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 disorganised 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: Quality 4.0; Customer satisfaction; digital Voice-of-Customers; Topic Modelling; Customers reviews; Key-attributes.

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 *et al.*, 2020)_Digital technologies support this challenge through the development of data-driven methodologies (Allen *et al.*, 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 *et al.*, 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

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 *et al.*, 2020). For this reason, a number of prior studies attempted to explore how to identify and categorise 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 recognised 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, in case of a high degree of achievement, result in dissatisfaction.

In order to make the use of Kano's categorisation more operational, Kuo *et al.* (2012) proposed the integration of Kano's model with the Importance-Performance Analysis (IPA). The IPA–Kano model is a tool for categorising 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 et al. (2008) introduced a distinction between *hedonic* and *utilitarian* benefits. While the former refers to the aesthetic, 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 analyse 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 *et al.*, 2020).

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 *et al.*, 2008)	Hedonic	Utilitarian	-	-	-

2.3 Digital VoC and topic modelling

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 *et al.*, 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 modelling algorithms to identify the most discussed topics (Özdağoğlu *et al.*, 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 *et al.*, 2003; Özdağoğlu *et al.*, 2018). Topic modelling algorithms do not require any prior annotations or labelling of the documents since the topics emerge from analysing the texts (Blei, 2012). In the last three decades, a wide variety of topic modelling techniques have been developed, including LSA (Latent Semantic analysis), PLSA (Probabilistic Latent Semantic Analysis), LDA (Latent Dirichlet Allocation) and STM (Structural Topic Model) (Kherwa and Bansal, 2020). Among the vast family of topic modelling techniques, the most appropriate algorithms for analysing digital VoC are probabilistic topic modelling 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 modelling 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 (M. Roberts *et al.*, 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 (F. Barravecchia *et al.*, 2020; Federico Barravecchia *et al.*, 2021). In particular, several attempts have been made to automatically classify product and service attributes according to original attributes categories proposed by Kano (Min *et al.*, 2018; Bi *et al.*, 2019; Chen *et al.*, 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 modelling algorithms (see Section 3.1). Output is a structured map that categorises 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 modelling algorithms, such as LDA (Blei *et al.*, 2003; Blei, 2012) or STM(Roberts *et al.*, 2014; M. E. Roberts *et al.*, 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 modelling 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 *et al.*, 2020).

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

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

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:

$$\sum_{t=1}^{T} MTP_t = 1. \quad (2)$$

Fig. 1 shows an example of the calculation of MTP.

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

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

Fig. 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.

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 analysed object) should be chosen.

The MRP represents the average proportion of an attribute in reviews with a specific rating (F. Barravecchia *et al.*, 2020). MRP can be calculated as follows:

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

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:

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

Fig. 2 shows an example of the calculation of MRP. The MRP profile can be associated with each attribute (see Fig. 2). This information shows the link between product or service attributes and customer (dis)satisfaction. As we can see from Fig. 2, different attributes present different MRP profiles. According to Barravecchia et al. (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).

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**

$$MRP_{3,1} = \frac{0+0.1}{2} = 0.05$$
$$MRP_{3,2} = \frac{0+0.5}{2} = 0.25$$
$$MRP_{3,3} = \frac{0.5+0.6}{2} = 0.35$$
$$MRP_{3,4} = \frac{0.3+0.7}{2} = 0.5$$
$$MRP_{3,5} = \frac{0.6+0.8}{2} = 0.7$$

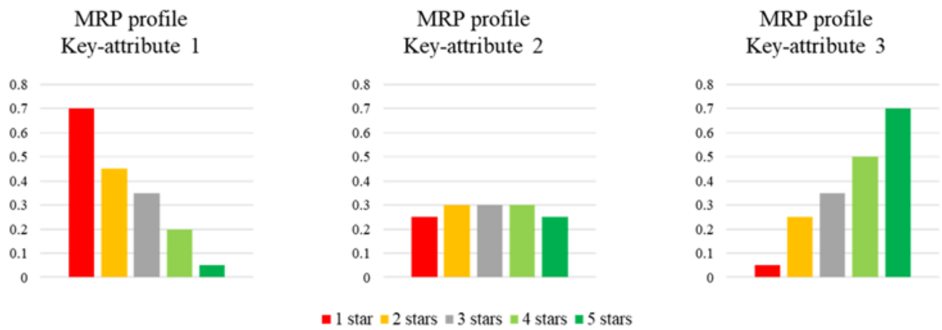

Fig. 2. Example of MRP calculation. Each row shows the rating, and the values of topical prevalence ($TP_{i,t}$) for each review, i.e., the proportion of the review discussing each of the three key attributes considered.

3.2 KA-VoC Map categories

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

The KA-VoC Map categorises 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.
- *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 analysed object.
- *Delights*, i.e., highly discussed attributes (high MTP) generating satisfaction (positive MRP profile). Customers recognise a value to these attributes, which are the primary sources of satisfaction.

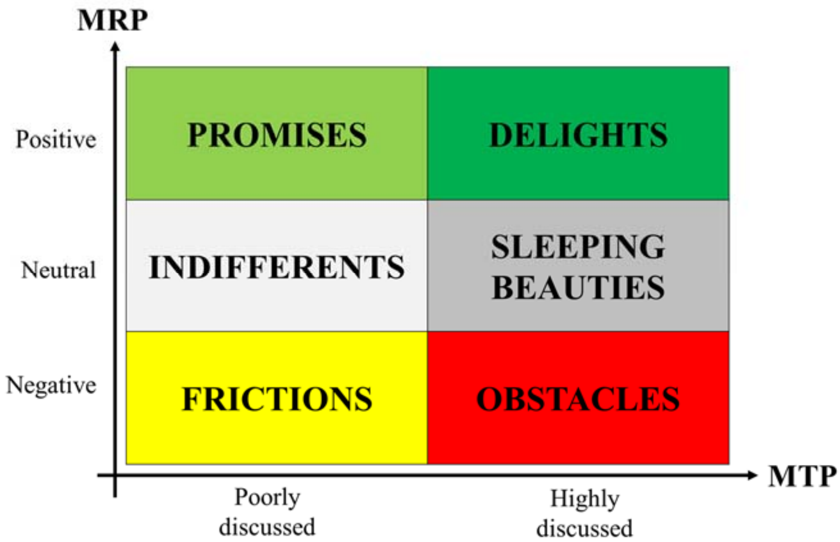

Fig. 3. KA-VoC Map. Categorisation of key-attributes.

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 *et al.*, 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 hypothesised 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 modelling algorithm. Table 2 summarises the main differences between the two approaches.

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 modelling)
What is being assessed?	Asymmetries in customer feelings based on hypothesised 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)

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 hypothesised 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.

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 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:

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

Identification of KAs scale level according to the MRP. The different MRP profile classification is more complex since a different MRP profile potentially characterises each attribute. In this paper, we propose a simple three-level classification (Federico Barravecchia *et al.*, 2020). MRP profiles are categorised into positive, negative, and neutral based on the rating level distribution of MRPs. To categorise 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 *et al.*, 2013):

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

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. Fig. 4 shows the classification of three representative profiles.

Table 3. Example of calculation of the Spearman-Rho Ranked-Order Correlation Coefficient

Rating (values)	MRP (values)	Rank (Rating)	Rank (MRP)	$R(X_i) - R(Y_i)$	$\big(R(X_i) - R(Y_i)\big)^2$
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

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

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 et al. (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:

$$\begin{cases} t \in \{negative\ key-attributes\}, & if\ \rho_S < -0.4 \\ t \in \{neutral\ key-attributes\}, & if -0.4 \le \rho_S \le +0.4 \\ t \in \{positive\ key-attributes\}, & if\ \rho_S > +0.4 \end{cases} \quad (8)$$

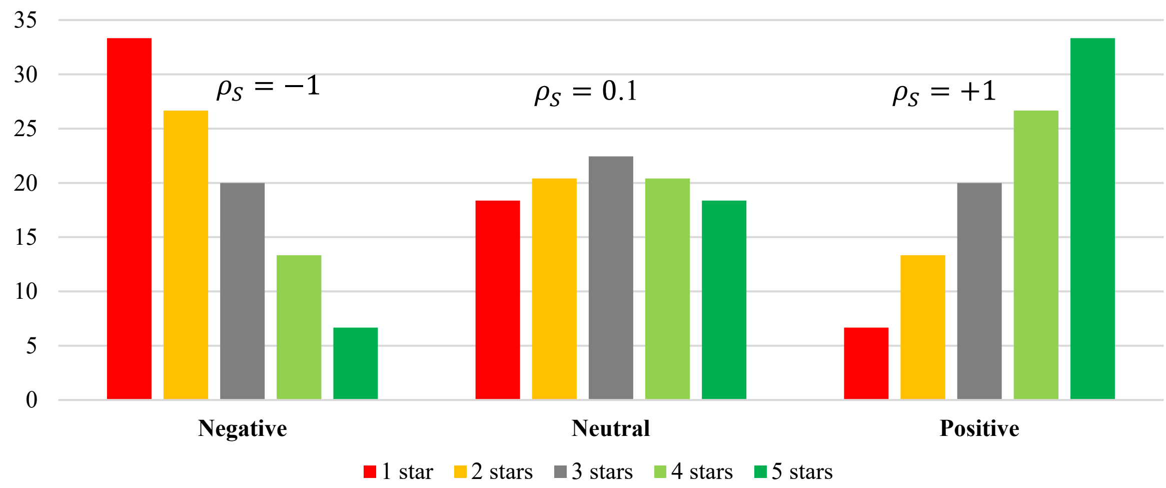

Fig. 4. Categorisation of MRP reference profiles. Three categories of profile are identified: (A) Negative profiles; (B) Neutral Profiles; (C) Positive Profiles.

4 Case study

This section provides a practical case study to illustrate the implementation of the proposed methodology. The subject of this case study is *Bluetooth headsets.*

The implementation of a topic modelling 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 cancelling, 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 modelling 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. Fig.5 and Fig. 6 show, respectively, the MTP values and MRP profiles for each of the identified KAs.

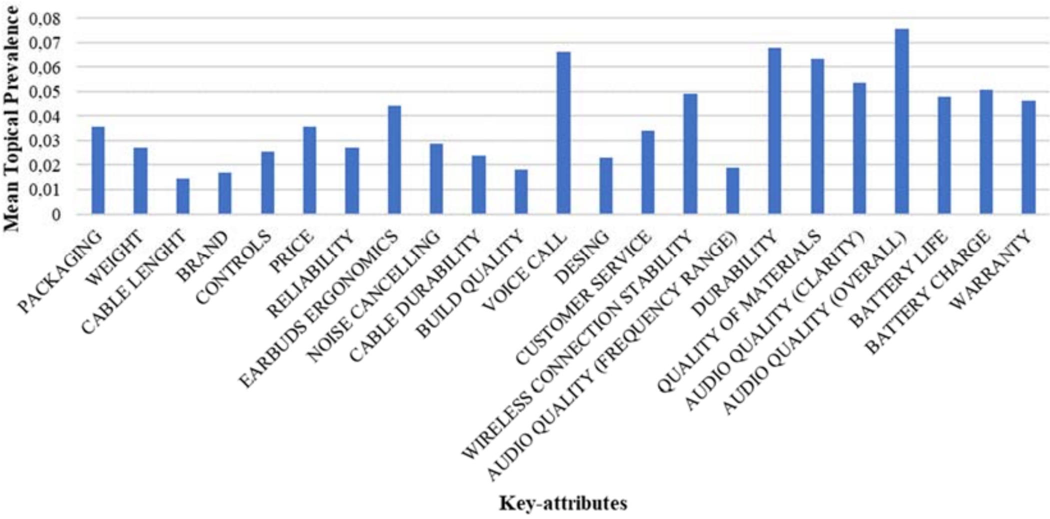

Fig. 5. MTP for each KA. The analysed product is Bluetooth headphones

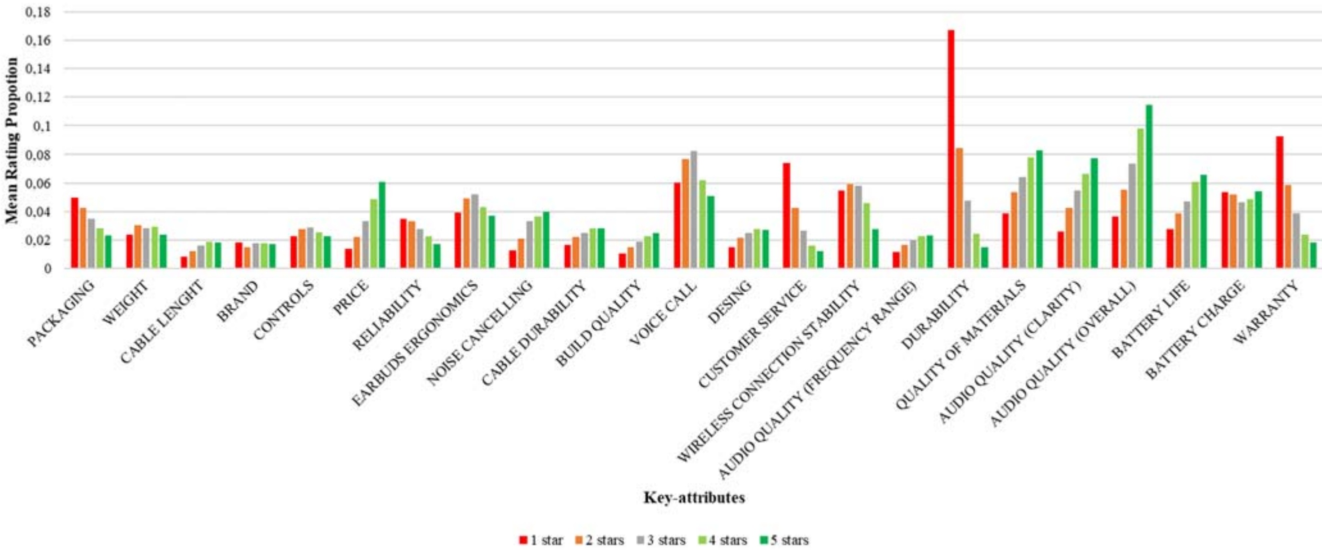

Fig. 6. MRP profiles for each KA. Product: Bluetooth headphones

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.

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 CANCELLING	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: $MTP\ threshold\ = {}^{1}\!/_{n} =\ 0{,}037$

By applying the procedure described in section 3.3, the identified KAs were allocated on the KA-VoC Map, as shown in Fig.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 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 cancelling, 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.

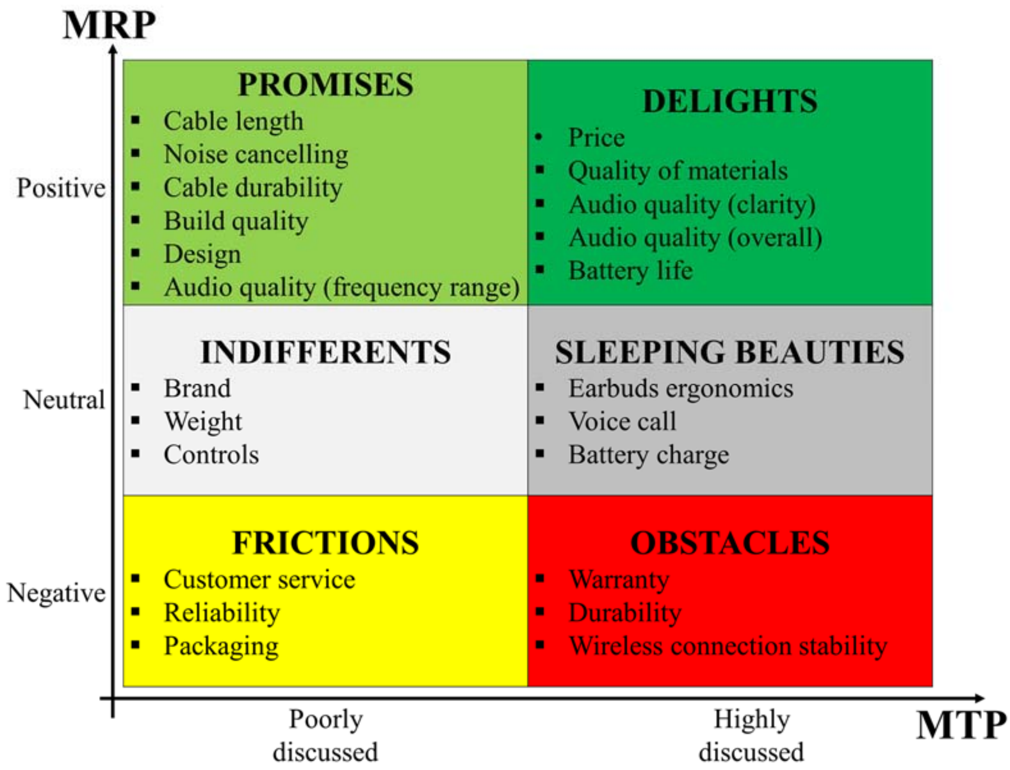

Fig. 7. KA-VoC Map Categorization of Bluetooth headphones based on the results of a topic modelling analysis.

5 KAs management

In order to capitalise 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, there may be a need to completely redesign some analysed 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 towards 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 recognise 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 characterise 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 summarises the main guidelines outlined in this section.

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 towards 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

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 Fig. 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.

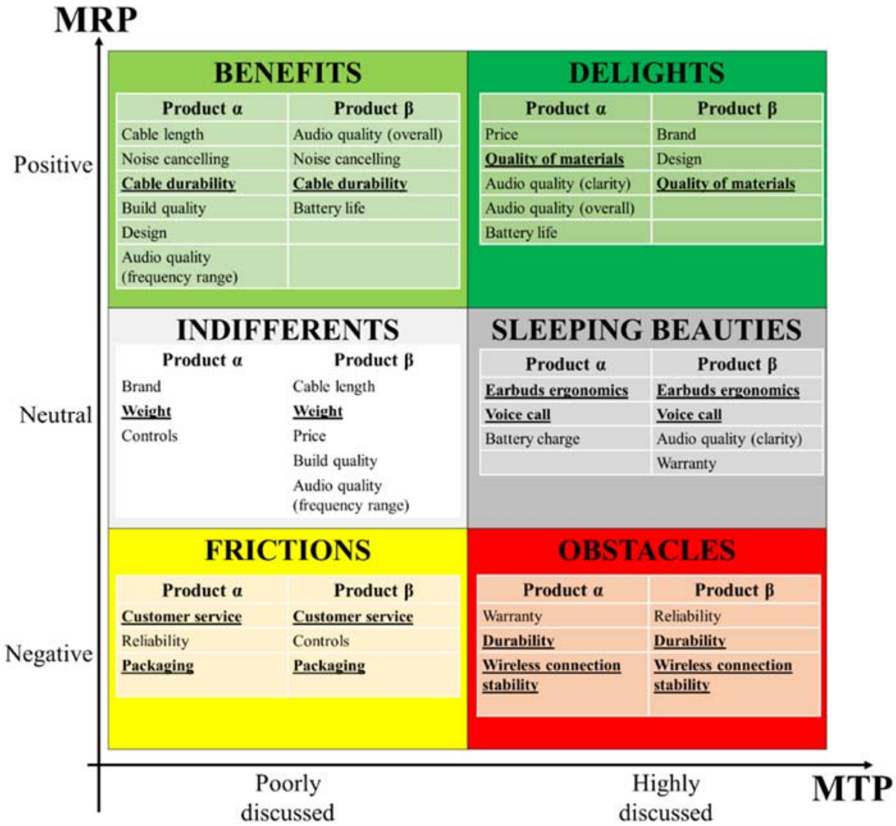

Fig.8. KA-VoC Map for two different models of wireless headphones (product α and product β). Bold and underlined are the KAs that do not change category in the two products under analysis.

In practical business analysis, KA-VoC Map could be used as a benchmarking tool for analysing 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, aesthetic, 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' perspective. Conversely, if the overlap is limited, this could indicate a more marked difference. Fig. 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 fulfilment of the various customer requirements.

- *The identification of potential improvements.* The different categorisation 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 Fig.8, is categorised as delight for product α, while it is categorised 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 Fig.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 categorise 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 modelling 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.

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DECLARATION

Ethical Approval

The authors respect the Ethical Guidelines of the Journal.

Consent to Participate

Not applicable

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Authors Contributions

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

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Competing Interests

The authors do not have conflict of interest

Availability of data and materials

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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 et al., 2019).

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

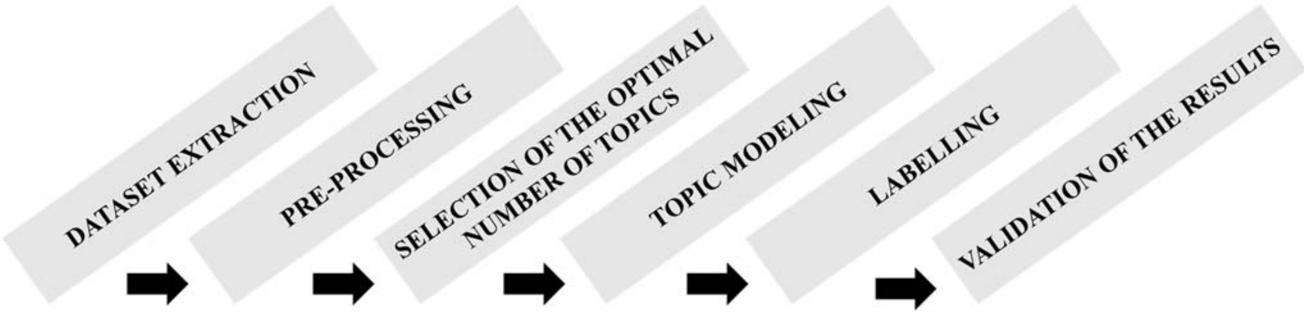

Fig. A.1. Activity flow of the methodology to identify KAs for customer satisfaction. Adapted from Mastrogiacomo et al. (2021).

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 Fig. A.2). The highest values are obtained at the extreme values of the 5-level rating scale.

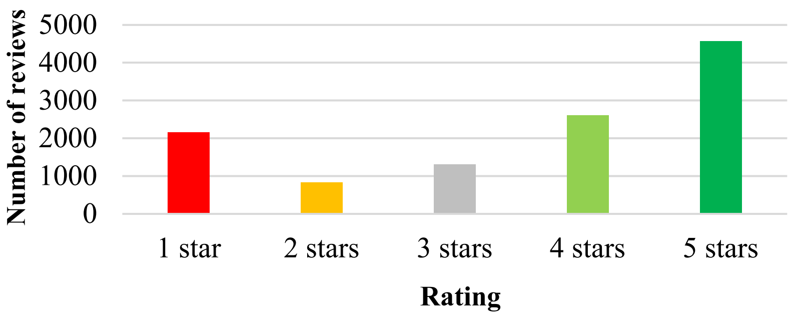

Fig. A.2 J-shaped distribution of the rating level in the analysed reviews.

The text of the reviews was initially pre-processed to improve the performance of the topic modelling 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 lemmatisation, 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 modelling algorithms is *T*, the number of topics able to describe the text corpus. The held-out likelihood was analysed to identify the optimal number of topics (Scott and Baldridge, 2013)(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 et al., 2019)(M. Roberts et al., 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)(Scott and Baldridge, 2013).

Fig. 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.

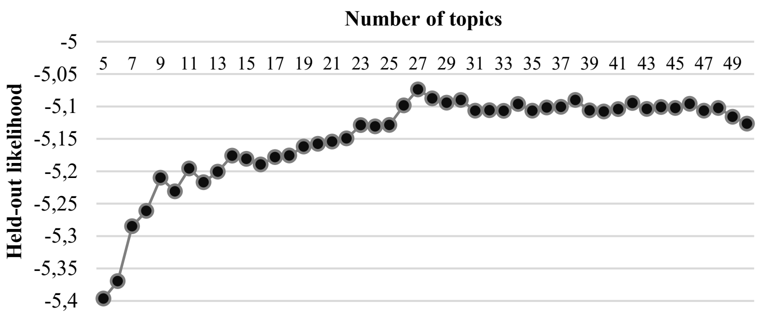

Fig. A.3. Held-out likelihood over the number of topics (from 5 to 50)

Defined the optimal number of topics, the topic modelling algorithm identified the latent topics discussed in a collection of documents (Özdağoğlu et al., 2018; Mastrogiacomo et al., 2021)(Özdağoğlu et al., 2018; Mastrogiacomo et al., 2021). In detail, in the proposed application the Structural Topic Model (M. E. Roberts et al., 2019)(M. E. Roberts et al., 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 analysed product but to a general level of satisfaction.

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 CANCELLING	*noise, cancelling, 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, centre, 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

The last step of the process consists of the validation of results (Barravecchia et al., 2021)(Barravecchia et al., 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 et al., 2021)(Barravecchia et al., 2021):

- *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).

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