.1108/ijqss-01-2021-0016.

Blei, D.M., Ng, A.Y. and Jordan, M.I. (2003), "Latent dirichlet allocation", *Journal of Machine Learning Research*, Vol. 3, pp. 993-1022.

Bolton, R.N., McColl-Kennedy, J.R., Cheung, L., Gallan, A., Orsingher, C., Witell, L. and Zaki, M. (2018), "Customer experience challenges: bringing together digital, physical and social realms", *Journal of Service Management*, Vol. 29 No. 5, pp. 776-808, doi: 10.1108/josm-04-2018-0113.

Brits, H. and du Plessis, L. (2007), "Application of focus group interviews for quality management: an action research project", *Systemic Practice and Action Research*, Vol. 20 No. 2, pp. 117-126, doi: 10.1007/s11213-006-9054-0.

Broday, E.E. (2022), "The evolution of quality: from inspection to quality 4.0", *International Journal of Quality and Service Sciences*, Vol. 14 No. 3, pp. 368-382, doi: 10.1108/ijqss-09-2021-0121.

Cambria, E., Schuller, B., Xia, Y. and Havasi, C. (2013), "New avenues in opinion mining and sentiment analysis", *IEEE Intelligent Systems*, Vol. 28 No. 2, pp. 15-21, doi: 10.1109/mis.2013.30.

Catelli, R., Fujita, H., De Pietro, G. and Esposito, M. (2022), "Deceptive reviews and sentiment polarity: effective link by exploiting BERT", *Expert Systems with Applications*, Vol. 209, 118290, doi: 10.1016/j.eswa.2022.118290.

Dahiya, A., Gautam, N. and Gautam, P.K. (2021), "Data mining methods and techniques for online customer review analysis: a literature review", *Journal of System and Management Sciences*, Vol. 11 No. 3, pp. 1-26.

Devlin, J., Chang, M.-W., Lee, K. and Toutanova, K. (2018), "Bert: pre-training of deep bidirectional transformers for language understanding", arXiv PreprintarXiv:1810.04805.

Dias, A.M., Carvalho, A.M. and Sampaio, P. (2022), "Quality 4.0: literature review analysis, definition and impacts of the digital transformation process on quality", *International Journal of Quality and Reliability Management*, Vol. 39 No. 6, pp. 1312-1335, doi: 10.1108/ijqrm-07-2021-0247.

Ding, K., Choo, W.C., Ng, K.Y. and Ng, S.I. (2020), "Employing structural topic modelling to explore perceived service quality attributes in airbnb accommodation", *International Journal of Hospitality Management*, Vol. 91, 102676, doi: 10.1016/j.ijhm.2020.102676.

Escobar, C.A., McGovern, M.E. and Morales-Menendez, R. (2021), "Quality 4.0: a review of big data challenges in manufacturing", *Journal of Intelligent Manufacturing*, Vol. 32 No. 8, pp. 2319-2334, doi: 10.1007/s10845-021-01765-4.

Franceschini, F. (2001), *Advanced Quality Function Deployment*, St. Lucie Press/CRC Press, Boca Raton, FL.

Franceschini, F. and Maisano, D. (2018), "A new proposal to improve the customer competitive benchmarking in QFD", *Quality Engineering*, Vol. 30 No. 4, pp. 730-761, doi: 10.1080/08982112.2018.1437178.

Franceschini, F., Galetto, M., Maisano, D. and Mastrogiacomo, L. (2015), "Prioritisation of engineering characteristics in QFD in the case of customer requirements orderings", *International Journal of Production Research*, Vol. 53 No. 13, pp. 3975-3988, doi: 10.1080/00207543.2014.980457.

Ha, T., Beijnon, B., Kim, S., Lee, S. and Kim, J.H. (2017), "Examining user perceptions of smartwatch through dynamic topic modeling", *Telematics and Informatics*, Vol. 34 No. 7, pp. 1262-1273, doi: 10.1016/j.tele.2017.05.011.

Jeong, Y., Yang, Y., Suk, J. and Kim, K. (2019), "A text-mining analysis of online reviews on car-sharing services", *International Conferences on Internet Technologies & Society 2019*, pp. 167-169, doi: 10.33965/its2019_201901p004.

Kano, N., Seraku, N., Takahashi, F. and Tsuji, S. (1984), "Attractive quality and must-be quality", *Journal of the Japanese Society for Quality Control*, Vol. 14 No. 2, pp. 39-48.

Lepistö, K., Saunila, M. and Ukko, J. (2024), "Enhancing customer satisfaction, personnel satisfaction and company reputation with total quality management: combining traditional and new views", *Benchmarking: An International Journal*, Vol. 31 No. 1, pp. 75-97, doi: 10.1108/bij-12-2021-0749.

Liu, B. (2012), "Sentiment analysis and opinion mining", *Synthesis Lectures on Human Language Technologies*, Vol. 5 No. 1, pp. 1-167.

Maisano, D.A., Carrera, G., Mastrogiacomo, L. and Franceschini, F. (2024), "A new method to prioritize the QFDs' engineering characteristics inspired by the law of comparative judgment", *Research in Engineering Design*, Vol. 35 No. 4, pp. 343-353, doi: 10.1007/s00163-024-00436-8.

Majumder, M.G., Gupta, S.D. and Paul, J. (2022), "Perceived usefulness of online customer reviews: a review mining approach using machine learning & exploratory data analysis", *Journal of Business Research*, Vol. 150, pp. 147-164.

Mandal, P.C. (2020), "Achieving excellence in services marketing: roles in customer delight", *International Journal of Business Excellence*, Vol. 20 No. 3, pp. 359-374, doi: 10.1504/ijbex.2020.106366.

Mastrogiacomo, L., Barravecchia, F., Franceschini, F. and Marimon, F. (2021), "Mining quality determinants of product-service systems from unstructured user-generated contents: the case of car-sharing", *Quality Engineering*, Vol. 33 No. 3, pp. 425-442, doi: 10.1080/08982112.2021.1877305.

Oliveira, D., Alvelos, H. and Rosa, M.J. (2025), "Quality 4.0: results from a systematic literature review", *The TQM Journal*, Vol. 37 No. 2, pp. 379-456, doi: 10.1108/tqm-01-2023-0018.

Ostrom, A.L., Field, J.M., Fotheringham, D., Subramony, M., Gustafsson, A., Lemon, K.N., Huang, M.-H. and McColl-Kennedy, J.R. (2021), "Service research priorities: managing and delivering service in turbulent times", *Journal of Service Research*, Vol. 24 No. 3, pp. 329-353, doi: 10.1177/10946705211021915.

Özdağoğlu, G., Kapucugil-İkiz, A. and Çelik, A.F. (2018), "Topic modelling-based decision framework for analysing digital voice of the customer", *Total Quality Management and Business Excellence*, Vol. 29 Nos 13-14, pp. 1545-1562, doi: 10.1080/14783363.2016.1273106.

Roberts, M.E., Stewart, B.M., Tingley, D., Lucas, C., Leder-Luis, J., Gadarian, S.K., Albertson, B. and Rand, D.G. (2014), "Structural topic models for open-ended survey responses", *American Journal of Political Science*, Vol. 58 No. 4, pp. 1064-1082, doi: 10.1111/ajps.12103.

Roberts, M.E., Stewart, B.M. and Tingley, D. (2019), "STM: R package for structural topic models", *Journal of Statistical Software*, Vol. 91 No. 2, pp. 1-40.

Shahin, M., Chen, F.F., Hosseinzadeh, A., Maghanaki, M. and Eghbalian, A. (2024), "A novel approach to voice of customer extraction using GPT-3.5 turbo: linking advanced NLP and Lean Six Sigma 4.0", *The International Journal of Advanced Manufacturing Technology*, Vol. 13 Nos 7-8, pp. 3615-3630, doi: 10.1007/s00170-024-13167-w.

Subhashini, L., Li, Y., Zhang, J., Atukorale, A.S. and Wu, Y. (2021), "Mining and classifying customer reviews: a survey", *Artificial Intelligence Review*, Vol. 54 No. 8, pp. 6343-6389, doi: 10.1007/s10462-021-09955-5.

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