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Product quality tracking based on digital Voice-of-Customers

Federico Barravecchia, Luca Mastrogiacomo and Fiorenzo Franceschini*

Department of Management and Production Engineering, Politecnico di Torino, Torino, Italy

Nowadays, word of mouth and the Voice-of-Customers have largely left their physical and relational dimension to be replaced by online digital platforms where users can describe their experiences and share them openly. However, the increasing availability of user-generated content, related to the usage of products and services, poses several challenges for research. A key priority is to understand how to use these large amounts of accessible and low-cost data to improve the quality of products and/or services and, consequently, customer satisfaction. The purpose of this paper is to show the potential of digital Voice-of-Customers (digital VoCs) as a source of information to monitor quality over time. The obtained insights may represent a first step towards developing quality tracking tools based on digital VoCs, thereby allowing the evolution of changes in perceived quality to be understood. Some examples accompany the description.

Keywords: Quality 4.0; quality tracking; digital Voice-of-Customers; topic modelling; user-generated content; customer review

1. Introduction

Quality is a strategic concern for any business, and understanding all the elements that can influence it is still a critical issue. These elements, referred to as quality determinants, allow organisations to measure, control, and improve customer satisfaction with products and services (Mukherjee, 2019).

Companies generally adopt quality tracking techniques to monitor the quality of a product/service over time after its provision (Kamsu-Foguem et al., 2013; Xu et al., 2021). A major source of information for quality tracking techniques is the so-called 'Voice of Customers' (VoCs), i.e. customers' feedback about their experiences gained after the use of products or services (Jach et al., 2021). However, customers who are asked to fill in surveys or questionnaires often find traditional quality tracking techniques intrusive (DeVellis, 2016). An alternative way of obtaining such information is using free contents available on the web, the so-called digital Voice-of-Customers (digital VoCs), such as customer reviews about products or services on web blogs, social networks, and review aggregators (Amat-Lefort et al., 2022; Barravecchia et al., 2022a, 2022b; Özdağoğlu et al., 2018). Artificial intelligence tools can allow useful information to be extracted from these data (Barravecchia et al., 2022a). The application of topic modelling algorithms to digital VoC analysis is one of the most effective data mining methods. In a nutshell, these machine learning algorithms allow latent topics discussed within extensive collections of unstructured textual documents to be identified. When applied to digital VoCs, these algorithms have proved to be able to extract the latent quality determinants they refer to (Barravecchia et al., 2020a, 2022a; Mastrogiacomo et al., 2021).

*Corresponding author. Email: fiorenzo.franceschini@polito.it

To date, digital VoC analytics has not yet been used to explore the evolution of such determinants over time. The current challenge is to understand how to leverage on digital VoC analysis to monitor quality determinants over time. This study aims to address the following research question: *How can a product/service quality tracking process be implemented on the basis of digital VoC analysis?*

The rest of the paper is organised as follows. Section 2 provides the conceptual background and the significant research that has been conducted on quality tracking and digital VoCs. Section 3 introduces some design parameters of a quality tracking tool based on digital VoC analysis. Section 4 focuses on how to practically track the quality of a product/service using digital VoCs. The potential of some of the proposed approaches is shown in section 5 by presenting two real case studies. Section 6 discusses the implications of this approach for the designing/redesigning of a product/service. Finally, the concluding section summarises the main contributions of the work, its limitations, and possible future research directions.

2. Conceptual background

2.1. *Quality tracking*

Companies implement different strategies to track the evolution of the quality of their products/services in order to ensure that: (i) quality is maintained over time, (ii) anomalies or criticalities are identified, and (iii) potential areas for improvement are uncovered. There are basically three practical approaches that can be adopted to analyse the evolution of quality over time (Bandaru et al., 2015; Hallencreutz & Parmler, 2021):

- *post-purchase evaluation*: this approach is performed by asking a customer to evaluate a purchased product or service after it has been delivered or used (Kumar & Anjaly, 2017);
- *periodic quality survey*: this approach, which is generally based on the administration of questionnaires or structured interviews, provides snapshots of the customers' perceptions (Izogo & Ogba, 2015; Su & Hwang, 2020);
- *continuous monitoring of quality*: this approach involves the ongoing monitoring of quality over time by means of surveys or customers' interviews (Chen et al., 2015; Gregorio & Cronemyr, 2011; McColl-Kennedy & Schneider, 2000).

The main limitations of these approaches are that (i) they are expensive, in terms of required time and resources, (ii) they can only reach a limited number of customers, and (iii) the interviewed customers might find them somewhat intrusive.

2.2. *Quality tracking and digital VoCs*

When industry was facing its fourth industrial revolution, research on quality management was also facing its own transformation to the new Quality 4.0 paradigm (Kannan & Garad, 2020; Zonnenshain & Kenett, 2020). The digitalisation of businesses has generated unique opportunities for managing the quality of products and services (Sony et al., 2020). In this context, awareness of the value of data generated directly by users is growing. In recent years, the vast amount of data released by web users has opened up new possibilities for tracking the quality of products and services (Liu et al., 2019).

Digital VoCs can be defined as self-released reviews, opinions, or feedback on the use of products or services freely published by customers on publicly accessible online digital platforms (Özdağoğlu et al., 2018). These contents can be found in different forms (texts, audios, photos, videos), but are primarily composed of unstructured texts published on social networks, discussion forums, blogs, review aggregators, or e-commerce platforms.

Collecting and analysing digital VoCs make it possible to understand the feedback of customers in a more reliable way than through traditional techniques (Allen et al., 2018; Bi et al., 2019; Zhan et al., 2009). Analysing the self-released information of customers about their experience with products/services can help manufacturers and service providers to overcome the limitations of traditional VoC collection techniques (Mastrogiacomo et al., 2021).

Improvements in data mining techniques have made it possible to use innovative tools to collect and interpret textual digital VoCs (Mastrogiacomo et al., 2021). Table 1 shows a schematic comparison of traditional quality tracking methods and quality tracking based on digital VoC analysis.

2.3. *Topic modelling and digital VoCs*

The main difficulty in using a digital VoC is that it is often composed of unstructured texts (Joung et al., 2019), as opposed to structured data, which can be obtained through questionnaires or surveys. No standard procedure is followed for the collection of unstructured data, and their automatic analysis, therefore, presents some criticalities.

In order to overcome this challenge, it is possible to make use of algorithms belonging to a specific branch of data mining named text mining, i.e. techniques aimed at the automatic analysis of unstructured textual documents (Berry & Kogan, 2010; Carnerud, 2020). These techniques allow hidden relationships to be found within data. One of the most widely used is Topic modelling. The term Topic Modelling refers to a family of statistical methodologies that allows the latent topics discussed within a collection of documents to be extracted (Blei, 2012). In other words, these algorithms do not require human coding or the classification of data, as they can 'read' a collection of documents and automatically extract the most discussed topics (Blei, 2012).

The hypothesis behind topic modelling techniques is that the author of a document initially determines the topics he/she wants to address and then creates the document by

Table 1. Schematic comparison of traditional quality tracking methods and quality tracking based on digital VoC analysis.

	Traditional quality tracking	Digital VoC quality tracking
Source of information	Interviews, focus groups, surveys, structured questionnaires.	User-generated content, customer reviews, social media posts, forums
What is being assessed?	Parameters/features of products or services	Latent Quality Determinants
Inspected variables	The key measured variables are considered to be known	Latent Quality Determinants are extracted from digital VoCs
Focus	Identification of critical product/service features to achieve improvements	Identification of the quality determinants perceived the most by customers to drive design and continuous improvement activities
Information Update	Periodic and guided	Constant and not guided
Analysis tools	Statistical data analysis	Text mining Statistical data analysis

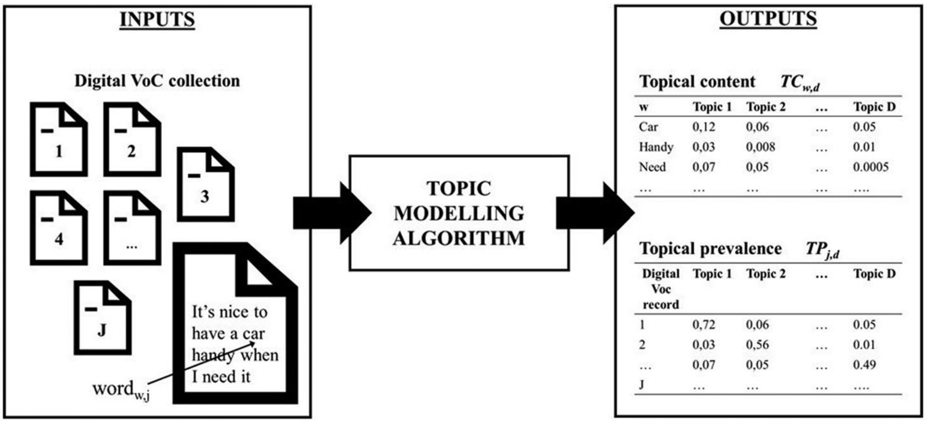


Figure 1. Graphical representation of the functioning of topic modelling algorithms. The input consists of J digital VoC records. The output consists of: $TC_{w,d}$ (Topical content matrix), i.e. the weights associated with each w-th keyword that characterises the d-th topic; TPj,d (Topical prevalence matrix), i.e. multinomial probability distribution that indicates the proportion of the d-th topic discussed within the j-th document.

mixing the topics chosen in the initial phase in different proportions. It is, therefore, possible to find the chosen set of topics discussed in the documents through an inferential procedure. Topic modelling algorithms determine what topics are most likely to have generated a corpus of texts, and this procedure is called 'generative process' (Blei, 2012). Figure 1 represents the conceptual scheme of a topic modelling algorithm. Given an extensive collection of digital VoCs, topic modelling algorithms deal with the problems of (Blei et al., 2003):

- identifying a set of topics that describe a text corpus (i.e. the collection of digital VoC);
- associating a set of keywords to each topic (*topical content*: $TC_{w,d}$),

where:

o $w \in \{1, \ldots, W\}$ are the keywords of the vocabulary related to the digital VoC collection;
o W is the total number of words contained in the digital VoC vocabulary;
o $d \in \{1, \ldots, D\}$ are the topics identified by the topic modelling algorithm;
o D is the total number of identified topics.

- defining a specific mixture of these topics for each digital record (topical prevalence: $TP_{j,d}$)

where:

o $j \in \{1, \ldots, J\}$ are the analysed digital VoC records;
o J is the total number of analysed digital VoC records;

o $\sum_{d=1}^{D} TP_{j,d} = 1 \quad \forall j$

The application of a topic modelling algorithm includes the following steps:

(1) Generating the vocabulary of words for the collection of documents.
(2) Representing each document as a 'bag of words', i.e. a list of words contained in the documents.
(3) Associating each document with an initial probability distribution with respect to the topics that have to be extracted.
(4) Associating each topic with an initial probability distribution with respect to the vocabulary words.
(5) Estimating the topic model, through the algorithm, on the basis of the probabilities assigned, the document similarities and the co-occurrence of words.
(6) Correcting the distribution, through a series of iterations, run by the algorithm, until the distribution of the topics in the documents converges to the distribution of the words in the topics.

Topic modelling algorithms, when applied to digital VoCs, extract the latent quality determinants of products or services that can positively or negatively influence the perceived quality (Barravecchia et al., 2020a; Mastrogiacomo et al., 2021). It can be assumed that if a topic is discussed, then it is important for the customer, and it is therefore critical for his/her perception of quality.

Full details on the application of topic modelling can be found in Mastrogiacomo et al. (2021).

3. Quality tracking design parameters

Recent studies have pointed out a variation in the intensity and typology of quality determinants discussed over time for a specific product (Mastrogiacomo et al., 2021). However, a structured procedure that can be used to analyse the behaviour of quality determinants over time has not yet been proposed. Understanding this aspect is critical, since it allows anomalous or emerging patterns to be identified and future trends to be predicted.

The design of a quality tracking scheme for digital VoCs needs to consider four aspects:

- *The time window*. Digital VoCs produced by the customers may be available over many months or even years; therefore, the analysts should first decide on the length of the time window.
- *The analysis of newly captured data*. Digital VoCs are constantly being updated, since customers may regularly release new feedback. The analysts should decide how to approach newly available data.
- *The sampling period*. Performing a quality monitoring over time requires the definition of a sampling period, i.e. how often digital VoC records (customer reviews) should be grouped to collect a sample.
- *The scheme of quality tracking*. When designing a quality tracking tool, it is necessary to establish whether to target the same or different samples of customers over time.

Each design aspect is analysed in detail in the following sections.

3.1. *The time window*

As seen in Section 2.3, a topic modelling algorithm receives a set of digital VoC records as input and produces a topic model as output. The topic model describes the content of textual records. Different sets of digital VoC records generate topic models that are not quantitatively comparable, since the classification of digital VoC records (topical prevalence) is performed using different topics. The choice of the time window influences how the outcomes can be analysed for quality tracking purposes.

Figure 2 shows three possible alternative strategies regarding the selection of the time window. The analysis can be extended to cover: (i) a global time window; (ii) a mobile time window or (iii) a local time window.

Most of the topic modelling analyses in the literature have used all the available digital VoC records (global time window) (Mastrogiacomo et al., 2021). When a *global time window* is selected, the digital VoC records are given as input to the topic modelling algorithm (see Figure 2(A)) and, consequently, all the digital VoC records are classified by the same topic model.

The outcome of this kind of investigation is a long-term analysis that identifies the most critical quality determinants. The main limitation of this approach is that it can fail to capture the emergence of new and/or temporary quality determinants.

An alternative approach is to apply a topic modelling algorithm to a single sample of digital VoC records (*local time window*). For example, if the sampling period is equal to one month, the topic modelling algorithm is only applied each month to monthly records (see Figure 2(C)). Since the resulting model is based only on a single sample of digital VoC

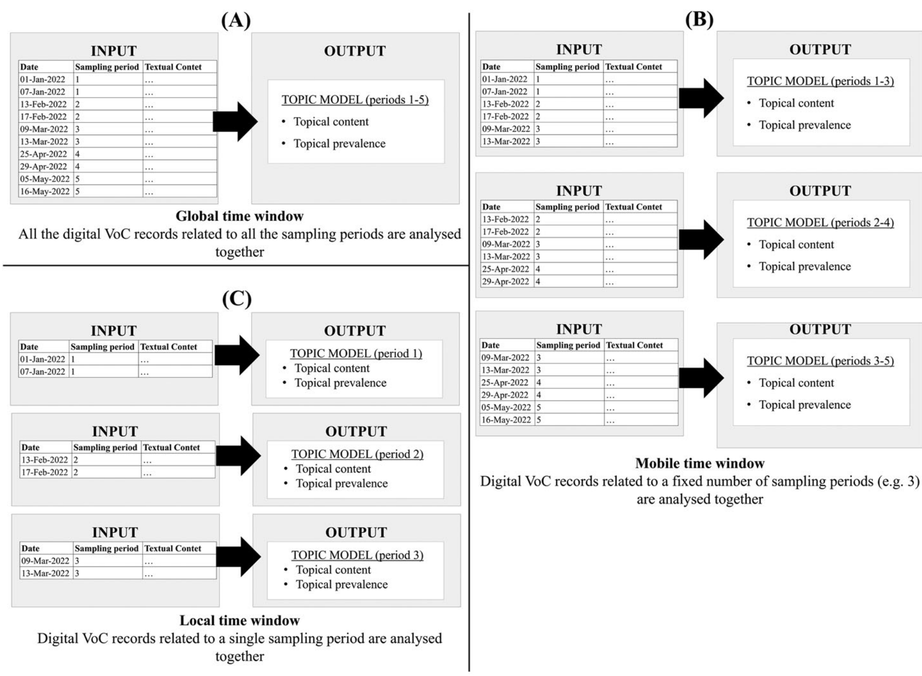


Figure 2. Illustration of three possible alternative strategies that can be used to select the time window: (A) A global time window; (B) A mobile time window; (C) A local time window. The schemes illustrate the input and output of the topic modelling algorithm applied to analyse digital VoCs.

records, it is difficult to compare the obtained results with those of other sampling periods. The only way of conducting a comparison between different periods is to qualitatively assess whether certain quality determinants were discussed or new quality determinants were introduced. The main advantage of such an approach is that it allows emerging quality determinants to be promptly identified.

However, an intermediate approach can be drawn up between these two strategies. Digital VoCs can be analysed considering a *mobile time window* (see Figure 2(B)). Let us consider, for example, a sampling period equal to one month and a mobile time window of three months. In this case, when collecting a new monthly sample, the topic modelling algorithm is applied to the set of records released in the last month and in the previous two months. This approach allows a quantitative analysis of the potential trend of quality determinants to be made and the emergence of new quality determinants to be intercepted.

Table 2 shows a comparison of the proposed alternative strategies.

3.2. *The analysis of newly captured data*

The second aspect involves the analysis of newly available data produced by customers. There are two possible ways of analysing these data:

- *Reapplying the topic modelling algorithm to all the considered data* (see Figure 3 (A)). Any new data related to a new sampling period are added to the analysed time window, and a new model is generated on the basis of the old and new data.
- *Classifying the newly digital VoCs on the basis of an existing model* (see Figure 3 (B)). Any new data are not analysed by a topic modelling algorithm, but the content of the new digital VoC records is classified on the basis of a pre-existing topic model.

Table 2. PROs and CONSs of the alternative time window strategies.

Alternative	Pros	Cons
Global time window	• Comprehensive overview of the evolution of the most critical quality determinants • All the digital VoC records are classified using the same topic model. • Ability to track the evolution of quality determinants over extended periods	• Limited ability to identify new/ emerging quality determinants • Quality determinants discussed for short periods run the risk of not being identified
Mobile time window	• Ability to identify new and emerging quality determinants	• The topic modelling algorithm is applied to each new period • Limited period of analysis
Local time window	• High ability to identify new and emerging quality determinants	• It is difficult to quantitatively compare the results from different periods • The topic modelling algorithm is applied to each new period

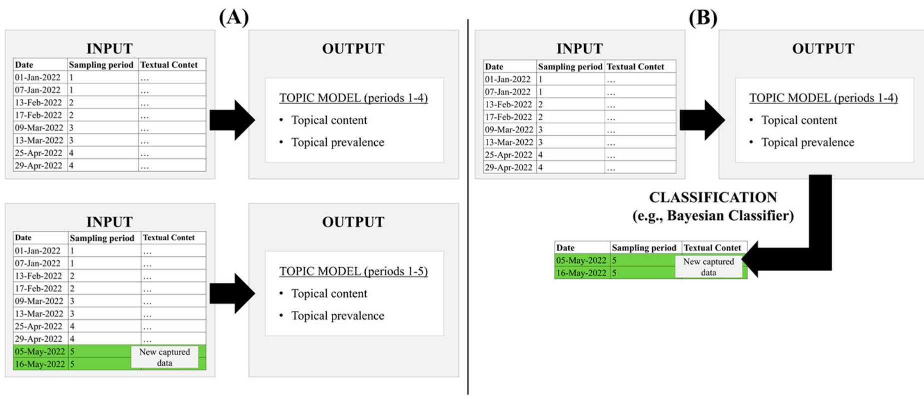


Figure 3. Illustration of two alternative ways of analysing newly available data. (A) Reapplication of the topic modelling algorithm to all the considered data. (B) Classification of the new digital VoCs on the basis of an existing topic model (for example, using a Bayesian classifier).

In the latter case, the problem can be traced back to a text classification application. The problem of textual document classification has been widely discussed by the text mining research community (Aggarwal & Zhai, 2012). A variety of practical approaches are available for this purpose. As an example, Bayesian (Generative) Classifiers or other similar methods may be used to classify digital VoCs (Aggarwal & Zhai, 2012).

3.3. *The sampling period*

As previously mentioned, the analysis of digital VoCs involve using records released by customers at different times. In order to analyse how quality determinants evolve over time, it is necessary to group digital VoC records into samples. However, the extent of the sampling period affects the quality of the tracking results.

A small sampling period allows anomalies to be promptly detected, but the obtained results can show noise and highly nervous dynamics. On the other hand, selecting a long sampling period produces results with less noise and variability, but does not allow anomalies to be detected early on.

3.4. *The scheme of quality tracking*

Two different quality tracking schemes can be identified (Ahire & Dreyfus, 2000; Franceschini, 2002; Sarkar & Rajagopalan, 2018):

- *Horizontal quality tracking*, which allows quality characteristics to be analysed over time by targeting the same sample of customers in successive sampling periods (see Figure 4(A));
- *Vertical quality tracking*, which allows quality characteristics to be analysed over time by targeting different samples of customers in successive sampling periods (see Figure 4(B)).

The choice of which quality tracking scheme should be adopted depends on the type of VoCs that are being analysed. It is difficult to implement a traditional quality tracking scheme for digital VoCs produced freely by users (vertical/horizontal quality tracking). In this case, it is not possible to control the composition of the sample over time.

However, a 'hybrid' type of quality tracking can be implemented for the analysis of digital VoCs. In this case, each investigation involves the analysis of digital VoCs produced by different samples of customers.

4. Digital VoC data analysis

Different schemes of digital VoC analysis can be conducted for quality tracking purposes. Table 3 summarises four possible levels of analysis, ranging from qualitative to quantitative investigation. Each level of analysis is analysed in detail in the following sections.

4.1. *Level 1 – emergence/disappearance of quality determinants*

A first preliminary analysis of the quality determinants can be carried out by means of a qualitative comparison of their labels (and the associated keywords). The aim of this analysis is to assess any emerging or missing quality determinants with respect to previous temporal analyses (see Section 3.1). When comparing sets of quality determinants from investigations carried out in two successive time windows, the three conditions outlined in Figure 5 can be identified:

- *continuity* between successive observations, that is, when a quality determinant is recognised in both time windows;

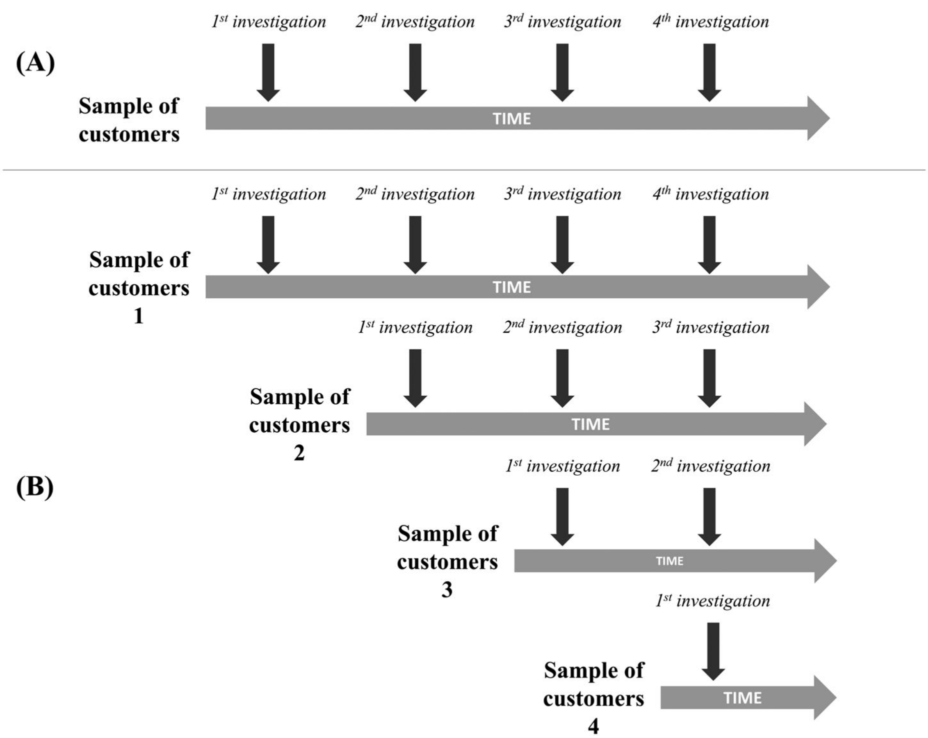


Figure 4. Schematic representation of the two types of quality tracking: (A) horizontal quality tracking; (B) vertical quality tracking.

Table 3. Analysis levels for digital VoCs used for quality tracking. The 'Time window of the analysis' column shows the applicability of the time window strategies for the different analysis levels.

			Time window of the analysis (see Section 3.1)		
Level	Description	Type	Global	Mobile	Local
1	Emergence/ Disappearance of the quality determinants	Qualitative	No	Yes	Yes
2	Qualitative trend analysis of the quality determinants	Qualitative	Yes	Yes	No
3	Quantitative trend analysis of the quality determinants	Quantitative	Yes	Yes	No
4	Detection of anomalous behaviour of the quality determinants	Quantitative	Yes	Yes	No

- *emergence* of a new quality determinant, that is, when a quality determinant is not recognised in the older time window, but is present in the more recent one.
- *disappearance* of a quality determinant, that is, when a quality determinant is recognised in the older time window, but is no longer present in the more recent one.

4.2. *Structuring the output of topic modelling for trend analysis*

The output of topic modelling is traditionally expressed by considering the proportion of how frequently topics (quality determinants) are discussed by customers. Each quality determinant can be associated with a *Mean Topic Proportion* (MTP) indicator related to a well-defined time window (Barravecchia et al., 2020a). The MTP represents the average weight of the d-th quality determinant, and it can be calculated as follows:

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

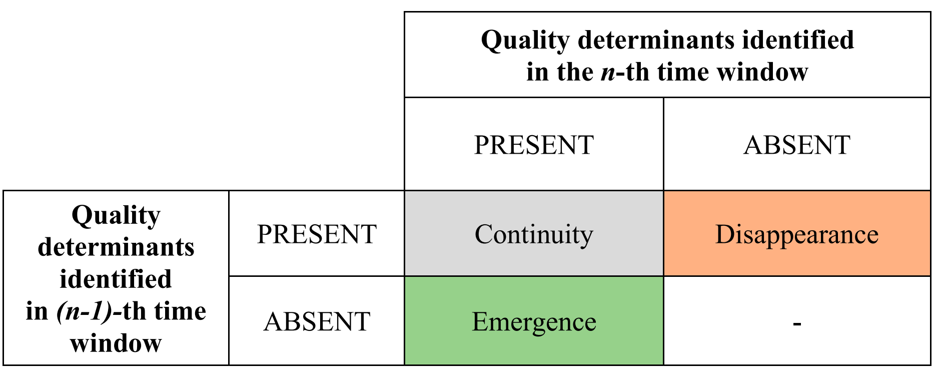


Figure 5. Comparison of sets of quality determinants identified in different periods

where N is the number of digital VoC records considered in the analysis and $TP_{j,d}$ is the topical prevalence related to the d-th quality determinant in the j-th digital VoC record.

The sum of the MTPs related to all the identified quality determinants is equal to 1:

$$\sum_{d=1}^{D} MTP_d = 1 \tag{2}$$

Table 4 shows an illustrative example of the calculation of the MTP indicator. The example is related to a time window containing nine digital VoC records released in three different sampling periods. The exemplificative product manifests three quality determinants (A, B and C). It can be observed that the three quality determinants have a very similar MTP values, ranging from 0.31 to 0.36.

In order to perform the proposed analysis, it is necessary to introduce a topic distribution measure over specific sampling periods. To this end, we propose the calculation of the *Interval Mean Topical Prevalence* ($IMTP_{d,t}$) indicator, which represents the average topical prevalence of digital VoCs for the d-th quality determinants related to the t-th sampling period:

$$IMTP_{d,t} = \frac{\sum_{j}^{R_t} TP_{j,d}}{|R_t|} \tag{3}$$

where R_t is the set of digital VoC records collected in the t-th sampling period, and $|R_t|$ is the cardinality of the R_t set (sample size of the VoC records).

For each t-th sampling period, the sum of the $IMTP_{d,t}$ related to all the identified quality determinants is equal to 1:

$$\sum_{d=1}^{D} IMTP_{d,t} = 1 \quad \forall\, t \in (1, \ldots, T) \tag{4}$$

where D is the number of identified topics, and T is the total number of sampling periods.

Table 5 shows the IMTP values related to the three analysed sampling periods and the three quality determinants reported in Table 4. From these data, we can see that the three determinants present very different patterns when considering IMTP, although they are very similar in terms of MTP.

4.3. *Level 2 – qualitative trend analysis of quality determinants*

On the basis of the variation of IMTP over time, it is possible to categorise the quality determinants into three distinct categories:

- *Overall decreasing quality determinants:* i.e. those determinants for which a decrease over time in the IMTP values is observed. See, for example, Figure 6(A).
- *Overall constant quality determinants*: i.e. those determinants for which the IMTP values are almost stable over time. See, for example, Figure 6(B).
- *Overall increasing quality determinants*: i.e. those determinants for which there is an increase in the IMTP values over time. See, for example, Figure 6(C).

Table 4. Output of the topic modelling algorithm and an example of the calculation of the MTP indicator for three quality determinants (A, B and C) released in three different sampling periods (January, February and March 2022).

Digital VoC record	Date	Sampling period (t)	Topical Prevalence ($TP_{j,d}$)		
			Quality determinant A	Quality determinant B	Quality determinant C
1	3 January 2022	1	0.8	0.15	0.05
2	15 January 2022		0.1	0.7	0.2
3	17 January 2022		0.8	0.15	0.05
4	11 February 2022	2	0.25	0.7	0.05
5	16 February 2022		0.45	0.15	0.4
6	18 February 2022		0.35	0.1	0.55
7	9 March 2022	3	0.15	0.65	0.2
8	13 March 2022		0.2	0.1	0.7
9	22 March 2022		0.1	0.3	0.6
		MTP	(0.8 + 0,1 + 0,8 + 0.25 + 0.45 +0.35 + 0.15 + 0.2 + 0.1)/9 = 0.36	(0.15 + 0.7 + 0.15 + 0.7 + 0.15 +0.1 + 0.65 + 0.1 + 0.3)/9 = 0.33	(0.05 + 0.2 + 0.05 + 0.05 + 0.4 +0.55 + 0.2 + 0.7 + 0.6)/9 = 0.31

Table 5. Example of the calculation of the IMTP indicator. The initial data are reported in Table 4.

	$IMTP_{d,t}$		
Sampling period (t)	Quality determinant A	Quality determinant B	Quality determinant C
1	$IMTP_{A,1} = (0.8 + 0.1 + 0.8)/3 = 0.57$	0.33	0.1
2	$IMTP_{A,2} = (0.25 + 0.45 + 0.35)/3 = 0.35$	0.32	0.33
3	$IMTP_{A,3} = (0.15 + 0.2 + 0.1)/3 = 0.15$	0.35	0.5

The *Spearman-Rho Ranked-Order Correlation Coefficient (ρ_S)* is proposed to classify IMTP profiles into the three aforementioned categories, where ρ_S is a nonparametric rank correlation measure that assesses to what extent the relationship between two variables can be described using a monotonic function. Spearman's ρ_S can be computed as follows (Myers et al., 2013):

$$\rho_S = 1 - \frac{6 \cdot \sum_{t=1}^{T} (R(X_t) - R(Y_t))^2}{T \cdot (T^2 - 1)} \tag{5}$$

where: $R(X_t)$ represents the rank of the sampling period; $R(Y_t)$ represents the rank of the $IMTP_{d,t}$ of the digital VoCs published in the t-th sampling period; T is the number of considered sampling periods.

Table 6 shows an example of the calculation of the *Spearman-Rho Ranked-Order Correlation Coefficient.*

Spearman's ρ ranges between −1 and +1. Spearman's ρ is equal to +1 when the IMTP profile is monotonically increasing, while it is equal to −1 when it is monotonically decreasing. According to Myers et al. (2013), IMTP profiles with Spearman's ρ ranging between −0.4 and +0.4 can be classified as neutral. Consequently, each d-th quality determinant can be classified as follows:

$$\begin{cases} \text{if } \rho_S < +0.4 & \text{then } d \in \{\text{Decreasing quality determinants}\} \\ \text{if } -0.4 \leq \rho_S \leq +0.4 & \text{then } d \in \{\text{Constant quality determinants}\} \\ \text{if } \rho_S > +0.4 & \text{then } d \in \{\text{Increasing quality determinants}\} \end{cases}$$

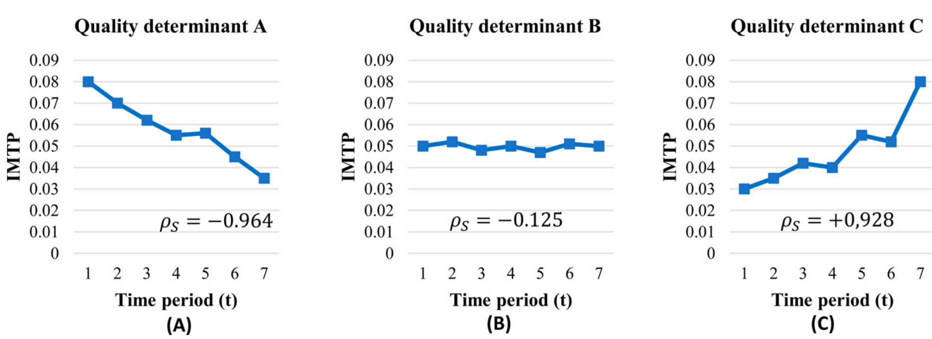


Figure 6. Examples of IMTP profiles. (A) Example of an overall decreasing profile. (B) Example of an overall constant profile. (C) Example of an overall increasing profile.

Table 6. Example of the calculation of the Spearman-Rho Ranked-Order Correlation Coefficient related to quality determinant A in Figure 6.A.

Sampling period (t)	$IMTP_{A,t}$	$R(X_t)$	$R(Y_t)$	ρ_S
1	0.08	7	1	$= 1 - \dfrac{6 \cdot \begin{bmatrix} (7-1)^2 + (6-2)^2 + (5-3)^2 + (4-5)^2 \\ +(3-4)^2 + (2-6)^2 + (1-7)^2 \end{bmatrix}}{7 \cdot (7^2 - 1)}$
2	0.07	6	2	
3	0.062	5	3	
4	0.055	4	5	
5	0.056	3	4	
6	0.045	2	6	$= -0.964$
7	0.035	1	7	

4.4. *Level 3 – quantitative trend analysis of quality determinants*

In order to extend level 2 analysis, it is possible to identify to what extent the discussion of quality determinants increases or decreases over time. As an example, Figure 7 shows the behaviour of two different quality determinants, both of which can be classified as increasing. However, it is clear that the amplitude with which the two determinants increase is very different. Quality tracking tools may intercept these differences in trend amplitude. A variety of methods can be adopted to support such an analysis.

We propose the use of the *IMTP Average Slope*, i.e. the slope of the linear regression line of the computed IMTPs, to analyse the amplitude of the IMTP trend. The *IMTP Average Slope* for the d-th quality determinant can be calculated as:

$$IMTP\ slope_d = \frac{\sum_{t=1}^{T} (t - \bar{t})(IMTP_{d,t} - \overline{IMTP_d})}{\sum_{t=1}^{T} (t - \bar{t})^2} \tag{6}$$

where: t is the sampling period, $t \in (1, \ldots, T)$; T is the total number of considered sampling periods; $\bar{t}$ is the average sampling period $\left(\bar{t} = \sum_{t=1}^{T} (t)/T\right)$; $\overline{IMTP_d}$ is the average value of the *IMTP* for the d-th quality determinant $\left(\overline{IMTP_d} = \sum_{t=1}^{T} IMTP_{d,t}/T\right)$.

Table 7 shows an example of the calculation of the *IMTP Average Slope*.

The *IMPT average slope* is positive when a quality determinant can be classified as increasing, while it is negative when the quality determinant decreases.

Following the example shown in Figure 7, the exemplificative 'quality determinant A' presents an *IMTP Average Slope* equal to 0.0189, and 'quality determinant B' has an *IMTP Average Slope* of 0.0461. Both can be classified as increasing quality determinants, but the *IMTP Average Slopes* evidence a marked difference in their amplitude of increase.

4.5. *Level 4 – detection of anomalous behaviour of quality determinants*

The 4th level of analysis (see Table 3) is aimed at analysing IMTP profiles to detect anomalies and changes in the behaviour of the quality determinants. According to the theory of outlier identification (Singh & Upadhyaya, 2012), three types of anomalies in IMPT profiles can be identified:

- *global outlier*, where there may be a sudden change in the IMTP profile in a given sampling period, after which the profile returns immediately to its previous state (see Figure 8(A));

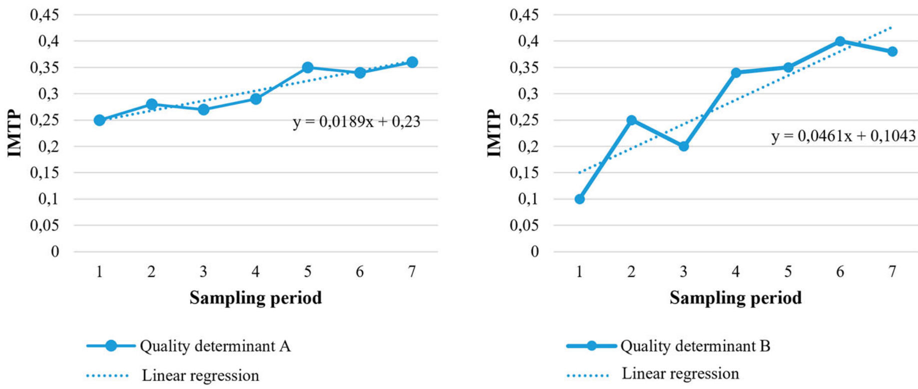


Figure 7. Example of two quality determinants with different trend amplitudes

Table 7. Example of the calculation of the IMTP Average Slope related to quality determinant B in Figure 7.

Sampling period (t)	$IMTP_{B,t}$	$\bar{t}$	$\overline{IMTP_B}$	$IMTP\ slope_B$
1	0.1	4	0.29	$= \dfrac{\begin{bmatrix}(1-4)(0.1-0.29)+(2-4)(0.25-0.29)\\ +\ldots+(7-4)(0.38-0.29\end{bmatrix}}{[(1-4)^2+(2-4)^2+\ldots+(7-4)^2]}$
2	0.25			
3	0.2			
4	0.34			
5	0.35			$= 0.0461$
6	0.4			
7	0.38			

- *temporary change*, where there may be a sudden change in the IMTP profile in a given sampling period, after which the IMTP profile returns gradually to its previous state (see Figure 8(B));
- *structural change*, where there is a sudden change that persists over time, which causes a change in the level or the course of the IMPT profile (see Figure 8(C)).

Sudden changes in the level of discussion and 'out of control' patterns can indicate issues that have an impact on the overall customer experience. Automated anomaly detection systems in the IMTP of quality determinants can provide valuable insights into how to manage a product or service. Some preliminary works in this direction, which have used, for example, statistical control charts, have already been provided (Ashton et al., 2014, 2015; Ashton & Evangelopoulos, 2012; Franceschini & Romano, 1999).

5. Case studies

5.1. *Case study 1: restaurant chain*

This section proposes a case study to illustrate the emergence/disappearance of quality determinants (see Section 4.1). The collection of analysed digital VoCs concerns a restaurant chain with a large presence in the UK.

The quality tracking design parameters were set as follows:

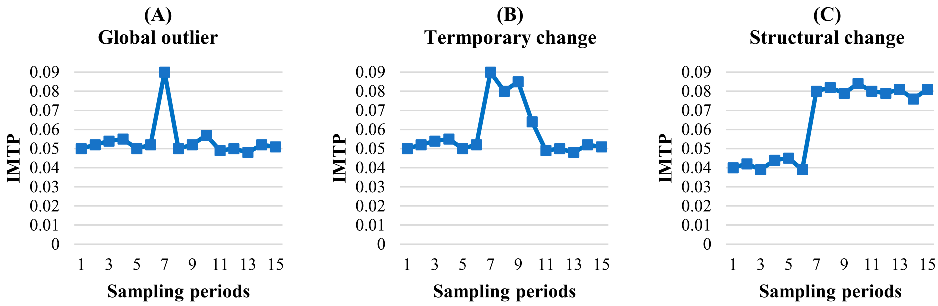


Figure 8. Examples of IMTP profiles with anomalies. (A) Global outlier. (B) Temporary change. (C) Structural Change.

- *time window*: mobile time window of four months;
- *analysis of newly captured data*: reapplication of the topic modelling algorithm;
- *sampling period*: 1 month;
- *scheme of quality tracking*: hybrid quality tracking.

Figure 9 shows the analysis results concerning the first mobile time window of four mounts (1-4) (see Figure 9(A)), and the second mobile time window related to 2–5 months (see Figure 9(B)). The underlying logic is shown in section 3.1 (see Figure 2(B)). The analysis was carried out when the Covid pandemic regulations were introduced.

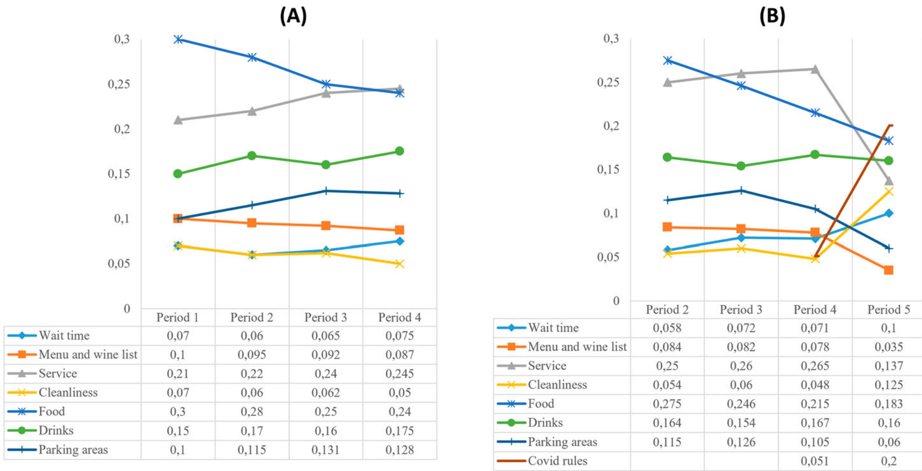
The emergence of a new quality determinant, related to new user needs, can be observed. The second application of the topic modelling algorithm shows a quality determinant labelled ‘Covid rules’, which concerns the restaurant’s ability to comply with the restrictions introduced to contain the pandemic. The other quality determinants present a condition of continuity (they were identified in both analyses).

It can be observed that the emergence of a new quality determinant caused a decrease in IMTP of the other determinants that presented a condition of continuity between the two analysed periods. IMTP values can be interpreted as indicators of the relative importance of quality determinants. The emergence of an additional quality determinant involved a decrease in the relative importance of the others (see Eq. 4).

5.2. *Case study 2: car-sharing*

This section proposes a case study to show how a qualitative trend analysis of quality determinants (see Section 4.2) can be implemented. The considered collection of digital VoCs pertains to the product-service system of car-sharing. A total of 17,000 reviews (i.e. digital VoC records) related to different providers operating in the United States, the UK and Canada were collected. The reviews included in the database covered a period of 14 years, from January 2006 to December 2019. Only English-language reviews were selected from 22 car-sharing providers (Car2go, DriveNow, Maven, Zipcar, Goget, etc.). The employed topic modelling algorithm was the Structural Topic Model (STM) (Roberts et al., 2019).

Figure 10 shows the labels of the 20 identified quality determinants and the related Mean Topical Prevalences (MTP).



(A)	Period 1	Period 2	Period 3	Period 4
Wait time	0,07	0,06	0,065	0,075
Menu and wine list	0,1	0,095	0,092	0,087
Service	0,21	0,22	0,24	0,245
Cleanliness	0,07	0,06	0,062	0,05
Food	0,3	0,28	0,25	0,24
Drinks	0,15	0,17	0,16	0,175
Parking areas	0,1	0,115	0,131	0,128

(B)	Period 2	Period 3	Period 4	Period 5
Wait time	0,058	0,072	0,071	0,1
Menu and wine list	0,084	0,082	0,078	0,035
Service	0,25	0,26	0,265	0,137
Cleanliness	0,054	0,06	0,048	0,125
Food	0,275	0,246	0,215	0,183
Drinks	0,164	0,154	0,167	0,16
Parking areas	0,115	0,126	0,105	0,06
Covid rules			0,051	0,2

Figure 9. Results of the application of the topic modelling algorithm to a digital VoC collection concerning a restaurant chain. (A) Quality determinants identified in the first mobile time window, from period 1 to period 4. (B) Quality determinants identified in the second mobile time window, from period 2 to period 5.

The specific goal of this analysis was to assess how car-sharing quality determinants evolved over time, from the launching of the services in 2006–2019. In this context, the quality tracking design parameters were set as follows:

- *time window*: global time window from 2006 to 2019;
- *analysis of newly captured data*: only past data were considered in the analysis;
- *sampling period*: 6 months;
- *scheme of quality tracking*: hybrid quality tracking.

Following the procedure proposed in Section 4.2, the 20 identified quality determinants were classified into three categories: overall decreasing quality determinants, overall constant quality determinants, and overall increasing quality determinants. Table 8 reports the results of the classification and three exemplifying IMTP profiles. The results show that all the determinants related to the vehicle have remained approximately constant. The category of constant quality determinants includes ‘accident and damage management’, ‘parking area’, ‘end trip experience’, ‘car condition’, ‘car proximity’, ‘car availability’, ‘car start-up issues’, and ‘car reservation’. The category of increasing quality determinants contains all the quality determinants related to the relationship between provider and customers, such as: ‘customer service (physical office)’, ‘registration process’, ‘charges and fees’, ‘app. Reliability’, ‘customer service responsiveness’, ‘customer service courtesy’, and ‘billing and membership’. Finally, the decreasing category contains the determinants concerning the affordability and convenience of the service (‘convenience’, ‘use rates’, ‘efficacy’, ‘sharing benefits’, and ‘intermodal transportation’).

In short, the classification based on the IMTP trends identified a positive trend related to communication and customer service, stationary behaviour for the determinants related to the vehicle and a negative trend for the determinants related to convenience. This information could be useful for service planners and quality managers to address a redesigning of the service.

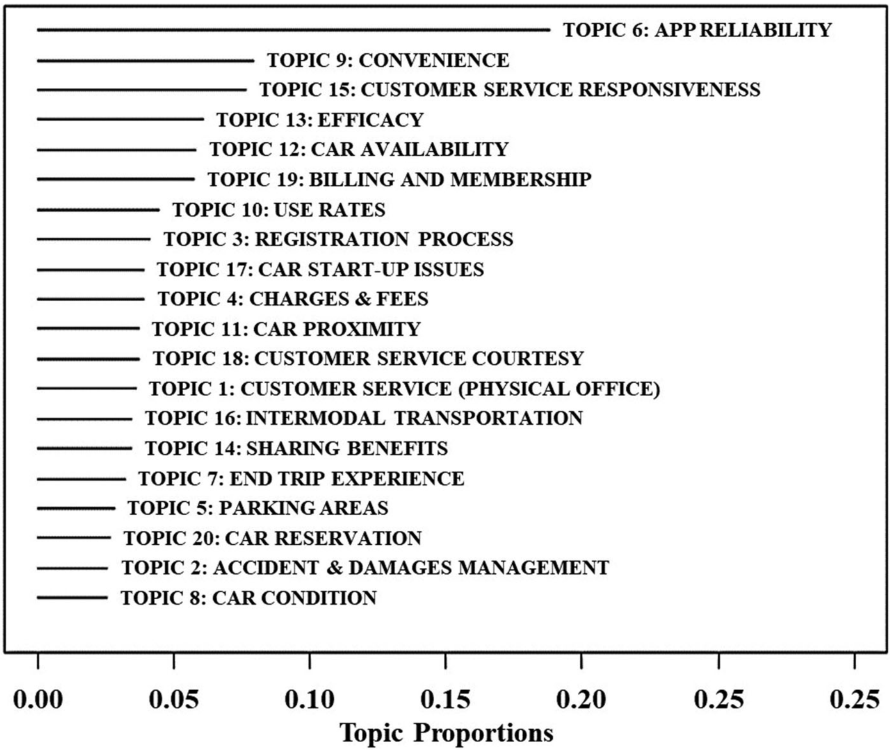


Figure 10. Mean Topic Proportion (MTP) of the 20 quality determinants related to the car-sharing case study.

6. Quality tracking and implications for the designing or redesigning of products/services

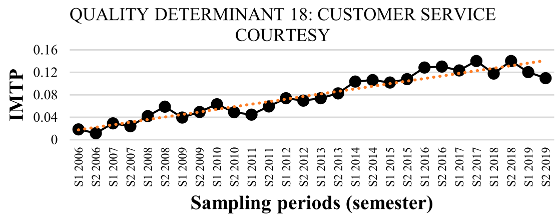
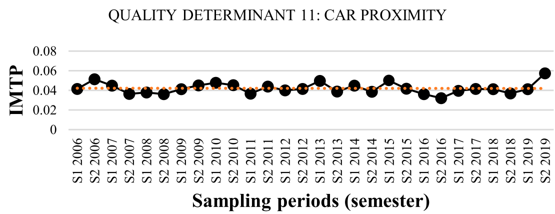
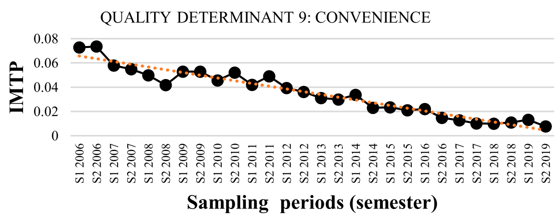
Evidence concerning the trends of IMTP profiles of quality determinants can be used to drive the designing or redesigning of products and services.

Knowing the trends of quality determinants may be useful for designers to understand the evolution of customers' needs in order to anticipate market demands (Barravecchia et al., 2020b).

Figure 11 shows a schematic representation of a process aimed at a continuous improvement and redesigning of a product/service. Accordingly, the redesigning process can be characterised by the following steps:

(1) Identification of the quality determinants. These elements are the most frequently discussed by customers and are, therefore, the ones with the greatest impact on perceived quality.
(2) Analysis of the IMTP profiles. Such analysis results in recognising determinants whose interest is increasing, decreasing, or remaining stable over time.
(3) Quality determinant behaviour can be exploited to prioritise intervention areas in order to improve the quality of the product/service under analysis. Greater priority should be given to potential interventions aimed at improving quality determinants with an increasing level of discussion (IMPT). On the other hand, less priority may

Table 8. Result of the qualitative trend classification of quality determinants.

Category	Profile example	List of car-sharing quality determinants
Increasing quality determinants $\rho_S < -0.4$		• 1: customer service (physical office) • 3: registration process • 4: charges and fees • 6: app. reliability • 15 customer service responsiveness • 18: customer service courtesy • 19: billing and membership
Constant quality determinants $-0.4 \leq \rho_S \leq +0.4$		• 2: accident and damage • 5: parking areas • 7: end trip experience • 8: car condition • 11: car proximity • 12: car availability • 17: car start-up issues • 20: car reservation
Decreasing quality determinants $\rho_S > +0.4$		• 9: convenience • 10: use rates • 13: efficacy • 14: sharing benefits • 16: intermodal transportation

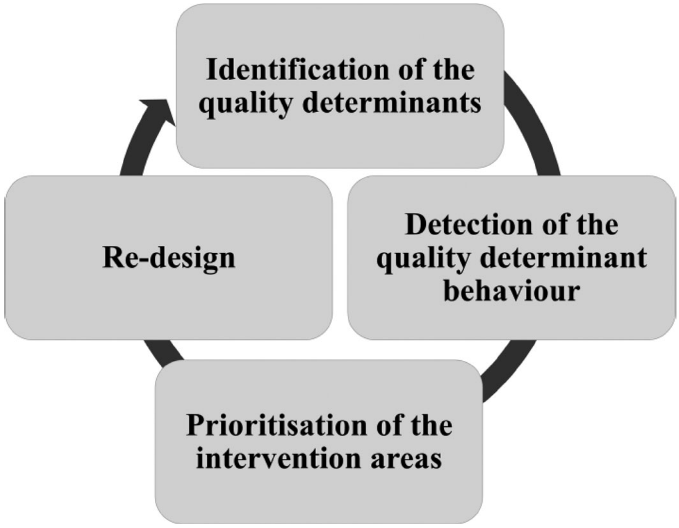


Figure 11. Schematic representation of a continuous improvement process based on a digital VoC analysis.

be given to aspects that are becoming less important for customers (overall decreasing quality determinants)

(4) Redesigning of the analysed product/service. Designers can resort to insights based on the actual needs of customers and to the evolution of quality determinants over time to improve the product/service under analysis.

This redesigning process can be considered a continuous process. Each iteration identifies how the quality determinants are evolving and what the most critical areas that have to be improved are.

As an example, let us consider the results of the case study dealt with in section 5.2:

(1) Twenty different quality determinants inherent to the 'car-sharing' product-service system were identified.
(2) The qualitative trend analysis of the quality determinants (see Section 4.3) resulted in the identification of quality determinants that had increased their respective level of discussion (IMTP) over time (for example, 'customer service responsiveness' and 'customer service courtesy') and quality determinants that had decreased their importance (for example, 'convenience' and 'use rates').
(3) It clearly emerges, from the case study, that the attention of car-sharing customers is increasingly focusing on the intangible aspects of the service; the relationship between customer and company throughout all the different communication channels (physical office, application, customer service, etc.) shows an increasingly greater importance than the affordability and convenience of the service.

    These results could allow designers to identify the most critical areas of intervention, for example, the improvement of the responsiveness of the customer service. Moreover, the trend analysis also revealed those aspects/characteristics of the service that may require fewer resources in favour of others that are more critical, for example, the convenience of the service.

(4) Taking all this information together, a designer could redesign the service and introduce changes that are in line with the evolving customers' needs. For example, changes could be made to improve service responsiveness by providing additional human resources, increasing the uptimes, and/or enhancing service staff training.

The application of continuous improvement actions, based on digital VoC analysis and quality tracking tools, can lead to multiple benefits. First, such actions allow an effective mapping of the evolution of the customer needs over time, which can help to drive product designer and developer choices. Second, such tools reduce the demand for the resources necessary to capture and analyse customer insights, with respect to using traditional survey methods.

7. Discussion and conclusions

Consumers are willing to share their feelings about products and/or services, thereby producing the so-called digital Voice-of-Customers (digital VoCs). This free and widely available information can be used to track the quality of products and services over time.

This paper has explored a novel research stream that is aimed at analysing the evolution of perceived quality over time. Topic modelling algorithms identify the quality determinants of a product or service from digital VoCs. Analysing quality determinants evolution allows valuable information to be extracted for quality management and design purposes.

In order to perform product/service quality tracking through digital VoC analysis this paper analyses four preliminary questions that need to be addressed: (i) *What time windows should be analysed*? (ii) *How should newly captured data be analysed*? (iii) *What sampling period should be chosen*? (iv) *What type of quality tracking should be used*?

Furthermore, this paper offers a description of the different levels of analysis that can be addressed to achieve effective quality tracking purposes. The proposed levels of analysis range from qualitative analyses on the emergence/disappearance of quality determinants to quantitative analyses of trends and anomalies. Two practical case studies have shown how digital VoCs can be analysed for quality tracking purposes and the potential outcomes.

From a conceptual point of view, this study proposes a novel framework of quality tracking approaches that may be useful to drive future developments of digital VoC analysis methodologies. These results may also be of interest for quality practitioners, as they clarify the procedures that should be adopted to implement quality tracking.

A limitation of the proposed quality tracking approach is that only the explicit needs and related quality determinants of customers are taken into account. Implicit needs are not directly captured by the method. An additional uncontrollable factor in the proposed approach is the composition of the digital VoC sample. In practical applications, it is difficult to collect a representative sample when data are gathered from external sources (using web scraping techniques). Some customers might be more prone to sharing their experiences related to product/service usage, but others may be less prone. This could introduce a bias into the results of the analysis. Nevertheless, the size of the analysed sample, which usually consists of tens or even hundreds of thousands of customers, should limit the presence of bias.

The primary goal of this research has been to open the way towards the development of new tools to support organisations in controlling and improving the quality of their products. The findings of this study can stimulate research on quality tracking techniques in different directions.

The proposed different levels of analysis focus on monitoring the extent to which the quality determinants are discussed in the digital VoC. Further investigation is needed to complement this analysis with information on how quality determinants are discussed (e.g. whether with a positive or negative connotation). For this purpose, applying sentiment analysis algorithms or using rating information may be promising solutions.

The proposed level 4 analysis introduces quantitative tools to detect anomalous behaviour of quality determinants. Further research is needed to understand the tools most appropriate. For example, what type of control chart can be effectively used to monitor digital VoC?

Finally, this study preliminary investigated the employment of digital VoC analysis to support the designing or redesigning of products/services. This would be a fruitful area for further work. More research is needed to examine how this approach can be combined with established design tools. For instance, the outputs of the digital VoC analysis could be integrated with Quality Function Deployment for defining and prioritising customer requirements.

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Data availability statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

ORCID

Federico Barravecchia http://orcid.org/0000-0001-7180-4346
Luca Mastrogiacomo http://orcid.org/0000-0002-8454-5918
Fiorenzo Franceschini http://orcid.org/0000-0001-7131-4419

References

Aggarwal, C. C., & Zhai, C. (2012). A survey of text classification algorithms. In C. C. Aggarwal & C. Zhai (Eds.), *Mining text data* (pp. 163–222). Springer.

Ahire, S. L., & Dreyfus, P. (2000). The impact of design management and process management on quality: An empirical investigation. *Journal of Operations Management*, *18*(5), 549–575. https://doi.org/10.1016/S0272-6963(00)00029-2

Allen, T. T., Sui, Z., & Akbari, K. (2018). Exploratory text data analysis for quality hypothesis generation. *Quality Engineering*, *30*(4), 701–712. https://doi.org/10.1080/08982112.2018.1481216

Amat-Lefort, N., Barravecchia, F., & Mastrogiacomo, L. (2022). Quality 4.0: Big data analytics to explore service quality attributes and their relation to user sentiment in Airbnb reviews.

International Journal of Quality & Reliability Management. Advance online publication. doi:10.1108/IJQRM-01-2022-0024

Ashton, T., & Evangelopoulos, N. (2012). Control charts for customer comments: A case study and a research agenda. In M. Rao (Ed.), *Proceeding of the Southwest Decision Sciences Institute* (pp. 661–669).

Ashton, T., Evangelopoulos, N., & Prybutok, V. (2014). Extending monitoring methods to textual data: A research agenda. *Quality & Quantity*, *48*(4), 2277–2294. https://doi.org/10.1007/s11135-013-9891-8

Ashton, T., Evangelopoulos, N., & Prybutok, V. R. (2015). Quantitative quality control from qualitative data: Control charts with latent semantic analysis. *Quality & Quantity*, *49*(3), 1081–1099. https://doi.org/10.1007/s11135-014-0036-5

Bandaru, S., Gaur, A., Deb, K., Khare, V., Chougule, R., & Bandyopadhyay, P. (2015). Development, analysis and applications of a quantitative methodology for assessing customer satisfaction using evolutionary optimization. *Applied Soft Computing*, *30*, 265–278. https://doi.org/10.1016/j.asoc.2015.01.014

Barravecchia, F., Mastrogiacomo, L., & Franceschini, F. (2020a). Categorizing quality determinants in mining user-generated contents. *Sustainability*, *12*(23), 9944. https://doi.org/10.3390/su12239944

Barravecchia, F., Mastrogiacomo, L., & Franceschini, F. (2020b). The player-interface method: A structured approach to support product-service systems concept generation. *Journal of Engineering Design*, *31*(5), 331–348. https://doi.org/10.1080/09544828.2020.1743822

Barravecchia, F., Mastrogiacomo, L., & Franceschini, F. (2022a). Digital voice-of-customer processing by topic modelling algorithms: Insights to validate empirical results. *International Journal of Quality & Reliability Management*, *39*(6), 1453–1470. https://doi.org/10.1108/IJQRM-07-2021-0217

Barravecchia, F., Mastrogiacomo, L., & Franceschini, F. (2022b). KA-VoC Map: Classifying product Key-attributes from digital voice-of-customer. *Quality Engineering*, *34*(3), 344–358. https://doi.org/10.1080/08982112.2022.2057805

Berry, M. W., & Kogan, J. (2010). *Text mining: Applications and theory*. John Wiley & Sons.

Bi, J.-W., Liu, Y., Fan, Z.-P., & Cambria, E. (2019). Modelling customer satisfaction from online reviews using ensemble neural network and effect-based kano model. *International Journal of Production Research*, *57*(22), 7068–7088. https://doi.org/10.1080/00207543.2019.1574989

Blei, D. M. (2012). Probabilistic topic models. *Communications of the ACM*, *55*(4), 77–84. https://doi.org/10.1145/2133806.2133826

Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent dirichlet allocation. *Journal of Machine Learning Research*, *3*, 993–1022.

Carnerud, D. (2020). The quality movement's three operational paradigms: A text mining venture. *The TQM Journal*, *32*(6), 1577–1598. https://doi.org/10.1108/TQM-05-2019-0134

Chen, K.-S., Chang, T.-C., Wang, K.-J., & Huang, C.-T. (2015). Developing control charts in monitoring service quality based on the number of customer complaints. *Total Quality Management & Business Excellence*, *26*(5–6), 675–689. https://doi.org/10.1080/14783363.2013.874198

DeVellis, R. F. (2016). *Scale development: Theory and applications*. Sage publications. California, United States.

Franceschini, F. (2002). *Advanced quality function deployment*. St. Lucie Press / CRC Press.

Franceschini, F., & Romano, D. (1999). Control chart for linguistic variables: A method based on the use of linguistic quantifiers. *International Journal of Production Research*, *37*(16), 3791–3801. https://doi.org/10.1080/002075499190059

Gregorio, R., & Cronemyr, P. (2011). From expectations and needs of service customers to control chart specification limits. *The TQM Journal*, *23*(2), 164–178. https://doi.org/10.1108/17542731111110221

Hallencreutz, J., & Parmler, J. (2021). Important drivers for customer satisfaction – From product focus to image and service quality. *Total Quality Management & Business Excellence*, *32*(5–6), 501–510. https://doi.org/10.1080/14783363.2019.1594756

Izogo, E. E., & Ogba, I.-E. (2015). Service quality, customer satisfaction and loyalty in automobile repair services sector. *International Journal of Quality & Reliability Management*, *32*(3), 250–269. https://doi.org/10.1108/IJQRM-05-2013-0075

Jach, P., Antony, J., Thomson, S. P., Cudney, B., & Furterer, S. (2021). Voice of the customer as a tool for service quality analysis in public transport. *The TQM Journal*, *34*(3), 448–475. https://doi.org/10.1108/TQM-05-2021-0134

Joung, J., Jung, K., Ko, S., & Kim, K. (2019). Customer complaints analysis using text mining and outcome-driven innovation method for market-oriented product development. *Sustainability*, *11*(1), 40. https://doi.org/10.3390/su11010040

Kamsu-Foguem, B., Rigal, F., & Mauget, F. (2013). Mining association rules for the quality improvement of the production process. *Expert Systems with Applications*, *40*(4), 1034–1045. https://doi.org/10.1016/j.eswa.2012.08.039

Kannan, K. S. P. N., & Garad, A. (2020). Competencies of quality professionals in the era of industry 4.0: A case study of electronics manufacturer from Malaysia. *International Journal of Quality & Reliability Management*, *38*(3), 839–871. https://doi.org/10.1108/IJQRM-04-2019-0124

Kumar, A., & B. Anjaly. (2017). How to measure post-purchase customer experience in online retailing? A scale development study. *International Journal of Retail & Distribution Management*, *45*(12), 1277–1297.

Liu, Y., Jiang, C., & Zhao, H. (2019). Assessing product competitive advantages from the perspective of customers by mining user-generated content on social media. *Decision Support Systems*, *123*, 113079. https://doi.org/10.1016/j.dss.2019.113079

Mastrogiacomo, L., Barravecchia, F., Franceschini, F., & Marimon, F. (2021). Mining quality determinants of Product-Service Systems from unstructured User-Generated Contents: The case of car-sharing. *Quality Engineering*, *33*(3), 425–442. https://doi.org/10.1080/08982112.2021.1877305

McColl-Kennedy, J., & Schneider, U. (2000). Measuring customer satisfaction: Why, what and how. *Total Quality Management*, *11*(7), 883–896. https://doi.org/10.1080/09544120050135434

Mukherjee, S. P. (2019). *Quality, domains and dimensions*. Springer.

Myers, J. L., Well, A. D., & Lorch Jr, R. F. (2013). *Research design and statistical analysis*. Routledge.

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

Roberts, M. E., Stewart, B. M., & Tingley, D. (2019). STM: R package for structural topic models. *Journal of Statistical Software*, *91*(2), 1–40. https://doi.org/10.18637/jss.v091.i02

Sarkar, S., & Rajagopalan, B. (2018). Consumer safety complaints and organizational learning: Evidence from the automotive industry. *International Journal of Quality & Reliability Management*, *35*(10), 2094–2118. https://doi.org/10.1108/IJQRM-03-2017-0048

Singh, K., & Upadhyaya, S. (2012). Outlier detection: Applications and techniques. *International Journal of Computer Science Issues (IJCSI)*, *9*(1), 307.

Sony, M., Antony, J., & Douglas, J. A. (2020). Essential ingredients for the implementation of Quality 4.0. *The TQM Journal*, *32*(4), 779–793. https://doi.org/10.1108/TQM-12-2019-0275

Su, Y., & Hwang, J.-S. (2020). Integration of customer satisfaction and sustained use of a product for value assessment. *Total Quality Management & Business Excellence*, *31*(15–16), 1760–1773. https://doi.org/10.1080/14783363.2018.1509697

Xu, W., Guo, C., Guo, S., Wang, L., & Li, X. (2021). A novel quality comprehensive evaluation method based on product gene for solving the manufacturing quality tracking problem of large equipment. *Computers & Industrial Engineering*, *152*, 107032. https://doi.org/10.1016/j.cie.2020.107032

Zhan, J., Loh, H. T., & Liu, Y. (2009). Gather customer concerns from online product reviews – A text summarization approach. *Expert Systems with Applications*, *36*(2, Part 1), 2107–2115. https://doi.org/10.1016/j.eswa.2007.12.039

Zonnenshain, A., & Kenett, R. S. (2020). Quality 4.0—The challenging future of quality engineering. *Quality Engineering*, *32*(4), 614–626. doi:10.1080/08982112.2019.1706744