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KA-VoC Map: Classifying product Key-Attributes from digital Voice-of-Customer

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ABSTRACT
Manufacturers and service providers need new tools to leverage the value of the digital Voice-of-Customer (VoC). These unstructured and disorganized data need ad-hoc approaches for their analysis and interpretation. In this view, this article proposes an innovative methodology aiming at classifying the Key-Attributes (KA) of products and services that may influence customer (dis)satisfaction. The proposed methodology relies on the analysis of digital VoC to extract relevant information for classifying key-attributes. A novel tool called KA-VoC Map is at the basis of the proposed classification. The KA-VoC Map combines two dimensions of analysis: the extent and the way a Key-Attribute is discussed within the digital VoC. The methodology classifies KAs into six categories: obstacles, frictions, indifferent, sleeping beauties, promises, and delights. For each category, the most appropriate management strategy is also suggested. Finally, an empirical study is provided to illustrate the effectiveness of the proposed method.

KEYWORDS
Customers reviews; Customer satisfaction; digital Voice-of-Customers; Key-attributes; Quality 4.0; Topic Modeling

1. Introduction

Companies know that customer opinions can be a great source of learning. Information from customers about their dissatisfaction or satisfaction is critical in improving the performance and effectiveness of products and services (Zhou and He 2019). This kind of information can be rather "expensive" since gathered through interviews, questionnaires, and market analysis (Bi et al. 2019; Mastrogiacomo et al. 2021). In recent years, there has been a growing interest in identifying customer needs more efficiently and objectively (Chiarini 2020; Sony, Antony, and Douglas 2020). Digital technologies support this challenge through the development of data-driven methodologies (Allen, Sui, and Akbari 2018; Belhadi et al. 2021; Elg et al. 2021).

Traditionally, word-of-mouth analysis served as input for quality management. Today, word-of-mouth has left its physical and relational dimension to move to digital (Kaplan and Haenlein 2010), so that customers can now share their experience of products and services using forums, blogs, and web platforms, producing the so-called digital Voice-of-Customers (VoC) (Özdağoğlu, Kapucugil-Ikiz, and Çelik 2018).

Understanding why customers are dissatisfied (or satisfied) remains a challenge every company faces regardless of industry, country, or market. All too often, however, the value of digital VoC is captured exclusively by digital platform operators, and manufacturers and service providers lack adequate tools to process and leverage these data (Stentoft et al. 2021).

Over the past 20 years, data mining research has made great strides, and new perspectives are opening up on digital VoC analysis. Tools and techniques that were once accessible to a few experts are now widespread and more practical (Mastrogiacomo, Barravecchia, and Franceschini 2019; Barravecchia, Mastrogiacomo, and Franceschini 2021). For the analysis of digital VoC, the most popular text mining approach is topic modeling. Topic modeling algorithms applied to extensive collections of digital VoC allow the mining and the detection of the so-called Key-Attributes (KAs), i.e., attributes or features of products or services that critically affect customer satisfaction.

Most studies in the field have focused only on how to process and analyze digital VoC to identify KAs. However, there has been little discussion concerning how to leverage this information to categorize and

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prioritize KAs. To bridge this gap, this paper addresses the following research question: *How can digital VoC be leveraged to categorize KAs of customer satisfaction?*

In detail, this paper introduces a novel categorization of product or service KAs based on the results of topic modeling algorithms applied to large databases of digital VoC. The research investigates how to categorize KAs on the basis of two complementary dimensions: the extent and the way a KA is discussed. Based on these two dimensions, an operational tool—hereafter named KA-VoC Map—is proposed. The KA-VoC Map aims at supporting designers in categorizing the KAs of products/services with respect to their impact on customer satisfaction and the overall customer experience. Other taxonomies for classifying product/service attributes are also available (*e.g.*, Kano 1984), but none of them relies on the evaluation of digital VoC.

The remainder of the paper is structured as follows. Section 2 provides some theoretical elements and significant research related to the issues under analysis. Section 3 introduces the KA-VoC Map and the related taxonomy of attributes, while Section 4 proposes a case study. Some guidelines for managing and designing the identified KAs are proposed in Section 5. Section 6 discusses the the KA-VoC Map as benchmarking tool. Finally, the concluding section summarizes the contributions of the work, its limitations, and possible future research.

2. Literature review and related research

2.1. Customer satisfaction

Customer satisfaction is defined as "the degree to which the customer expectations have been fulfilled" (International Organization for Standardization 2015). Besides this definition, plenty of definitions have been provided; most of them stress the "confirmation-disconfirmation process," according to which satisfaction is achieved when customers' perceptions match their expectations.

Customer satisfaction proved to represent a core determinant of success in the competitive market. The ability of product or service providers to create a high degree of satisfaction is essential for product differentiation and for the development of a resilient relationship with customers.

In order to manage customer satisfaction, it is critical to learn customer needs so as to develop product or service attributes accordingly (Wang 2013; Jiang et al. 2019; Zhou and He 2019; Barravecchia, Mastrogiacomo, and Franceschini 2020). For this reason, a number of prior studies attempted to explore how to identify and categorize the key features of products and services influencing customer satisfaction. Traditionally, this was achieved through questionnaires and interviews. Today, there are many innovative and effective ways to gather information about customer expectations and needs (Mastrogiacomo et al. 2021).

2.2. Taxonomies of attributes of product or services

The classification of the attributes of products or services with respect to their influence on customer (dis)satisfaction has been a continuing concern within quality management and design research (Chen and Lee 2009). The reference models developed since the 1980s have had no recent "successors." Current efforts in this area focus primarily on developing tools to support model applications (Chen and Lee 2009; Mikulić and Prebežac 2011; Borgianni and Rotini 2015).

Without aiming to be exhaustive, Table 1 reports some relevant classifications.

The most famous and recognized classification of attributes of products and services is surely the one proposed by Kano in 1984 (Kano 1984). The original Japanese labels have been translated in various ways. However, all refer to the original five quality elements defined by Kano: delighters (also known as attractive or exciters), must-be (also known as basics or threshold), one-dimensional (also known as performance or linear), indifferent, and reverse. *Delighters* are the features that, when they are present, cause a positive reaction. *Must-be* are the features that the product must have in order to meet customer demands. One-dimensional attributes are those for which a better performance will improve customer satisfaction. *Indifferent* refers to neither good nor bad aspects, as they do not result in either customer satisfaction or dissatisfaction. Finally, *reverse* refers to attributes that,

Table 1. Taxonomies of product or service attributes.

Reference	Category 1	Category 2	Category 3	Category 4	Category 5
Kano 1984	Delighters	Must-Be	One-Dimensional	Indifferent	Reverse
Oliver 1995	Monovalent Satisfiers	Monovalent Dissatisfiers	Bivalent Satisfiers	Null Relationships	–
Chitturi, Raghunathan, and Mahajan 2008	Hedonic	Utilitarian	–	–	–

in case of a high degree of achievement, result in dissatisfaction.

In order to make the use of Kano's categorization more operational, Kuo, Chen, and Deng (2012) proposed the integration of Kano's model with the Importance-Performance Analysis (IPA). The IPA–Kano model is a tool for categorizing and diagnosing quality attributes and providing specific strategies for attributes in each category.

In 1995, taking into account the relationship between need fulfillment and satisfaction Oliver (1995) proposes a similar taxonomy: *monovalent dissatisfiers*, *monovalent satisfiers*, and *bivalent satisfiers*, *null relationships*. More recently, Chitturi, Raghunathan, and Mahajan (2008) introduced a distinction between *hedonic* and *utilitarian* benefits. While the former refers to the esthetic, experiential, and enjoyment-related benefits, the latter refers to the functional, instrumental, and practical benefits of a consumption offering.

Each of the taxonomies proposed in the literature analyses the problem from different points of view, focusing on the effects on customer satisfaction. The classification of product and service attributes is mostly done using traditional tools such as questionnaires and interviews. By their nature, these tools are applicable to a small subset of customers.

With the advent of new digital technologies, a new understanding of how to analyze and manage customer satisfaction is necessary (Zonnenshain and Kenett 2020). Artificial intelligence and available online data generated from a large population of customers may be the key to addressing this new challenge (Sony, Antony, and Douglas 2020).

2.3. Digital VoC and topic modeling

Digital VoC is the set of customers' feedback about their experiences and expectations on products or services published on publicly accessible websites. Digital VoC production is growing rapidly. Consumers share their experiences and perceptions about products and services through websites, forums, and social media (Chen, Zhang, and Liu 2019).

Digital VoC and, specifically, online reviews can offer a low-cost source of information for understanding customer requirements and expectations (Liu et al. 2019). Despite many platforms (e.g., Google, Facebook) are attempting to limit the download of large amounts of digital VoC, a variety of software applications are available for web scraping. Moreover, text mining programs often include libraries for web scraping. Besides the textual content of the reviews, these tools often allow the collection of relevant metadata such as title, author, date, rating, nationality (Mastrogiacomo et al. 2021).

Currently, several methods exist to mine insights from digital VoC. Most use topic modeling algorithms to identify the most discussed topics (Özdağoğlu, Kapucugil-İkiz, and Çelik 2018). These methods are typically based on machine-learning algorithms that can detect latent topics running through a large collection of unstructured textual documents (Blei, Ng, and Jordan 2003; Özdağoğlu, Kapucugil-İkiz, and Çelik 2018). Topic modeling algorithms do not require any prior annotations or labeling of the documents since the topics emerge from analyzing the texts (Blei 2012). In the last three decades, a wide variety of topic modeling techniques have been developed, including Latent Semantic Analysis (LSA) Probabilistic Latent Semantic Analysis (PLSA) Latent Dirichlet Allocation (LDA), and Structural Topic Model (STM) (Kherwa and Bansal 2020). Among the vast family of topic modeling techniques, the most appropriate algorithms for analyzing digital VoC are probabilistic topic modeling algorithms (Mastrogiacomo et al. 2021). In particular, STM proved to outperform LDA in the presence of covariate information (i.e., metadata associated with each textual document (Wesslen 2018). This aspect is considered critical for the analysis of digital VoC. In many cases, textual feedback on the customer experience is associated with additional information such as the rating assigned to the product/service, the type of product/service used, nationality of the user, etc.

Given a big set of documents, probabilistic topic modeling algorithms deals with the problems of: (i) identifying a set of topics that describe a text corpus (i.e., a collection of text documents from a variety of sources); (ii) associating a set of keywords to each topic and (iii) defining a specific mixture of these topics for each document (Roberts, Stewart, and Tingley 2019). The logic of the application of these approaches is that if a topic is discussed (within the digital VoC), then it is critical to the definition of the quality of the object (product, service, or product-service system) (Mastrogiacomo et al. 2021).

Recent evidence suggests that digital VoC analysis can be leveraged not only to identify attributes of products and services but also for their classification according to user perceptions (Barravecchia, Mastrogiacomo, and Franceschini 2020; Barravecchia, Mastrogiacomo, and Franceschini 2021). In particular, several attempts have been made to automatically classify product and service attributes according to the original attributes categories proposed by Kano (Min, Yun, and Geum 2018; Bi et al. 2019; Chen, Zhang, and Liu 2019).

3. KA-VoC Map

This section introduces a practical novel approach for classifying and managing products or service KAs. The tool is called KA-VoC Map. Inputs are the results of the topic modeling algorithms (see Section 3.1). Output is a structured map that categorizes KAs on two dimensions: the way and the extent a key attribute is discussed (see Section 3.2). Section 3.3 proposes a practical procedure to structure and populate the KA-VoC Map. Section 4 provides a case study showing an application of the proposed method.

3.1. KA-VoC Map input

Probabilistic topic modeling algorithms, such as LDA (Blei, Ng, and Jordan 2003; Blei 2012) or STM (Roberts et al. 2014; Roberts, Stewart, and Tingley 2019), applied to the analysis of customer reviews provide two different results: (i) the list of the KAs (topics) discussed within a collection of documents in the form of a mixture of keywords (see an example in Table A.1) and (ii) the model of the reviews (i.e., the digital VoC) as a mixture of discussed attributes. Specifically, for this second output, the probabilistic topic modeling algorithm identifies a multinomial distribution related to each review that indicates the probability that the review discusses a specific topic, the so-called topical prevalence.

From the processing of this information, it is possible to derive two indicators, the *Mean Topical Prevalence* (MTP) and the *Mean Rating Proportion* (MRP) (Barravecchia, Mastrogiacomo, and Franceschini 2020).

The MTP represents how much a key-attribute is, on average, discussed within the analyzed set of digital VoC. It can be calculated as follows:

$$MTP_t = \frac{\sum_{i=1}^{N} TP_{i,t}}{N} \quad \forall\ t \tag{1}$$

Where N is the number of considered reviews and $TP_{i,t}$ is the topical prevalence of the t-th key-attribute in the i-th review.

The sum of the *MTPs* related to all the identified KAs is equal to 1:

$$\sum_{t=1}^{T} MTP_t = 1. \tag{2}$$

OUTPUT OF THE TOPIC MODELING ALGORITHM

$TP_{i,t}$

Review	Rating	Key-attribute 1	Key-attribute 2	Key-attribute 3
Review 1	1	0.7	0.3	0
Review 2	1	0.7	0.2	0.1
Review 3	2	0.9	0.1	0
Review 4	2	0	0.5	0.5
Review 5	3	0.4	0	0.6
Review 6	3	0.3	0.6	0.1
Review 7	4	0.1	0.6	0.3
Review 8	4	0.3	0	0.7
Review 9	5	0.1	0.3	0.6
Review 10	5	0	0.2	0.8

MTP Key-attribute 3

$$MTP_3 = \frac{0 + 0.1 + 0 + 0.5 + 0.6 + 0.1 + 0.3 + 0.7 + 0.6 + 0.8}{10} = 0{,}37$$

Figure 1. Example of MTP calculation. Each row shows the rating and the values of topical prevalence ($TP_{i,t}$) for each review, i.e., the proportion of the review discussing each of the three key attributes considered.

Figure 1 shows an example of the calculation of MTP.

The MTP value may be distorted by the source from which the digital VoC is collected (Mastrogiacomo et al. 2021). For example, digital VoC collected from the App Store is likely to contain more information about the performance of the app than about the characteristics of the overall related service. In order to overcome this problem, neutral digital VoC sources (i.e., not focused on a specific component of the analyzed object) should be chosen.

The MRP represents the average proportion of an attribute in reviews with a specific rating (Barravecchia, Mastrogiacomo, and Franceschini 2020). MRP can be calculated as follows:

$$MRP_{t,k} = \frac{\sum_{i \in R_k} TP_{i,t}}{|R_k|} \tag{3}$$

where t is the attribute; k is the level of the rating scale; R_k is the subset of reviews associated to a rating level equal to R_k; $TP_{i,t}$ is the topical prevalence of the t-th attribute in the i-th review; $|R_k|$ is the cardinality of R_k.

Note that the sum of the *MRPs* related to all the identified attributes and a specific rating level is equal to 1:

$$\sum_{t=1}^{T} MRP_{t,k} = 1\ \forall\ k. \tag{4}$$

Figure 2 shows an example of the calculation of MRP. The MRP profile can be associated with each attribute (see Figure 2). This information shows the link between product or service attributes and customer (dis)satisfaction. As we can see from Figure 2,

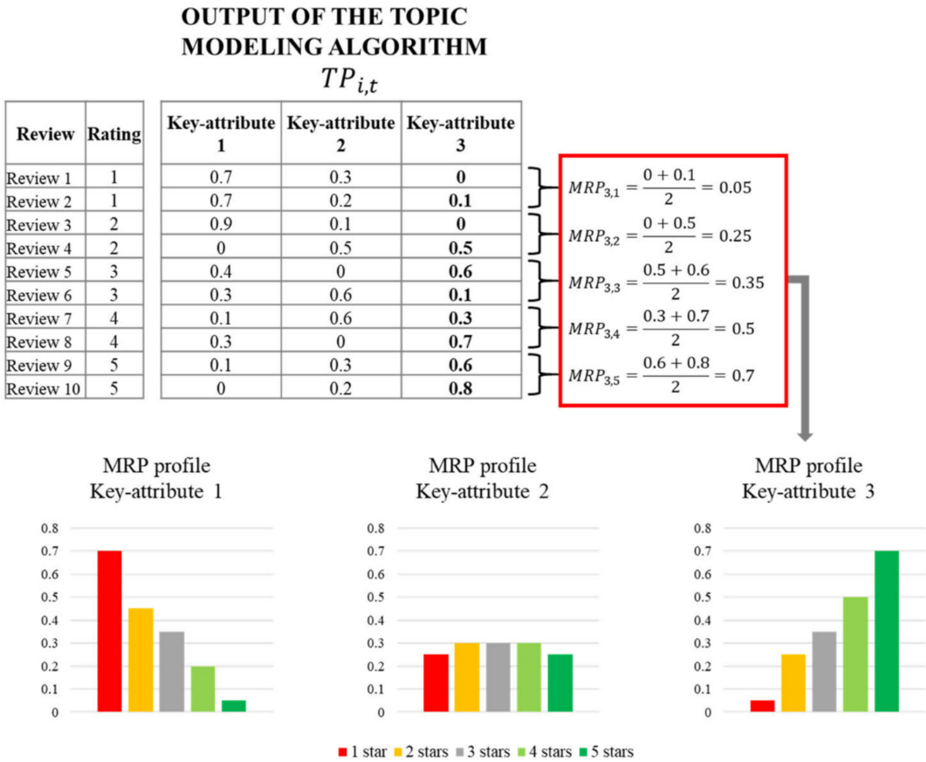

Figure 2. Example of MRP calculation. Each row shows the rating, and the values of topical prevalence ($TP_{i,:}$) for each review i.e., the proportion of the review discussing each of the three key attributes considered.

different attributes present different MRP profiles. According to Barravecchia, Mastrogiacomo, and Franceschini (2020), these profiles can be classified according to their shape into positive, negative, and neutral profiles. For example, the exemplifying key-attribute 3 has a positive profile, being more discussed by reviews with a positive rating. Exemplifying key-attribute 1 has a negative profile, being more discussed in reviews with negative ratings. Finally, attributes presenting a flat or symmetric profile centered on the intermediate rating can be classified as neutral (see exemplifying key-attribute 2).

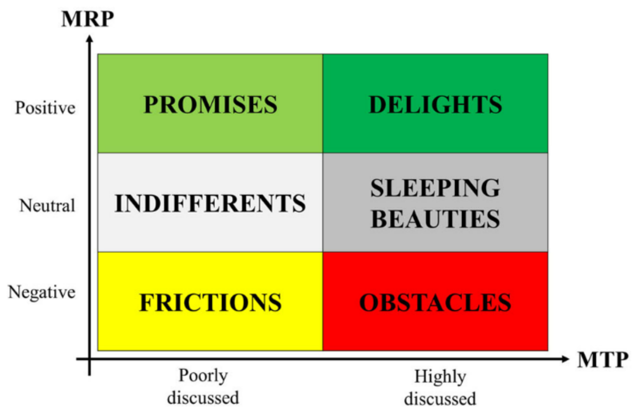

Figure 3. KA-VoC Map. Categorization of key-attributes.

3.2. KA-VoC Map categories

Figure 3 introduces the KA-VoC Map, a graphical tool to support Key-Attributes classification for customer (dis)satisfaction. The categorization is based on two complementary dimensions, MTP and MRP, which indicate the way and the extent a topic is discussed.

The KA-VoC Map categorizes attributes into different categories, each affecting customer satisfaction differently. Specifically, the KA-VoC Map identifies six different categories of attributes influencing customer (dis)satisfaction:

- *Obstacles*, i.e., highly discussed attributes (high MTP) and source of dissatisfaction (negative MRP profile). These attributes are the primary sources of dissatisfaction, being the main subjects of customer complaints.
- *Frictions*, i.e., poorly discussed attributes (low MTP) and source of dissatisfaction (negative MRP profile). These attributes represent minor issues, they are not widely discussed, but they mainly generate customer dissatisfaction.
- *Indifferents*, i.e., poorly discussed (low MTP) attributes that are neutral regarding customer satisfaction (neutral MRP profile). Being scarcely discussed, they are classified as not relevant because they do not have a clear and definite influence on satisfaction.

Table 2. Synthesis of the main differences between Kano model and KA-VoC Map.

	Kano model	KA-VoC Map
Source of information	Structured questionnaire (functional/dysfunctional questions)	Digital VoC
Customers sample size	Little (usually)	Very large
KA identification	KAs are supposed known (a preliminary analysis of customer requirements is needed to identify KAs)	KAs (topics) are identified through the analysis of Digital VoC (Topic modeling)
What is being assessed?	Asymmetries in customer feelings based on hypothesized provision/non-provision of customer benefits/values of KA	Sources of satisfaction/dissatisfaction (KAs)
KA Classification methods	Kano Special Evaluation Table (Kano 1984)	KA-VoC Map (see Fig.3)
Analysis perspectives	KAs Functionality/Dysfunctionality	*Mean Topical Prevalence* (how much a KA is discussed) and *Mean Rating Proportion* (how a KA is rated)

- *Sleeping beauties,* i.e., neutral attributes with respect to customer satisfaction (neutral MRP profile), but highly discussed (high MTP). These dimensions do not have a defined impact on customer satisfaction. They often represent dimensions that are considered essential and, therefore, cannot positively or negatively impress the customer. Being highly debated, they can be considered critical to customer satisfaction.
- *Promises*, i.e., poorly discussed attributes (low MTP) generating customer satisfaction (positive MRP profile). These dimensions represent minor advantages or emerging attributes provided by the analyzed object.
- *Delights*, i.e., highly discussed attributes (high MTP) generating satisfaction (positive MRP profile). Customers recognize a value to these attributes, which are the primary sources of satisfaction.

3.3. KA-VoC Map vs. Kano model: differences and similarities

At first glance, the taxonomy inspired by the KA-VoC Map appears quite similar to the one proposed by the Kano model (Kano 1984). However, it is essential to underline the significant difference between these two approaches. Both methods aim at classifying the KAs of products/services according to customer concerns (Sireli, Kauffmann, and Ozan 2007), but objectives and methods are rather distinct.

On the one hand, Kano's method, starting from a set of "known" KAs (usually determined by a preliminary analysis of customer requirements), assesses the asymmetries in customer feelings based on the hypothesized provision/non-provision of customer benefits/values (Mikulić and Prebežac 2011). Kano's classification is achieved by asking customers (usually on little samples) to fill in a structured questionnaire that includes two questions for each KA: the first one (positively formulated) to see how the presence of a KA is "functional" to a specific product/service; the second (formulated negatively) to see how its absence is "dysfunctional". On the other hand, the proposed approach, starting from the analysis of large samples of digital VoC, identifies and classifies the primary sources of satisfaction and dissatisfaction (i.e., KAs) - of the object under investigation - by a Topic modeling algorithm. Table 2 summarizes the main differences between the two approaches.

Although some labels associated with model categories are similar for the two approaches, their meanings are very different. For example, the delights/delighters category appears in both taxonomies. KA-VoC Map *delights* indicate customer positive perceptions (high MTP and positive MRP profile). Unlike the Kano delighters, the KA-VoC Map delights do not have a predicted influence on the hypothesized expectations if absent.

3.4. How to structure and populate the KA-VoC Map

In order to populate the KA-VoC Map, this section proposes an operational approach. The procedure can be divided into two steps: (i) identification of KAs scale level according to the MTP, and (ii) identification of KAs scale according to the MRP.

3.4.1. Identification of KAs scale level according to the MTP

The KA-VoC Map differentiates between "poorly discussed" and "highly discussed" attributes based on the MTP. The threshold that discriminates between highly and poorly discussed attributes is conventionally set to $^1/_n$, where n is the identified number of topics. This threshold defines whether an attribute is highly or poorly

Table 3. Example of calculation of the Spearman-Rho ranked-order correlation coefficient.

Rating (values)	MRP (values)	Rank (Rating)	Rank (MRP)	$R(X_i) - R(Y_i)$	$(R(X_i) - R(Y_i))^2$
1	0.2	5	2	3	9
2	0.5	4	1	3	9
3	0.15	3	3	0	0
4	0.10	2	4	−2	4
5	0.05	1	5	−4	16

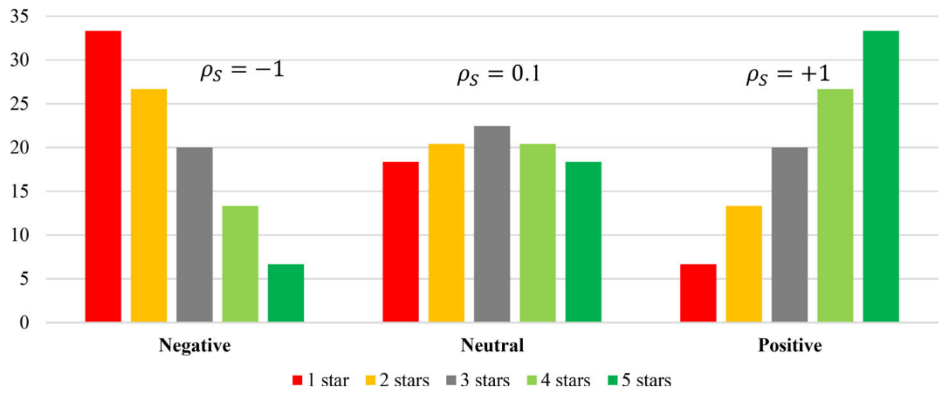

Figure 4. Categorization of MRP reference profiles. Three categories of profile are identified: (A) Negative profiles; (B) Neutral Profiles; (C) Positive Profiles.

discussed, i.e., whether the topic's MTP is higher or lower than the average MTP of all topics.

In a nutshell, each topic t could be classified according to the MRP classification criterion as follows:

$$\begin{cases} t \in \{\text{highly discussed topics}\}, \; if \; MTP_t \geq \frac{1}{n} \\ t \in \{\text{poorly discussed topics}\}, \; if \; MTP_t < \frac{1}{n} \end{cases} \tag{5}$$

3.4.2. Identification of KAs scale level according to the MRP

The different MRP profile classification is more complex since a different MRP profile potentially characterizes each attribute. In this paper, we propose a simple three-level classification (Barravecchia, Mastrogiacomo, and Franceschini 2020). MRP profiles are categorized into positive, negative, and neutral based on the rating level distribution of MRPs. To categorize MRP profiles, we propose the use of the *Spearman-Rho Ranked-Order Correlation Coefficient* (ρ_S), a nonparametric measure of rank correlation between the ranks of the rating levels and the ranks of the *MPR*. The Spearman's ρ_S can be computed as follows (Myers, Well, and Lorch 2013):

$$\rho_S = 1 - \frac{6 \cdot \sum_{i=1}^{n} (R(X_i) - R(Y_i))^2}{n \cdot (n^2 - 1)} \tag{6}$$

where:

- $R(X_i)$ represent the ranks of the rating levels.
- $R(Y_i)$ represent the ranks of the $MRP_{t,k}$, i.e., the ranks of the average proportion of a KA with a specific rating.
- n is the number of considered rating levels

Table 3 and Eq. (7) show an example of the calculation of the Spearman-Rho Ranked-Order Correlation Coefficient. Figure 4 shows the classification of three representative profiles.

$$\begin{aligned} \rho_S &= 1 - \frac{6 \cdot \sum_{i=1}^{n} (R(X_i) - R(Y_i))^2}{n \cdot (n^2 - 1)} \\ &= 1 - \frac{6 \cdot (9 + 9 + 0 + 4 + 16)}{5 \cdot (5^2 - 1)} = -0.9 \end{aligned} \tag{7}$$

Spearman's ρ ranges between -1 and $+1$. ρ_S is equal to $+1$ when the MRP profile is perfectly monotonically increasing, while it is equal to -1 when it is perfectly monotonically decreasing. According to Myers, Well, and Lorch (2013) MRP profiles with ρ_S ranging between -0.4 and $+0.4$ can be classified as neutral. Consequently, each topic t can be classified as follows:

$$\begin{cases} t \in \{negative \; key - attributes\}, \; if \; \rho_S < -0.4 \\ t \in \{neutral \; key - attributes\}, \; if -0.4 \leq \rho_S \leq +0.4 \\ t \in \{positive \; key - attributes\}, \; if \; \rho_S > +0.4 \end{cases} \tag{8}$$

4. Case study

This section provides a practical case study to illustrate the implementation of the proposed

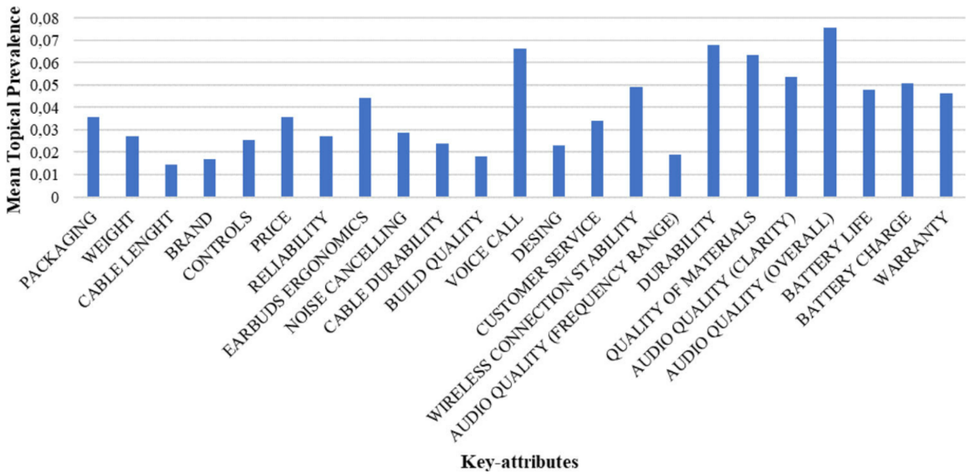

Figure 5. MTP for each KA. The analyzed product is Bluetooth headphones.

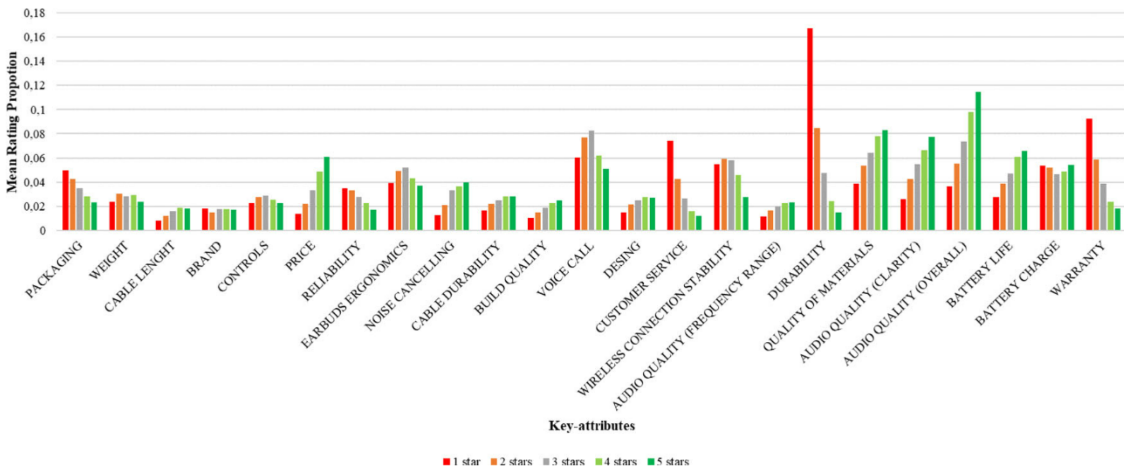

Figure 6. MRP profiles for each KA. Product: Bluetooth headphones.

methodology. The subject of this case study is *Bluetooth headsets.*

The implementation of a topic modeling algorithm on a vast collection of digital VoC enabled the identification of KAs. A complete description of the procedure is provided in Appendix A. The following 23 KAs were identified: packaging, weight, cable length, brand, controls, price, reliability, earbuds ergonomics, noise canceling, cable durability, build quality, voice call, design, customer service, wireless connection stability, audio quality (frequency range), durability, quality of materials, audio quality (clarity), audio quality (overall), battery life, battery charge, warranty.

The topic modeling algorithm produced two outputs: (i) the list of KAs of the product under analysis; (ii) the multinomial probability distributions indicating for each digital VoC record the KAs discussed within them (i.e., topical prevalence). The topical prevalence was used to calculate the MTP values associated with each KA (see Section 3.4). Ratings associated with each digital VoC record and topical prevalence distributions were considered to determine the MRP profiles. Figures 5 and 6 show, respectively, the MTP values and MRP profiles for each of the identified KAs.

The Spearman-Rho Ranked-Order Correlation Coefficient of the MRP profiles with the corresponding rating levels was calculated to classify each KA into three categories: "positive", "negative" and "neutral" profiles (see Section 3.4). Table 4 shows the values of Spearman's ρ and MTP and their respective classifications.

By applying the procedure described in section 3.3, the identified KAs were allocated on the KA-VoC Map, as shown in Figure 7. Warranty, durability, and wireless connection stability were identified as *obstacles* (negative MRP profile and highly discussed). Customer service, reliability, and packaging were included in the *frictions* category (negative MRP profile and poorly discussed). Brand, weight, and controls were perceived as *indifferents* (neutral MRP profile

Table 4. Spearman's ρ and MTP values for each KA with their corresponding classification.

Key-attribute	Spearman's ρ	MPR Classification	MTP	MTP Classification
PACKAGING	−1	Negative	0.036	Poorly discussed
WEIGHT	−0.3	Neutral	0.027	Poorly discussed
CABLE LENGHT	0.9	Positive	0.015	Poorly discussed
BRAND	−0.3	Neutral	0.017	Poorly discussed
CONTROLS	0.1	Neutral	0.025	Poorly discussed
PRICE	1	Positive	0.040	Highly discussed
RELIABILITY	−1	Negative	0.027	Poorly discussed
EARBUDS ERGONOMICS	−0.3	Neutral	0.044	Highly discussed
NOISE CANCELING	1	Positive	0.029	Poorly discussed
CABLE DURABILITY	0.9	Positive	0.024	Poorly discussed
BUILD QUALITY	1	Positive	0.018	Poorly discussed
VOICE CALL	−0.3	Neutral	0.066	Highly discussed
DESING	0.9	Positive	0.023	Poorly discussed
CUSTOMER SERVICE	−1	Negative	0.034	Poorly discussed
WIRELESS CONNECTION STABILITY	−0.7	Negative	0.049	Highly discussed
AUDIO QUALITY (FREQUENCY RANGE)	1	Positive	0.019	Poorly discussed
DURABILITY	−1	Negative	0.068	Highly discussed
QUALITY OF MATERIALS	1	Positive	0.063	Highly discussed
AUDIO QUALITY (CLARITY)	1	Positive	0.053	Highly discussed
AUDIO QUALITY (OVERALL)	1	Positive	0.076	Highly discussed
BATTERY LIFE	1	Positive	0.048	Highly discussed
BATTERY CHARGE	0.1	Neutral	0.051	Highly discussed
WARRANTY	−1	Negative	0.046	Highly discussed

Notes: $MTP\ threshold\ = {}^{1}/_{n} = .037$.

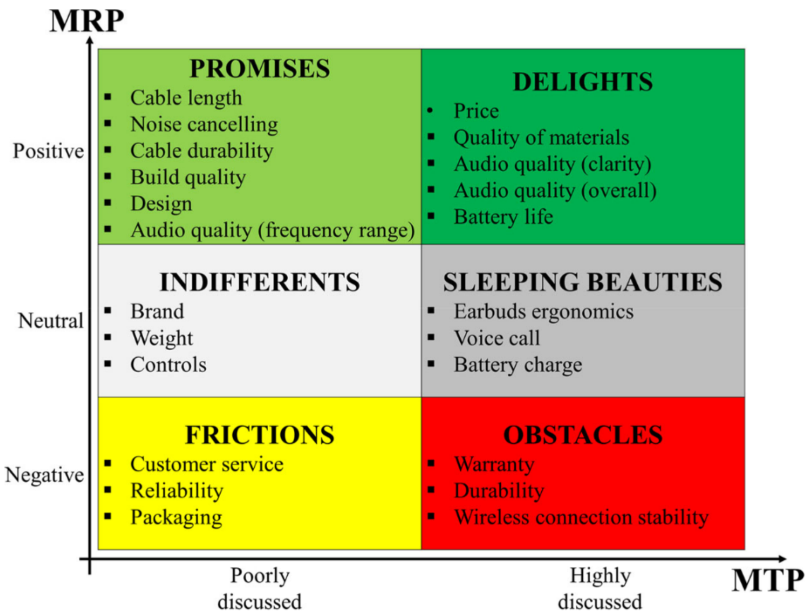

Figure 7. KA-VoC Map Categorization of Bluetooth headphones based on the results of a topic modeling analysis.

and poorly discussed). Earbuds ergonomics, voice call, and battery charge were classified as *sleeping beauties* (neutral MRP profile and highly discussed). The following attributes were considered as *promises* (positive MRP profile and poorly discussed): cable length, noise canceling, cable durability, build quality, design, and audio quality (frequency range). Finally, the following attributes were classified as *delights* (positive MRP profile and highly discussed): price, quality of materials, audio quality (clarity), audio quality (overall), and battery life.

5. KAs management

In order to capitalize the results of the application of the KA-VoC Map, this section suggests a list of actions that may be undertaken to manage the identified KAs:

- *Obstacles* are the primary sources of dissatisfaction. As the name suggests, they can be seen as barriers to achieving full customer satisfaction. Radical actions are necessary to remove them: processes and product features need to be changed. In some cases,

Table 5. General guidelines for managing KAs of customer (dis)satisfaction.

Category	Action	Description
Obstacles	Change	Radical change of processes or product features in order to address the strong dissatisfaction caused by these attributes
Friction	Improve	Incremental improvements are required to improve performance
Indifferents	Ignore	In contexts where resources are limited, it is better to focus on more relevant issues
Sleeping beauties	Monitor	Monitoring to prevent possible shifts toward the obstacle category
Promises	Preserve	Preservation and improvement in order to please customers and differentiate product or service from competitors
Delights	Communicate	Communication of the most appreciated attributes to current and potential customers

there may be a need to completely redesign some analyzed object elements since its actual configuration does not fully meet customer needs. When the performance of the attribute classified as an obstacle is dependent on the allocation of resources (e.g., customer service), it is necessary to increase their deployment. Communicating these improvements may encourage dissatisfied customers to remain loyal to the product or service provider.

- *Frictions* are sources of dissatisfaction too, but their discussion level is lower than that of obstacles (lower MTP). The reasons can be numerous, including: (i) infrequent issues; (ii) problems occurring only in specific usage modes; (iii) unsuitability to meet the needs of a particular target of customers; (iv) issues with a minor impact on overall user satisfaction. These considerations suggest that frictions are secondary sources of dissatisfaction. When frictions are found, the most appropriate approach is to incrementally improve their performance to meet customer expectations.
- *Indifferents* attributes are not much discussed (low MTP) and do not directly impact customer satisfaction (neutral MRP profile). For this reason, the best option is to ignore indifferent attributes. In contexts where resources are limited, it is better to address more relevant issues.
- The role of the *sleeping beauties* should not be underestimated. At a first analysis, it might seem that these attributes do not influence satisfaction and therefore are not critical in the value offering. However, these elements may be important for the quality perception of the object under analysis since many customers discuss them. A deterioration in the performance of an attribute classified as sleeping beauty can quickly cause a shift toward the obstacle category. Therefore, it is essential to monitor sleeping beauties to keep under control the impact they have on customer satisfaction.
- *Promises* are the secondary sources of satisfaction. The low MTP value is due to the fact that only specific customer segments recognize the value of these attributes. This evidence, however, does not detract from the importance of the promises attributes. Taken individually, promises attributes could be considered marginal, but all together, they characterize a product or service by distinguishing it from its competitors. For this reason, the promises attributes need to be preserved and improved in order to please the customer.
- In a comprehensive customer satisfaction management strategy, it is necessary to consider attributes classified as *delights* as well. Delights are the primary sources of satisfaction expressed by customers through the digital VoC, and for this reason, they should be the pillars of the value proposition of the product or service under analysis. Therefore, the best strategy is to continue to invest in improving the performance of delights and focus communication and advertising on these attributes.

Table 5 summarizes the main guidelines outlined in this section.

6. KA-VoC Map and benchmarking of similar products

It is important to highlight that the belonging of an attribute to a category is not intrinsic to the KA itself, but it reflects the effect of the attribute on customer perceptions. For this reason, similar products can have different KAs classifications.

The example in Figure 8 clearly shows this distinctive aspect of the tool. Two very similar models of wireless headphones, produced by different companies, provided different categorisations of their KAs.

In practical business analysis, KA-VoC Map could be used as a benchmarking tool for analyzing KAs of similar products or services. The purpose of comparing different offerings under the KA-VoC Map lens may include:

- *An overall estimation of the similarities and differences (physical and perceptual) of two products/services.* Usually, the similarity of different products/services is based only on their physical characteristics (technical, esthetic, functional). The KA-VoC Map can extend this assessment to include customer perceptions. If the overlap between the two classifications is high, it may imply that the two offerings perform similarly from the customers'

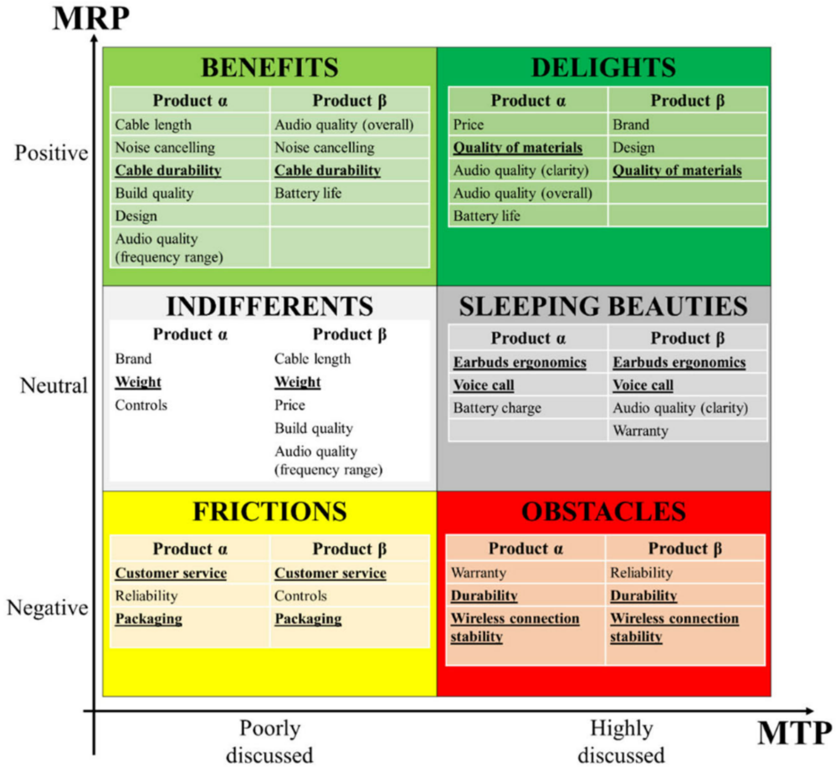

Figure 8. KA-VoC Map for two different models of wireless headphones (product α and product β). Bold and underlined are the KAs that do not change category in the two products under analysis.

perspective. Conversely, if the overlap is limited, this could indicate a more marked difference. Figure 8 shows a practical example where only 9 KAs out of 23 maintain the same category for two different models of wireless headphones. This highly differentiated classification of KAs can represent a different degree of fulfillment of the various customer requirements.

- *The identification of potential improvements.* The different categorization of KAs of similar products/services can drive the deployment of improvement actions. Lower levels of performance with respect to competitors offerings may reveal opportunities for improvement. For example, the KA "Audio quality (clarity)" reported in Figure 8, is categorized as delight for product α, while it is categorized as sleeping beauty for product β. This evidence can prompt the manufacturer of the β product to improve that feature.
- *The designing of communication and marketing strategies.* Marketing strategies can also be based on comparing different perceptions of similar products. For example (see Figure 8), the KA "warranty" is classified as an obstacle for the α-product. The manufacturer of β-product could advertise the best performance on this feature in order to gain customers from the competitor.

7. Conclusions

This paper provides a novel approach to identify and categorize KAs for customer satisfaction based on the analysis of digital VoC. The identification of the KAs related to a product or a service is performed using a topic modeling algorithm. Two indicators have been used to classify the identified key-attributes: the Mean Topical Prevalence, indicating how much an attribute is discussed, and the Mean Rating Proportion, indicating how that attribute affects the overall customer satisfaction. The combination of the values of these two indicators produces a classification of product or service attributes into six categories: *obstacles, frictions, indifferents, sleeping beauties, promises,* and *delights*.

To ease the classification and reading of the results, this article also introduces a graphical support tool, the KA-VoC Map, with practical guidelines to facilitate the management of the KAs.

The present study establishes a quantitative framework for classifying product or service attributes from the customer point of view, overcoming some of the limitations of traditional methods. Further research efforts will be made to understand the potential implication of this research in different domains, including product quality tracking, product quality improvement, and design/redesign.

Ethical approval

The authors respect the Ethical Guidelines of the Journal.

Authors contributions

The authors have provided an equal contribution to the drafting of the paper.

Declaration of interest statement

No potential conflict of interest was reported by the authors.

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Appendix A

This Appendix reports the methodology applied to identify the KAs of the product Bluetooth earphones. The investigation is based on the application of the Structural Topic Model (STM) algorithm, which allows to include the metadata associated with the digital VoC for the definition of the topic model. The algorithm was implemented on the open-source R software using the STM package (M. E. Roberts, Stewart, and Tingley 2019).

Following Mastrogiacomo et al. (2021), the identification of product KAs from digital VoC can be structured in six steps (see Figure A.1).

The first step involves data extraction. In the case under analysis, about 14500 reviews were downloaded. Downloaded reviews have an average length of 130 characters and present a typical J-shaped distribution of ratings (see Figure A.2). The highest values are obtained at the extreme values of the 5-level rating scale.

The text of the reviews was initially pre-processed to improve the performance of the topic modeling algorithm. Pre-processing included the following main activities:

- Removal of stop words (e.g. "the", "and", "when", "is", "at", "which"), punctuation, numbers, words with a low frequency, words generally not related to topical content (e.g. "paper", "present", "problem");
- Text lemmatization, i.e., all the words with similar meaning but with different inflected forms were replaced with a unique lemma;
- Removal of reviews containing less than 10 words, considered too short for the proposed analysis.

An essential parameter required as input by topic modeling algorithms is T, the number of topics able to describe the text corpus. The held-out likelihood was analyzed to identify the optimal number of topics (Scott and Baldridge 2013) . This metric quantifies the likelihood of the model on a subset of the digital VoC (usually 10%) that were not used for the estimation of the model (M. Roberts, Stewart, and Tingley 2019) . Held-out likelihood can be seen as a measure of how the topic model is able to explain the overall variability in the text corpus (Scott and Baldridge 2013).

Figure A.3 shows the result of the analysis concerning the identification of the optimal number of topics for the case under analysis. The graph is related to the values of the held-out likelihood as a function of T (from 5 to 50). It can be observed that the maximum held-out likelihood value corresponds to a number of topics equal to 27. Considering this information, an optimal number of T = 27 topics was identified.

Defined the optimal number of topics, the topic modeling algorithm identified the latent topics discussed in a collection of documents (Özdağoğlu, Kapucugil-İkiz, and Çelik 2018; Mastrogiacomo et al. 2021). In detail, in the proposed application the Structural Topic Model (M. E. Roberts, Stewart, and Tingley 2019) resulted in the definition of 27 topics shown in Table A.1. The identified topics largely correspond to the KAs of the product under analysis. Topics 11, 18, 21, and 22 were not considered in the following analyses because not related to specific attributes or properties of the analyzed product but to a general level of satisfaction.

The last step of the process consists of the validation of results (Barravecchia, Mastrogiacomo, and Franceschini 2021). Obtained results were verified by comparing the assigned topic of a randomly selected sample composed of 150 reviews with a manual topic assignment performed by the authors. For each of the 150 reviews, the authors were requested to agree in the association of one or more of the 27 topics identified by STM. Four possible outcomes of the data validation test have been considered (Barravecchia, Mastrogiacomo, and Franceschini 2021):

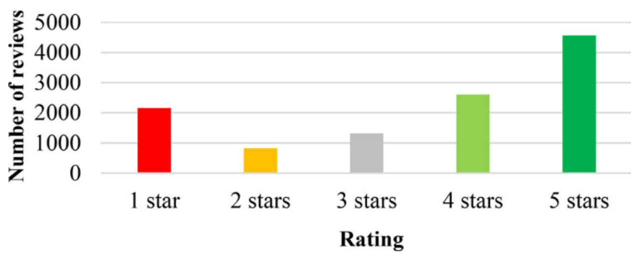

Figure A.2. J-shaped distribution of the rating level in the analyzed reviews.

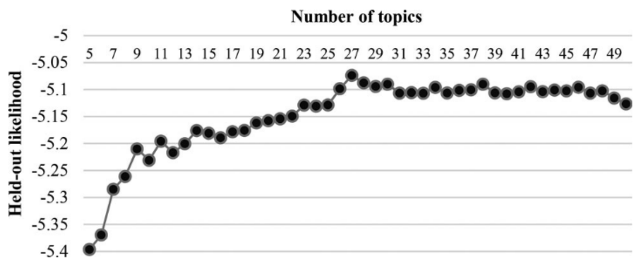

Figure A.3. Held-out likelihood over the number of topics (from 5 to 50).

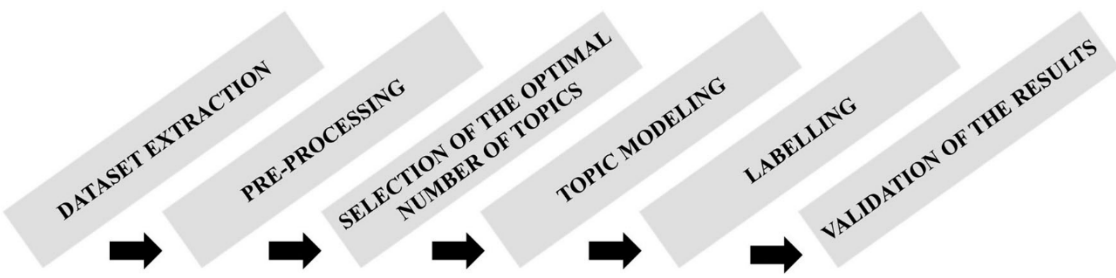

Figure A.1. Activity flow of the methodology to identify KAs for customer satisfaction. Adapted from Mastrogiacomo et al. (2021).

Table A.1. Topic label and related keywords for Bluetooth headphones. In the keywords related to topic 4 the real brand names have been replaced with Brand_A, Brand_B, Brand C. The last column indicates whether the identified topic represents a KA or not.

Topic	Topic Label	Keywords (highest probability)	KA
1	PACKAGING	*receive, product, packaging, item, red, box, origin, see, pack, check*	YES
2	WEIGHT	*around, light, run, weight, neck, switch, turn, gym, workout, magnet*	YES
3	CABLE LENGHT	*little, bit, cable, big, length, microphone, short, real, cut, compromise*	YES
4	BRAND	*Brand_A, perform, provide, suggest, Brand_B, company, model, name, trust, Brand_C*	YES
5	CONTROLS	*volume, button, set, change, control, plus, head, previous, press, heavy*	YES
6	PRICE	*price, rang, headset, excel, star, great, worth, other, segment, compare*	YES
7	RELIABILITY	*issue, problem, start, face, come, happen, cover, use, complaint, make*	YES
8	EARBUDS ERGONOMICS	*ear, fit, bud, pain, plug, ent, piec, fall, size, rubber*	YES
9	NOISE CANCELING	*noise, canceling, feature, travel, outside, surround, isolation, reduction, effect, train*	YES
10	CABLE DURABILITY	*wire, build, durable, thin, delicate, fragile, break, poor, ill, aspect*	YES
11	LEVEL OF SATISFACTION	*output, kind, made, else, tri, close, bought, like, basic, compare*	**NO**
12	BUILD QUALITY	*easy, handy, care, tangle, carry, free, jack, rough, strong, case*	YES
13	VOICE CALL	*music, call, mic, listen, voice, hear, play, able, person, talk*	YES
14	DESING	*look, feel, design, wear, small, adjust, might, hand, premium, rate*	YES
15	CUSTOMER SERVICE	*service, customer, avail, support, give, center, refund, call, care, response*	YES
16	WIRELESS CONNECTION STABILITY	*connection, Bluetooth, device, disconnect, thing, mobile, phone, automatic, Samsung, pocket*	YES
17	AUDIO QUALITY (FREQUENCY RANGE)	*high, mark, point, mid, end, really, lack, term, frequency, heard*	YES
18	LEVEL OF SATISFACTION	*earphone, one, wireless, normal, just, market, regular, recent, beauty, local*	**NO**
19	DURABILITY	*work, stop, day, week, worst, sudden, piece, faulty, pleas, waste*	YES
20	QUALITY OF MATERIALS	*quality, material, offer, value, thing, fantast, cheap, made, god, accessory*	YES
21	LEVEL OF SATISFACTION	*awesome, love, absolute, simply, thank, hour, class, fan, wonder, good*	**NO**
22	LEVEL OF SATISFACTION	*time, long, first, take, second, wont, lost, stuck, third, ring, disappoint*	**NO**
23	AUDIO QUALITY (CLARITY)	*bass, clear, low, clarity, treble, balance, loud, crystal, deep, pure*	YES
24	AUDIO QUALITY (OVERALL)	*sound, nice, quality, overall, superb, paisa, brilliant, happy, brought, clarity*	YES
25	BATTERY LIFE	*battery, life, backup, approx, louder, rest, descent, entire, hrs, vary*	YES
26	BATTERYCHARGE	*hour, charge, day, usage, full, continue, fast, minute, hours, quick*	YES
27	WARRANTY	*month, year, warranty, proper, speaker, damage, help, claim, function, broke*	YES

Table A.2. Validation indicators (Costa et al. 2007; Mastrogiacomo et al. 2021).

Name	Definition	Formula	Codomain	Value
Recall	It is the ratio between the correctly predicted positive observations and all observations in actual class.	$R = \frac{tp}{(tp + fn)}$	[0;1]	0.81
Precision	It is a measure which estimates the probability that a positive prediction is correct.	$P = \frac{tp}{(tp + fp)}$	[0;1]	0.78
F measure	It is the weighted average of Precision and Recall indicators. This score takes both false positives and false negatives into account.	$F = 2 \times \frac{P \times R}{P + R}$	[0;1]	0,79
Accuracy	It evaluates the effectiveness of the algorithm by its percentage of correct predictions.	$A = \frac{(tp + tn)}{tp + tn + fp + fb)}$	[0;1]	0,96

- *True positive* (tp): Agreement between authors and algorithm in the assignment of a review to a topic
- *True negative* (tn): Agreement between authors and algorithm not to assign a review to a topic
- *False positive* (fp): misalignment between the assignment of the review to a topic by STM and the non-assignment by the manual evaluator
- *False negative* (fn): misalignment between the assignment of the review to a topic by the manual evaluator and the non-assignment by STM

Based on the comparison between manual and STM topic assignment, four verification indicators were calculated (see Table A.2). These metrics show a generally good correspondence between the assignment produced by STM and the authors. The accuracy of 96% proves good effectiveness of the method to predict the content of the reviews, correctly identifying true positive and true negative. The Recall and Precision indicators, respectively equal to 81% and 78%, show that the method performs well in identifying the topics (true positive).