MOBIQual: a common framework to manage the productservice system quality of shared mobility

Flexible Services and Manufacturing Journal (2024) 36:1359–1398
https://doi.org/10.1007/s10696-023-09520-y

MOBI-Qual: a common framework to manage the product-service system quality of shared mobility

Federico Barravecchia[1] · **Luca Mastrogiacomo**[1] · **Martí Casadesús Fa**[2] · **Fiorenzo Franceschini**[1]

Accepted: 23 October 2023 / Published online: 11 November 2023

Abstract

Shared mobility is transforming urban transportation. The increasing demand for more efficient and sustainable transportation options has driven the growth of the shared mobility sector, attracting operators ranging from new entrants to traditional manufacturers looking to diversify their markets. Despite its popularity, there is currently a lack of tools to support the design and management of the quality of shared mobility. Seeking to contribute towards bridging this gap, this paper presents a comprehensive quality framework, refereed as *MOBI-Qual*. *MOBI-Qual* was developed using a bottom-up approach, wherein quality determinants were defined based on an extensive analysis of digital Voice-of-Customer data, specifically customer review. A topic modelling algorithm was utilized to extract the quality determinants for the most prevalent shared mobility modes. Following this, a common framework was established through a comparison of these quality determinants. The proposed framework comprises eleven quality determinants that comprehensively cover various aspects of shared mobility.

Keywords Shared mobility · Quality · MOBI-Qual · Product-service systems · Digital Voice-of-Customer · Topic modelling

✉ Fiorenzo Franceschini
fiorenzo.franceschini@polito.it

Federico Barravecchia
federico.barravecchia@polito.it

Luca Mastrogiacomo
luca.mastrogiacomo@polito.it

Martí Casadesús Fa
marti.casadesus@udg.edu

1 Department of Management and Production Engineering (DIGEP), Politecnico di Torino, Turin, Italy

2 Department of Business Management and Product Design, Universitat de Girona, Girona, Spain

1 Introduction

Shared mobility has become increasingly popular in recent years as a way to reduce traffic congestion and improve access to transportation (Machado et al. 2018; Prencipe et al. 2022). The shared mobility market, which includes services such as car sharing, bike sharing, and e-scooter sharing, has the potential to offer a convenient and affordable alternative to traditional forms of transportation (Hensher et al. 2020). The industry is undergoing rapid transformation, with a strong emphasis on digitalization, connectivity, and customer-centricity (Siegfried 2022). To thrive in this dynamic landscape, providers of shared mobility must develop innovative business strategies that align with the ever-evolving customer expectations.

Despite the widespread adoption of shared mobility, there has been a paucity of research specifically examining the quality of these services. The existing predetermined frameworks of quality determinants for products or services (such as those proposed by Garvin 1987; Parasuraman et al. 1988) may not fit the contexts where tangible and intangible elements must be taken into account concurrently (Mastrogiacomo et al. 2021). This is particularly relevant for Product-Service Systems (PSS), such as shared mobility services, which require specialised approaches (Barravecchia et al. 2021).

Within the limited existing research, a few studies analyzed the quality of specific shared mobility modes. However, despite these efforts, a significant gap remains in the literature: the absence of a comprehensive tool capable of analyzing the quality of shared mobility in a holistic manner. It's therefore essential to deepen our understanding of shared mobility quality, especially for stakeholders who wish to enhance benefits and minimize the negative impacts of these services.

From this perspective, the primary aim of our study is to construct a theoretical foundation that deepens our comprehension of shared mobility quality. To this end, this study introduces the *MOBI-Qual* framework, a comprehensive collection of shared mobility's quality determinants. This framework was developed through a consolidation of quality determinants identified in different digital Voice-of-Customer datasets, related to the three most prevalent shared mobility modes: car sharing, bike sharing, and e-scooter sharing.

Although the analytical methods employed in this study, grounded in the Topic Modelling algorithm, are not novel, their concurrent application across various domains of shared mobility is worthy of attention. The proposed approach produced a holistic model that captures the complexity of different shared mobility landscapes.

The remainder of the paper unfolds as follows. Section 2 offers an in-depth introduction to shared mobility, also incorporating references to prior studies on the quality of shared mobility. Section 3 discusses the theoretical background underpinning the digital Voice-of-Customer (VoC) analysis employed in this research. Section 4 outlines the analytical methodology employed in this study. Following this, the proposed *MOBI-Qual* framework, along with the procedure pursued for its development, is articulated in Sect. 5. The paper concludes with a discussion of the study's contributions, limitations, and possibile future research in the final section.

2 Shared mobility: modes and quality studies

The sharing economy leverages technology to facilitate peer-to-peer exchange of underutilised goods or services (Schlagwein et al. 2020). This process is facilitated by an intermediary platform, and importantly, does not involve the transfer of ownership, enabling resources to be shared rather than owned outright. This model has been adapted to a variety of sectors, including mobility. Shared mobility allows users to access shared vehicles on a short-term basis as needed and includes a range of services such as car sharing, bike sharing, ride sharing and on-demand ride services (Fikar and Hirsch 2018; Shaheen et al. 2020).

The growth of shared mobility has been driven by advances in digital technology and the implementation of GPS-based systems, which enable providers to monitor the position and status of shared vehicles and allow users to easily locate the nearest available vehicle using a mobile app.

A review of the existing literature revealed a lack of tools and methodologies for understanding and managing the quality of shared mobility services. The few studies that addressed this topic had also some limitations, such as small sample sizes (Ashqar et al. 2022; Beirigo et al. 2022; Kumar et al. 2022) and a lack of consideration for different shared mobility modes (Barravecchia et al. 2020a, b; Mastrogiacomo et al. 2021). This gap in the literature highlights the need for a more comprehensive and systematic approach to assessing the quality of shared mobility.

To gain a comprehensive understanding of the quality of shared mobility services, this study jointly examined the three most popular shared mobility modes: car sharing, bike sharing, and e-scooter sharing (Castellanos et al. 2022).

2.1 Car sharing

Car sharing users can access a fleet of shared cars on an as-needed basis and pay a usage and/or membership-based fee to get the benefits of a private vehicle without the related cost of ownership (e.g., fuel, maintenance, insurance) (Shaheen et al. 2020). Car sharing is developing extremely dynamically, not only in terms of users but also in terms of service schemes, application areas, organisational solutions, and players in the market. Various car sharing schemes have been developed (Ferrero et al. 2018); the most prevalent are:

- *Roundtrip car sharing*, also known as station-based car sharing, requires cars to be returned to the same location from where it was picked up.
- *One-way car sharing*, also known as point-to-point or free-floating car sharing, allows members to pick up and drop off a car in different locations within a delimited area.

Car sharing has been shown to have a number of positive effects on individuals, communities, and the environment. For individuals, car sharing can provide a convenient and cost-effective transportation option, especially for those who do not own a car or do not use it frequently. By allowing individuals to access a car when needed rather than owning one, car sharing can help to reduce the financial burden of car ownership and maintenance (Qian et al. 2022). It can also reduce the need for personal car storage, freeing up space in urban areas where space is often limited. At the community level, car sharing can help to reduce traffic congestion and air pollution, as fewer cars are needed to meet the transportation demand of a given population. Car sharing can also have positive environmental impacts, as it can help to reduce greenhouse gas emissions by reducing the number of cars on the road. This can contribute to the efforts to combat climate change and improve air quality. In recent years, vehicle electrification is also affecting car sharing by further improving its environmental sustainability performance (Prencipe et al. 2022).

Car sharing has seen a steady rise in popularity in urban areas, with a reported 38 million subscribers in 2018 and a total of 198,000 vehicles in 47 different countries. In the same year, car sharing generated over $9 billion in revenue, and it is expected to reach over $14 billion by 2024 (Statista 2021). These figures demonstrate the significant growth and potential of the car sharing industry in recent years and suggest that it will continue to be a major player in the urban transportation landscape in the coming years.

Mugion et al. (2019) found that the perceived quality of a car sharing service plays a significant role in determining a person's intention to use the service. Mattia et al. (2019) developed a framework for understanding the psychological factors that influence the intention to re-use free-floating car sharing services. Barravecchia et al. (2020a, b) also proposed a preliminary framework for understanding the determinants of the quality of car sharing services. These studies suggest that the quality of car sharing services is an important feature for both users and providers of these services.

2.2 Bike sharing

Bike sharing is a sustainable and increasingly popular form of transportation that is being adopted by more and more cities around the world. Public administrations are increasingly offering bike-sharing services to their citizens as an alternative to traditional modes of transportation. Bike sharing allows users to rent bikes on an as-needed basis, either from a network of bike-sharing stations or from a designated area in the case of dockless bike sharing (Shaheen et al. 2020).

Bike sharing can have a number of positive effects. Bike sharing can help reduce traffic congestion and pollution in urban areas, as it provides a convenient and sustainable alternative to driving (Wang and Zhou 2017). This can improve air quality and public health, as well as reduce noise levels in cities. Bike sharing can also have economic benefits, as it can provide a low-cost form of transportation for those who may not have access to a car or who choose to use a bike as an alternative to public transit (Qiu and He 2018). Furthermore, bike sharing can encourage physical activity, as biking is a form of exercise that can support a healthy lifestyle (Otero et al. 2018). Overall, bike sharing can be a valuable tool for promoting sustainability, improving public health, and enhancing the quality of life in urban areas.

The bike-sharing industry experienced significant growth in recent years. In 2019, revenues for bike-sharing services reached approximately $5 billion, and by 2020, this figure had grown to $6.9 billion, with a total of 669 million users (Statista 2021). These numbers are expected to continue to rise in the coming years, with forecasts predicting that revenues for bike-sharing services could reach $9.6 billion by 2024, serving a total of 860 million users. (Statista 2021).

Most previous research on bike-sharing focused on forecasting demand and optimising dock locations. However, there have also been a few studies that have examined the quality of bike-sharing services. Bordagaray et al. (2012) developed a methodology for modelling the perceived quality of bike-sharing services in order to identify the variables that influence user perceptions of quality and their relative importance. Their study found that safety and information were the most important factors in determining the perceived quality of bike-sharing. Hsu et al. (2018) proposed a model for improving the quality of bike-sharing services based on 24 criteria derived from the SERVQUAL model. Morton (2018) used the SERVPERF model to develop a set of items for measuring the quality of bike-sharing services and user satisfaction. Similarly, Ma et al. (2019) proposed a list of service quality evaluation criteria based on the SERVPERF model. These studies highlight the importance of considering the quality of bike-sharing services and suggest that there are several factors that can influence user perceptions of quality.

2.3 E-scooter sharing

E-scooter sharing is a form of transportation in which users can rent electric scooters (e-scooters) on an as-needed basis. E-scooters are small, electric vehicles that can be easily rented and dropped off at various locations around a city. To use an e-scooter sharing service, users typically need to download a smartphone app and create an account. They can then locate and unlock an available e-scooter using the app, and pay for their ride using an electronic payment method. E-scooter sharing is becoming increasingly popular in urban areas as a convenient and environmentally friendly way to get around. It can be especially useful for short trips or as a last-mile transportation option to connect with public transit. E-scooter sharing has the potential to reduce traffic congestion and air pollution, and can provide a fun and affordable alternative to driving or using public transit (Wanganoo et al. 2022).

Despite some initial hesitation due to concerns about safety, the growth of e-scooter sharing has been rapid in recent years (Lee et al. 2021). E-scooter sharing is a relatively new form of shared mobility, with the first e-scooter sharing platform having been released in 2017. That year, e-scooter sharing generated only $11 million in revenue. However, the rapid expansion of the industry led to significant growth, with revenues reaching $1.34 billion in 2021 and the number of users surpassing 64 million (Statista 2021). The convenience and environmental benefits of e-scooter sharing, as well as the increasing availability of e-scooters in urban areas, are likely contributing factors to this growth.

There has been relatively little research on the quality of e-scooter sharing services. In a recent study, Hamerska et al. (2022) explored the factors that influence customer satisfaction or dissatisfaction in e-scooter sharing. They identified the features that shape the quality of e-scooter sharing and adapted the SERVQUAL model to define the assessment items for their study. Further research is needed to fully understand the factors that contribute to the quality of e-scooter sharing and how they can be effectively managed to provide optimal service to users.

3 Digital Voice-of-Customer

Digital VoC channels, which encompass platforms such as customer review websites, social media posts, and online discussions in blogs or communities, are frequently used by consumers to express their opinions about various products and services (Hennig-Thurau et al. 2010; Palese & Usai 2018).

The concept of digital VoC can be characterized by three key attributes (dos Santos 2021):

- It requires a personal contribution or creative effort, indicating the involvement of individual consumers in generating feedback;
- The generated content should be accessible to the public, or at least to a significant group of people, thus contributing to wider discourse;
- It is expected to be created outside the excercise of professional obligations, ensuring the independence and authenticity of the feedback.

In the domain of digital VoC, textual customer reviews have gathered significant attention from researchers. Such reviews offer detailed insights into customer experiences, viewpoints, and sentiments related to specific products or services, thus serving as a valuable resource for the analysis and comprehension of customer perceptions (Subhashini et al. 2021). By analyzing the content of these reviews, it is possible to uncover common themes, identify strengths and weaknesses of products or services, and gain a deeper understanding of customer preferences and expectations (Qi et al. 2016). Furthermore, the accessibility and ease of sharing textual customer reviews have made them an influential source of information for prospective customers (Maslowska et al. 2017).

3.1 Digital VoC analysis approaches

The broad availability of textual digital VoC facilitates large-scale data collection. Given the sheer volume of digital VoC, the focus has been on developing and applying methods that can effectively analyse its content, with a particular emphasis on extracting the topics discussed.

Topic modelling has emerged as a widely utilized tool for digital VoC analysis. When applied to digital VoC, topic modelling algorithms proved to be able to extract the latent quality determinants of products or services, i.e., the elements can significantly influence perceived quality (Özdağoğlu et al. 2018; Barravecchia et al. 2020a, b; Mastrogiacomo et al. 2021). It is reasonable to assume that if a topic is discussed, it is important to the customer and thus critical to his/her perception of quality.

In recent years, novel methods for digital Voice-of-Customer (VoC) analysis have emerged, employing advanced deep learning techniques (Ullah et al. 2023). Notably, the application of BERT (Bidirectional Encoder Representations from Transformers) embeddings combined with K-means clustering has gained considerable attention (Devlin et al. 2018; Catelli et al. 2022). BERT, a pre-trained deep learning model, excels in natural language processing tasks by capturing the semantic context of words and phrases in a language (Bharadiya 2023). It transforms digital VoC data into high-dimensional vector representations, or "embeddings", which serve as numerical proxies of the reviews, encapsulating the context and sentiment of the customer's voice. K-means clustering is then employed to group these BERT embeddings, effectively segmenting reviews into distinct topics.

For the specific requirements of this study, a traditional topic modeling approach was selected. In subsequent phases of the study, techniques within the BERT chain will be explored. The outcomes will subsequently be compared with those obtained using the topic modelling approach.

3.2 Applications of digital VoC analysis

Digital VoC analysis has found significant application in the field of product/service improvement and development (Trenz and Berger 2013). Researchers utilized digital VoC analysis to identify the quality determinants in various products and services (Jelodar et al. 2019), such as hotels and travel services (Ding et al. 2020; Park et al. 2020; Putranto et al. 2021; Amat-Lefort et al. 2022; Shang et al. 2022), technical services (Papadia et al. 2022), brokerage services (Yang and Fang 2004), mobile apps (Kim et al. 2022) and digital devices (Almars et al. 2019).

Some attempts have been made to apply digital VoC analysis tools in the context of shared mobility. Lock and Pettit (2020) conducted a study that explored the potential of using social media as a means to engage with citizens and customers of public transportation systems. Their research involved analyzing social media data through topic modelling and sentiment analysis algorithms, combined with passively collected big data forms, to gain insights into customer experiences and feedback regarding operational transport performance. Kühl et al. (2020) proposed an automated approach to prioritize and quantify customer needs using social media data specifically in the context of e-mobility. Mastrogiacomo et al. (2021) conducted research focused on identifying the determinants of quality in car sharing services. All these studies highlight the potential of digital VoC analysis to enhance our understanding of shared mobility quality.

4 Methodology for identifying quality determinants

For the purpose of topic modeling in this study, the structural topic modelling (STM) (Roberts et al. 2019a, b) was employed. The primary reasons guiding the choice of structural topic modeling (STM) include:

- *Probabilistic Modeling*: STM produces a probabilistic model, capturing the varied content across multiple topics for each digital VoC record analyzed. This allows for a more realistic and comprehensive representation of data.
- *Reliability*: STM has gained trust in digital VoC studies due to its consistent and replicable results across varied research settings. Its versatility in handling different types of digital VoC data underscores its reliability in extracting meaningful topics.
- *Input Parameters*: unlike other approaches that require a calibration process and a set of parameters to be specified, STM requires only the number of topics to be defined. This ensures easier setup and reduces the risk of over-tuning or bias.

This approach provided insights into the experiences and opinions of actual users of shared mobility services, offering a comprehensive understanding of their quality determinants (Barravecchia et al. 2020a, b, 2021; Mastrogiacomo et al. 2021; Amat-Lefort et al. 2022). The findings of this analysis will be used in subsequent sections to define a common quality framework applicable to all shared mobility modes.

The same analytical methodology was applied separately to each digital VoC dataset (pertaining to bike sharing, e-scooter sharing, and car sharing) to facilitate a direct comparison of the results. The applied methodology can be divided into five steps: (i) dataset extraction, (ii) pre-processing, (iii) topic modelling, (iv) labelling, and (v) validation of results. Figure 1 reports a synthetic scheme of the methodology described in detail in the following Sections.

4.1 Dataset extraction

The primary method for extracting digital Voice of Customer (VoC) data is through web scraping, which involves the automated and large-scale extraction of information from websites (Diouf et al. 2019).

To ensure comprehensive data collection, the leading shared mobility providers have been identified based on factors such as market share, geographical reach, and diversity of offerings. A different range of sources was selected to ensure a comprehensive dataset. The variation in sources can be attributed to the distinct

Fig. 1 Schematic representation of the digital VoC analysis methodology

online presence and review patterns observed for each type of shared mobility service. For instance, some sharing services may be recognized as more popular and consequently receive more reviews on specific platforms. Such multiplicity of sources guarantees that a broad spectrum of customer feedback is captured.

In detail, the software Octoparse (Octopus Data Inc. 2023) was utilized for the web scraping process. The scraper was programmed to target:

- *Review text*: the main content of a review, where customers express their experiences and opinions about the service.
- *Provider*: the shared mobility service provider that the review is about.
- *Website*: the specific website from which the review was extracted.
- *Type of sharing*: the specific type of shared mobility service being reviewed (car sharing, bike sharing, e-scooter sharing).
- *Operating country*: the country or region in which the provider operates.
- *Release date*: The date when the review was posted.

Table 1 details the specifications of the extracted digital VoC datasets. The authors made the complete dataset publicly available via the Harvard Dataverse platform (Barravecchia 2023). The dataset includes all the analyzed digital VoC records, each paired with its relevant metadata, as detailed in the preceding bullet points.

Table 1 Specifications of the extracted digital VoC datasets concerning bike sharing, e-scooter sharing and car sharing

	Bike sharing	E-scooter sharing	Car sharing
Sample size (no. of records)	16.407	27.284	17.406
Average length (no. of characters)	240	167	388
Release period (years)	2009–2021	2017–2021	2005–2021
Sources (websites)	Trustpilot	Trustpilot	Trustpilot
	Yelp	Yelp	Yelp
	Google play	Google play	Google play
			Facebook
			Google
			Apple store
Number of providers	25	16	17
Countries	United Kingdom	United Kingdom	United Kingdom
	United States	United States	United States
	Canada		Canada
			Australia
Sharing typology	Docked	Dockless	Roundtrip
	Dockless	Mixed	One-way
	Mixed		Mixed

4.2 Pre-processing

Before implementing topic modelling algorithms, it is necessary to process the text to ensure and enhance the algorithm's performance. This process is generally referred to as text pre-processing (Hickman et al. 2022). Pre-processing allows working with smaller data sizes, decreasing the time required for topic modelling and improving the quality of the results (Uysal and Gunal 2014). The pre-processing phase included the following operations (Mastrogiacomo et al. 2021):

- *Converting text to lowercase.*
- *Removal of punctuation.*
- *Removal of stop words*, which are all words functional to the language but lacking information, such as articles or prepositions.
- *Stemming*, i.e., the operation through which the words are brought back to their lexical root.
- *Removal of rare words*, which are often the result of typing errors or concern uncommon subjects.

4.3 Topic modelling

The strctural topic model (STM) algorithm was used to infer the major topics addressed within the analysed datasets of digital VoC. To this end, R Software, and the STM library were used (Roberts et al. 2019a, b). The code in R language containing the main functions used in the analysis is provided in Appendix 1. Recent papers and overviews of the STM algorithm exist for readers unfamiliar with its background (Roberts et al. 2014; Roberts et al. 2019a, b).

Topic modelling algorithms require to indicate the number of topics to be extracted (K). This parameter significantly impacts the quality and interpretability of the results. When K is small, the identified topics tend to be broad and general. However, as the number of topics increases, they become more specific and focused. While a higher value of K may capture finer-grained details, it can also lead to topics that are less coherent or meaningful (Sbalchiero and Eder 2020).

For the evaluation of the number of topics, the held-out likelihood was selected as the main indicator of the effectiveness of the model (Yi and Allan 2008). The held-out likelihood is a metric on the goodness of performance of the topic model calculated using a portion of the textual corpus as the training set to develop the model and the remaining portion of the corpus (held-out documents) as the test set (Wallach et al. 2009).

The number selected for maximising the held-out likelihood was 22 topics for the bike sharing, 24 for e-scooter sharing, and 20 for car sharing. Figure 2 depicts the variation of held-out likelihood as the number of topics ranges from 5 to 50. The subsequent phase of human validation of the results, as detailed in Sect. 4.5, confirmed the appropriateness of the chosen number of topics to be extracted.

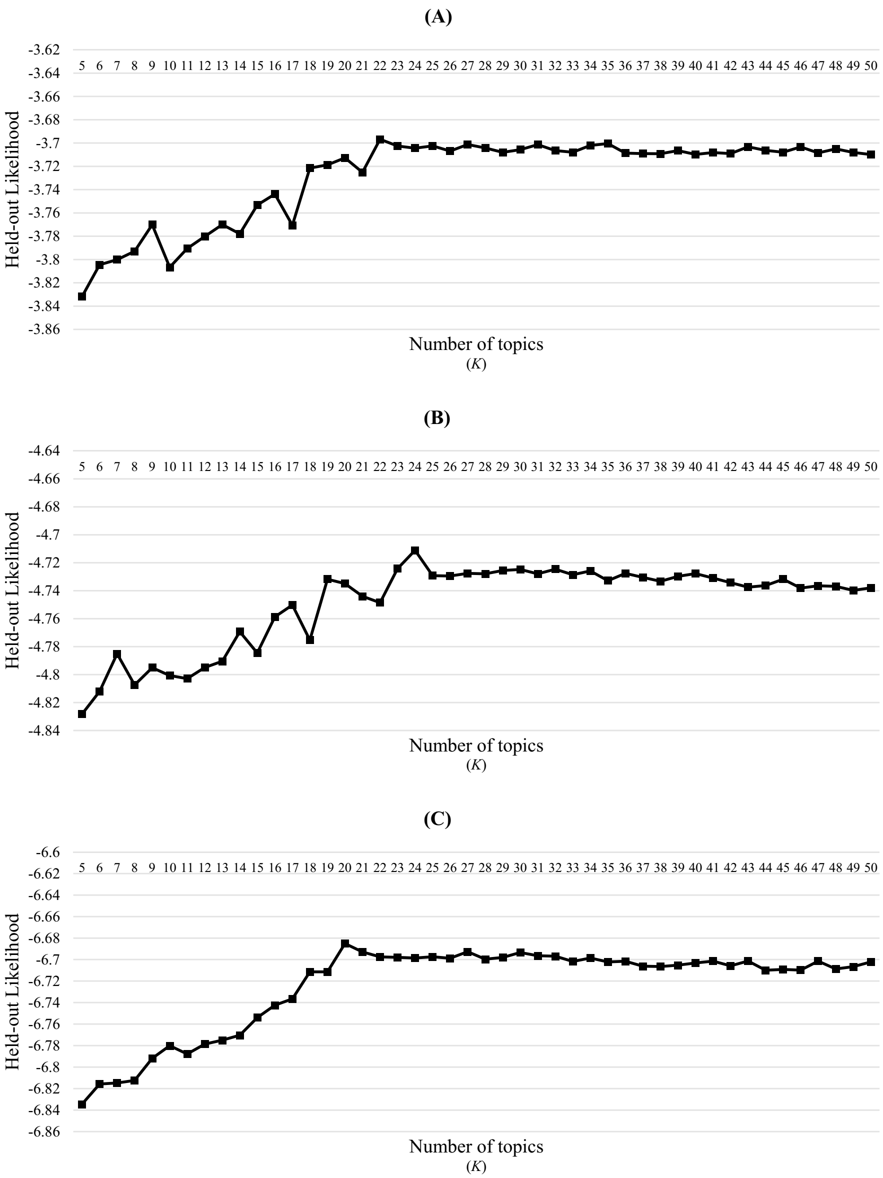

Fig. 2 Held-out likelihood of the topic model varying the number of topics (K): **A** bike sharing, **B** E-scooter sharing, **C** car sharing

Several factors may contribute to why the three topic models can have different numbers of topics. One factor could be the size and structure of the datasets. For example, a larger dataset with a greater variety of information may result in a greater number of topics being identified. Additionally, the language and style of the digital VoC may also affect the number of topics.

Once the number of topics was determined, a topic modeling algorithm was applied. The algorithm produced several outputs, including the distribution of topics within the document (*topical prevalence*) and the probability that a word belongs to a specific topic (*topical content*). In line with previous research, the extracted topics served as quality determinants for the analyzed shared mobility services.

4.4 Labelling

A panel of experts assisted in categorizing and understanding the various factors that contribute to the quality of shared mobility. This panel was composed of six experts, including researchers and practitioners. The experts were selected based on their expertise, combining insights from both academic scholars and industry professionals to provide a comprehensive perspective. Four were academic scholars whose selection was based on their research and contributions to shared mobility and related fields. In contrast, the two industry professionals were chosen for their practical experience in the shared mobility sector. Occupying senior roles within their respective organizations, they participated in the development and execution of shared mobility projects.

The panel of experts' main task was to provide a representative label for each quality determinant, thereby facilitating their interpretation. The labeling process was informed by considering:

- The keywords with the highest probability of belonging to each determinant;
- The digital VoC records for which the model estimated a higher probability of belonging to a given quality determinant.

To ensure reliability in the labeling process, a structured protocol was followed. Each expert independently evaluated and assigned labels to the quality determinants. Afterward, the labels assigned by the experts were compared and discussed in a consensus meeting. In the few instances where discrepancies were identified, an iterative process was implemented to encourage open discussion and consider additional data. This approach facilitated the negotiation of differing viewpoints and fostered the collective development of a consensus. Only when all experts were in agreement, a final label was assigned to a quality determinant. This process, combining independent analysis with collaborative discussion, helped to ensure that each label was robustly scrutinized and agreed upon. As a result, the potential for bias or error was significantly minimized, enhancing the reliability of the findings.

Table 2 reports the labels of the identified determinants. A full description of the determinants and related keywords is reported in Appendix 2 in Tables 6, 7 and 8, respectively, related to bike sharing, e-scooter sharing and car sharing.

Figure 3 provides an overview of the Mean Topical Prevalence assigned to all quality determinants based on the analysis of digital VoC for the three different shared mobility modes: bike sharing, e-scooter sharing, and car sharing.

The functionality and reliability of the mobile application emerged as one of the most discussed quality determinants across all three shared mobility modes.

Table 2 Quality determinants of bike sharing, e-scooter sharing and car sharing provided by the topic modelling algorithm

No	Bike sharing	E-scooter sharing	Car sharing
1	Battery issues	Passes and programs	Customer service (physical office)
2	Short distance commuting	Scooter location	Accident and damages
3	Bike condition	Licence validation	Registration process
4	Registration / login issues	Ease of use	Charges & fees
5	Sightseeing benefits	Start-up / scan issues	Parking areas
6	Economic convenience	Use rates	App reliability
7	Use rates	Use and parking areas	End trip issues
8	Dock proximity	Phone login issues	Car condition
9	App bugs	Customer service	Convenience
10	Notification system	Convenience	Use rates
11	Membership	Speed limits and management	Car proximity
12	Ease of use	App reliability	Car availability
13	Use areas	Safety	Efficacy
14	Bike and docks availability	Experience pleasantness	Sharing benefits
15	Map features	Riding experience	Customer service responsiveness
16	Safety	Recharging mode	Intermodal transportation
17	Unlock issues	Alternative transportation comparison	Car start-up issues
18	App reliability	Payment	Customer service courtesy
19	Charges & fees	Scooter condition	Billing and membership
20	Payment	Charging policy	Car reservation
21	Alternative transportation comparison	Customer service responsiveness	–
22	Customer service	App download issues	–
23	–	Use rates issues	–
24	–	App bugs	–

This highlights the critical role that user-friendly and reliable applications play in shaping customer experiences and satisfaction in shared mobility services. In the context of Bike sharing, topics related to "Use rates", "Payment", and "Customer service" also surface prominently in discussions. For E-scooter sharing, prevalent determinants are "Charging policy", "Use rates issues", and "Ease of use". With regards to car sharing, the discussion is mainly addressed to quality determinants "Customer service responsiveness" and "Convenience". Overall, this analysis provides a detailed understanding of how different aspects of each shared mobility service affect user perception and satisfaction, offering valuable insights for service providers aiming to improve their offerings.

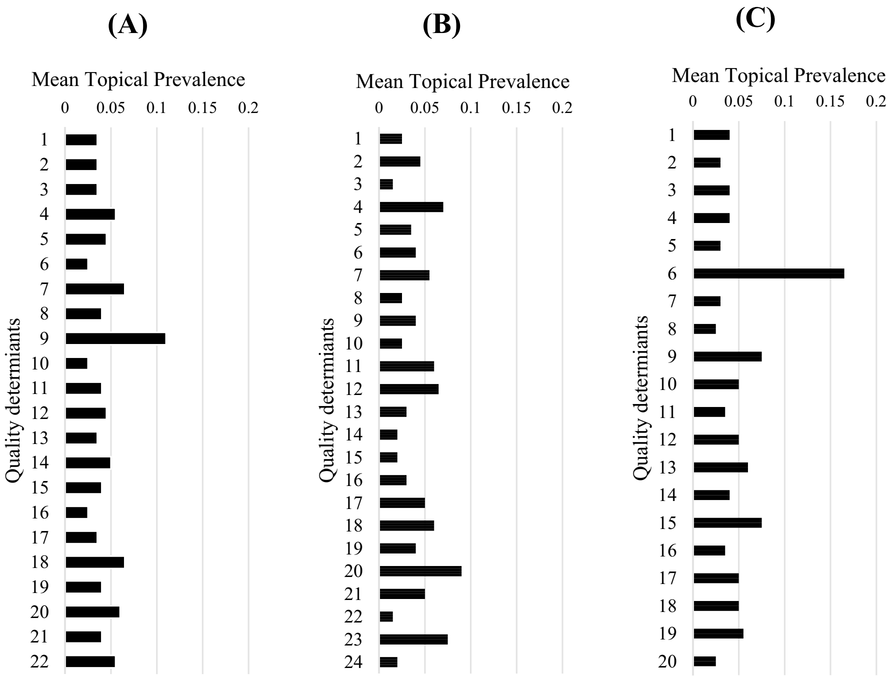

Fig. 3 Mean topical prevalence for the identified quality determinants (see the labels in Table 2). **A** Bike sharing. **B** E-scooter sharing. **C** Car sharing

4.5 Human validation of results

While advanced algorithms offer powerful tools for topic modelling, human validation remains an important step in ensuring the reliability of the generated outputs (Chang et al. 2009). Due to the complex nature of language, it is through the lens of human understanding, that it is possible to verify the accuracy of the results produced by the topic modelling algorithm. Consequently, human validation was employed in this study as a mechanism to confirm the outputs produced by the topic modelling algorithm.

To this end, the classification carried out by human evaluators on a random sample of one hundred digital VoC records was compared with the classification resulting from the topic modelling algorithm (Barravecchia et al. 2021). The comparison allowed a set of performance validation indicators (detailed in Appendix 3) to be calculated. Table 3 shows these indicators calculated for the three analysed datasets (bike sharing, e-scooter sharing, and car sharing), with an indication of experimental target values (Barravecchia et al. 2021). Overall, these results indicate that the developed topic models describe the contents of the analysed digital VoC appropriately.

Moreover, following the methodology proposed by Chang et al. (2009), two distinct evaluation measures, *word intrusion* and *topic intrusion*, were employed to ascertain the coherence and relevance of the topics identified within the respective models.

Table 3 Performance validation indicators. Target values provided by Barravecchia et al. (2022)

Indicator	Bike sharing	E-scooter sharing	Car sharing	Target values
Accuracy	0.95	0.95	0.96	> 0.95
Precision	0.75	0.74	0.91	> 0.70
Recall	0.75	0.67	0.68	> 0.70
F1 score	0.75	0.71	0.78	> 0.70
Fall-out	0.03	0.03	0.01	< 0.05
Miss rate	0.18	0.22	0.25	< 0.20
Specificity	0.97	0.96	0.99	> 0.90
Negative predictive value	0.95	0.96	0.96	> 0.90
False omission rate	0.03	0.04	0.04	< 0.05
False discovery rate	0.09	0.10	0.09	< 0.05

For the *Word Intrusion* assessment, the top 8 representative words were selected for each topic (as detailed in Table 6 in Appendix 2), and an ‘intruder’ word, not inherent to the specific topic, was introduced. Subsequently, ten human evaluators were tasked with identifying this inserted word.

In the *Topic Intrusion* procedure, a sample of 100 reviews was randomly chosen from each dataset. The most probable topics were associated with each of these reviews. An ‘intruder topic’, not originally part of the top probable topics for the review, was then added. These modified topic sets were then presented to the ten human evaluators, and the detection of the least congruent topic for each review was expected of them.

Following these methodologies, the model’s performance metrics were derived as follows:

$$Word\ intrusion\ success\ rate = \left(\frac{Number\ of\ correct\ word\ intruder\ identifications}{Total\ number\ of\ evaluation}\right) \times 100$$

$$Topic\ intrusion\ success\ rate = \left(\frac{Number\ of\ correct\ topic\ intruder\ identifications}{Total\ number\ of\ evaluation}\right) \times 100$$

where the *Number of correct word intruder identifications* and *Number of correct topic intruder identifications* represent the instances where human evaluators

Table 4 Results of word intrusion and topic intrusion tests (Chang et al. 2009)

Topic model	Word intrusion success rate (%)	Topic intrusion success rate (%)
Bike sharing	81	87
E-scooter sharing	87	91
Car sharing	84	89

accurately chose the word or topic intruder; the *Total number of evaluations* signifies the number of attempts made by evaluators to identify an intruding word or topic.

The results, as illustrated in Table 4, indicate a high success rate in both the word and topic intrusion tests across all three models.

Both validation methods employed in this study converge in their assessments, underscoring the adequacy of the developed topic models.

5 *MOBI-Qual* framework

This section is dedicated to detail the methodology and outcomes of the consolidation process employed to identify the set of quality determinants common to all shared mobility modes. This led to the development of a novel model, henceforth referred to as the *MOBI-Qual* framework.

5.1 Definition of the *MOBI-Qual* framework

The quality determinants of different shared mobility modes were compared to identify connections and overlaps. The process of constructing the *MOBI-Qual* framework is summarised in Fig. 4. In order to cluster the quality determinants of the three considered modes of shared mobility, two steps were taken. First, the similarity of the identified quality determinants was assessed by comparing the descriptive keywords. From this comparison, a preliminary clustering was obtained. Second, the panel of experts in shared mobility reviewed and refined the results of the first step, resulting in the final list of *MOBI-Qual* macro determinants.

Specifically, in the first step of the clustering procedure, the *topical content* was taken into account. The topic modelling algorithm associates each determinant with a multinomial probability distribution specifying the relative weight of each keyword. It is possible to represent this distribution with the *topical content vector*:

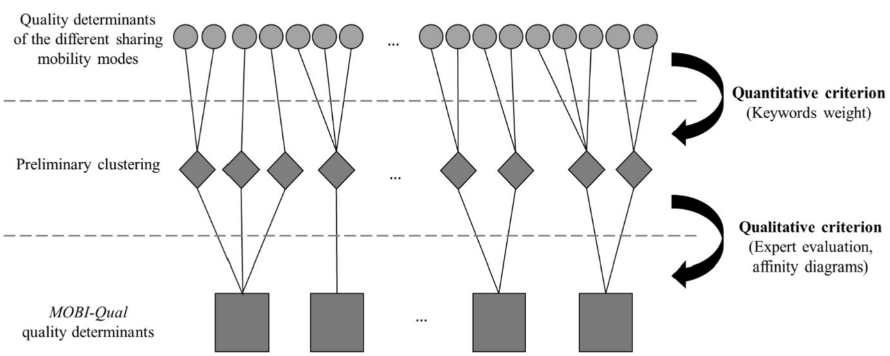

Fig. 4 Schematic representation of the process for the definition of the *MOBI-Qual* framework

$$TC_d = \left[tc_{1,d}, tc_{2,d}, tc_{3,d}, \ldots, tc_{w,d}, \ldots, tc_{W,d},\right]$$

where $tc_{w,d}$ is the weight associated to the w-th keyword of the vocabulary in the d-th quality determinant (topic); $w \in \{1, \ldots, W\}$ are the keywords of the vocabulary related to the digital VoC collection; W is the total number of keywords contained in the digital VoC vocabulary; $d \in \{1, \ldots, D\}$ are the quality determinants identified by the topic modelling algorithm; D is the total number of identified quality determinants.

In order to compare the topical content vectors from different topic models, it is necessary to establish a common vocabulary that includes all the relevant keywords. In this study, the vocabularies of the topic models for car sharing, bike-sharing, and e-scooter sharing were combined to create a shared vocabulary. The resulting topical content vectors included information about all the keywords in the common vocabulary, regardless of whether they were originally present in the individual topic model vocabularies. If a keyword was not present in the original vocabulary, it was assigned a weight of zero in the topical content vector. This allowed for the comparison of topical content vectors from different topic models.

The degree of similarity between two quality determinants was calculated as the cosine of the angle between the two topical content vectors through the scalar product:

$$\underset{of\ similarity}{Degree}{}_{i,k} = \frac{\langle TC_i, TC_k \rangle}{|TC_i| \cdot |TC_k|} = \frac{\sum_{w=1}^{W} \left(tc_{w,i} \cdot tc_{w,k}\right)}{\sqrt{\sum_{w=1}^{W} \left(tc_{w,i}\right)^2} \cdot \sqrt{\sum_{w=1}^{W} \left(tc_{w,k}\right)^2}} \in [0, 1]$$

where TC_i and TC_k are the topical content vectors for the i and k quality determinants, and $|TC_i|$ and $|TC_k|$ are the respective vector modules.

Keywords	*w*	*TC₁*	*TC₂*	*TC₃*
app	1	0,2	0,005	0,005
bike	2	0	0.1	0
car	3	0.05	0	0.1
company	4	0,005	0,3	0,05
connect	5	0,1	0,005	0,006
crash	6	0,1	0,005	0,005
customer	7	0,005	0,1	0,2
fix	8	0,095	0,005	0,003
load	9	0,12	0,005	0,002
open	10	0,08	0,005	0,004
problem	11	0,175	0,005	0,12
provide	12	0,01	0,06	0,2
service	13	0,005	0,2	0,2
support	14	0,005	0,2	0,1
update	15	0,05	0,005	0,005

$$\underset{of\ similarity}{Degree}{}_{1,2} = \frac{\langle TC_1, TC_2 \rangle}{|TC_1| \cdot |TC_2|} =$$

$$= \frac{(0{,}2 \cdot 0{,}005) + (0 \cdot 0{,}1) + \cdots + (0.05 \cdot 0.005)}{\sqrt{(0{,}2^2 + 0^2 + \cdots + 0.05^2)} \cdot \sqrt{(0.005^2 + 0{,}1^2 + \cdots + 0{,}005^2)}}$$

$$= 0.06$$

$$\underset{of\ similarity}{Degree}{}_{1,3} = \frac{\langle TC_1, TC_3 \rangle}{|TC_1| \cdot |TC_3|} = 0.24$$

$$\underset{of\ similarity}{Degree}{}_{2,3} = \frac{\langle TC_2, TC_3 \rangle}{|TC_2| \cdot |TC_3|} = 0.62$$

Fig. 5 Fictitious example of calculation of the degree of similarity between quality determinants

The degree of similarity introduced a quantitative criterion to compare different quality determinants by measuring how much the keywords and their associated weights of two quality determinants are similar.

For the sake of clarity, Fig. 5 provides a fictitious example of how the degree of similarity between quality determinants can be calculated.

In this example, the degree of similarity between determinants 2 and 3 is greater than that between determinants 1 and 3 or 1 and 2. The degree of similarity is equal to 1 when the two quality determinants are identical, while it is 0 when the two compared topical content vectors are perpendicular. In this study, it was observed that a degree of similarity above 0.40 signalled a significant overlap between the keywords of the two tested determinants. The threshold of 0.4 was determined on the basis of the characteristics of the data and the desired level of granularity in the clustering results. This criterion allowed about half of the determinants for the three shared mobility modes under analysis to be grouped (34 out of 66). Table 9 in Appendix 4 shows the results of this preliminary grouping.

Once the preliminary clusters were identified, the panel of experts evaluated the results and further aggregated the semantically related clusters. This analysis provided an aggregation of the determinants of quality related to different modes of shared mobility, which inherently present different vocabularies. Specifically, for each quality determinant, the panel of experts examined: (i) the meaning of the labels, (ii) the list of keywords, and (iii) the most representative digital VoC records. The quality determinants were grouped using affinity diagrams into conceptual macro-quality determinants useful for defining high-level references valid across different shared mobility modes (see Table 5).

5.2 *MOBY-Qual* macro quality determinants

The described procedure provided the following eleven macro quality determinants for shared mobility: (i) customer service, (ii) app reliability, (iii) charges and fees, (iv) vehicle conditions, (v) sharing benefits, (vi) physical accessibility, (vii) parking area, (viii) safety, (ix) easy-of-use, (x) digital accessibility, and (xi) payments.

Figure 6 represents the *Mean Topical Prevalence* (*MTP*) of each macro quality determinant and the contributions of the three shared mobility modes. The *MTP* represents the prevalence of each determinant, indicating their relative significance within the context of shared mobility. Furthermore, the figure also shows the contributions of the three shared mobility modes to the *MTP* of each macro quality determinant. This analysis helps identify which macro quality determinants have a stronger impact on certain shared mobility modes.

The findings suggest that *app reliability*, *sharing benefits*, *charges and fees*, and *customer service* emerge as the macro determinants that receive the most discussion across all three shared mobility modes. Based on this observation, it can be concluded that these factors are pivotal in shaping customer perceptions and levels of satisfaction.

App reliability is the most discussed quality determinants of shared mobility services ($MTP = 0.17$). In today's digital age, the reliability and functionality of mobile

Table 5 *MOBI-Qual*, a framework of quality determinants of shared mobility

MOBI-Qual macro quality determinants	Car sharing	Bike sharing	E-scooter sharing
1. Customer service	1-Customer service (physical office)	22-Customer service	9-Customer service
	15-Customer service Responsiveness		21-Customer service Responsiveness
	18-Customer service courtesy		
2. App reliability	6-App reliability	9-App bugs	12-App reliability
		10-Notification system	22-App download issues
		15-Map features	24-App bugs
		18-App reliability	
3. Charges and fees	4-Charges and fees	7-Use rates	1-Passes and programs
	10-Use rates	19-Charges & fees	6-Use rates
		11-Membership	20-Charging policy
			23-Use rate issues
4. Vehicle conditions	8-Car condition	1-Battery issues	16-Recharging mode
		3-Bike condition	19-Scooter condition
5. Sharing benefits	9-Convenience	2-Short distance commuting	10-Convenience
	13-Efficacy	5-Sightseeing benefits	14-Experience pleasantness
	14-Sharing benefits	6-Economic convenience	15-Riding experience
	16-Intermodal transportation	21-Alternative transportation comparison	17-Alternative transportation comparison
6. Physical accessibility	12-Car availability	14-Bike and dock availability	2-Scooter location
	11-Car proximity	8-Docks proximity	
7. Parking area	5-Parking area	13-Use areas	7-Use and parking areas
8. Safety	2-Accident and damages	16-Safety	11- Speed limits and management
			13-Safety

Table 5 (continued)

MOBI-Qual macro quality determinants	Car sharing	Bike sharing	E-scooter sharing
9. Ease-of-use	7-End trip issues	12-Ease of use	4-Ease of use
	17-Car start-up issues	17-Unlock issues	5-Start-up/scan issues
10. Digital accessibility	3-Registration process	4-Registration / login issues	3-Licence validation
	20-Car reservation		8-Phone login issues
11. Payments	19-Billing and membership	20-Payment	18-Payment

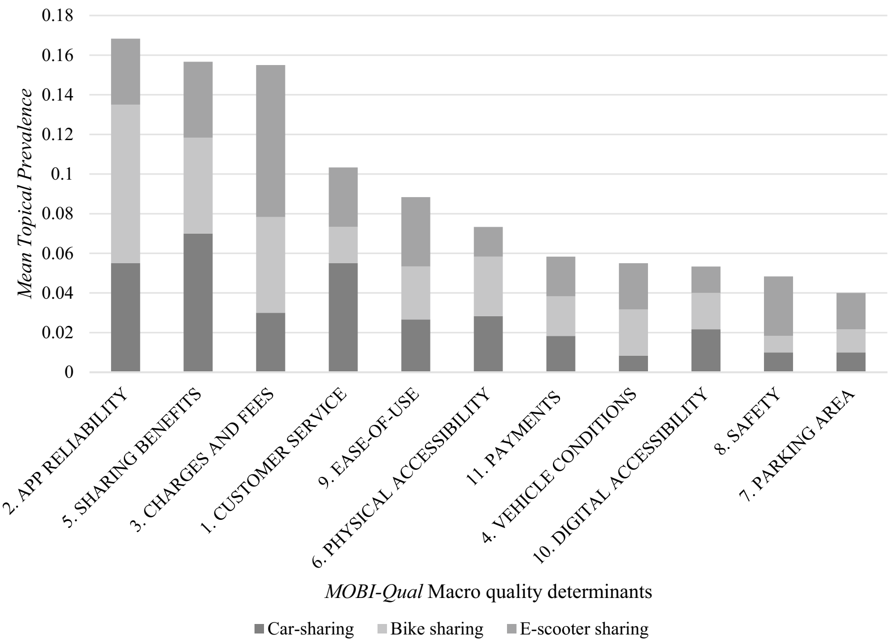

Fig. 6 Mean topical prevalences and contributions of *MOBI-Qual* macro quality determinant. The contribution of each shared mobility mode to the *MOBI-Qual* macro quality determinant is calculated by summing up the *MTP* values of the quality determinants that constitute the macro quality determinant for that mode (see Fig. 3)

applications are paramount in delivering a seamless user experience. Customers place a significant value on apps that are intuitive, stable, and provide accurate information regarding vehicle availability and reservation processes. Mobile applications are the primary interface through which users interact with shared mobility services. They rely on the app to locate and reserve vehicles, track their usage, and access important information.

Sharing benefits, characterized by the convenience, time-efficiency, and resource-savings that shared mobility provides compared to other transportation options, is a significant macro determinant of quality across all shared mobility modes ($MTP = 0.16$). This finding underscores the value customers place on the accessibility and flexibility offered by shared mobility services. The ability to conveniently access shared vehicles, whether it be cars, bikes, or e-scooters, reduces the need for personal vehicle ownership and promotes a more efficient allocation of transportation resources.

Charges and fees, with a Mean Topical Prevalence equal to 0.15, highlights the importance of transparent and reasonable pricing structures in establishing trust and ensuring that customers view shared mobility as a cost-effective alternative to traditional transportation options. Transparent pricing is essential for fostering trust and confidence among users. Customers expect clear and upfront information regarding the charges and fees associated with using shared mobility services. Hidden costs or unexpected charges can lead to dissatisfaction and erode trust in the service provider.

Customer service emerges as a significant macro determinant of quality in shared mobility services ($MTP = 0.10$). This finding emphasizes the critical role that customer service plays in shaping the overall customer experience. It highlights the importance customers place on the quality of interactions with service providers throughout their journey, from initial inquiries to issue resolution. Users value customer service that is responsive, prompt, and supportive.

The *ease-of-use* macro determinant shows that users value the simplicity and user-friendliness of the shared mobility platforms across all modes. This finding highlights the importance of intuitive interfaces, seamless booking processes, and clear instructions for accessing and operating the shared vehicles.

The aspect of *physical accessibility*, encompassing the availability, distribution, and proximity of vehicles within the service area, is critical for shared mobility quality. This observation underscores the importance of a well-designed fleet management system that ensures a sufficient number of vehicles are strategically placed throughout the service area, allowing customers to find and access them conveniently.

The macro determinant of *payments* encompasses the processing, accuracy, and reliability of payments, as well as the overall smoothness and efficiency of the payment process. This determinant highlights the importance placed by customers on the reliability of financial transactions within the shared mobility ecosystem. Users expect the assurance that they are accurately charged for the services they utilize, and they value a seamless and efficient payment experience.

The macro determinant of *vehicle conditions* refers to several important aspects, including cleanliness, tidiness, usability, residual autonomy (such as battery or fuel levels), and the ease of recharging or refueling. This determinant highlights the significance customers place on the overall state and functionality of the shared vehicles. The insight underscores that users value shared vehicles that are well-maintained, clean, and in good working condition. Additionally, the residual autonomy of the vehicles, whether it is the battery levels for electric vehicles or fuel levels for traditional ones, is an essential consideration.

The macro determinant of *digital accessibility* focuses on the speed and simplicity of the registration process and accessing the mobile application. Users expect a streamlined and intuitive registration process that allows them to quickly create an account and start using the shared mobility service. Digital accessibility is not limited to the initial registration process; it also encompasses the speed and responsiveness of the app. Users value a fast app that provides real-time information about vehicle availability, location, and reservation status.

The macro determinant of *safety* reflects the concerns customers have regarding the safety of using shared vehicles, the regulations governing their use, and the management of any potential damage or incidents that may occur during a trip. Customers expect shared vehicles to be well-maintained, meeting necessary safety standards, and undergoing regular inspections. In addition, customers are concerned about how incidents or damages are managed by the shared mobility providers. They expect prompt and efficient handling of any issues that arise during their trip, whether it be reporting damages, accidents, or other safety-related concerns.

The macro determinant of *parking areas* covers the availability of pickup and drop-off locations for shared vehicles, as well as the coverage area where the vehicles can be used and released. While it has a relatively lower contribution ($MTP = 0.04$), it is by no means less important than other determinants. Parking areas play a critical role in ensuring the convenience and accessibility of shared mobility services. Users expect a sufficient number of designated parking spots strategically located within the service area. Moreover, the coverage area is a crucial consideration for users. They value the flexibility of being able to pick up and drop off shared vehicles within a reasonably wide area, enabling them to conveniently access transportation options near their desired locations.

6 Conclusions

The main objective of the current study was to establish a unified framework that comprehensively defines the quality determinants of shared mobility. The resulting *MOBI-Qual* framework encompasses eleven determinants that provide a comprehensive and holistic understanding of shared mobility quality. These determinants include: (i) customer service, (ii) app reliability, (iii) charges and fees, (iv) vehicle conditions, (v) sharing benefits, (vi) physical accessibility, (vii) parking area, (viii) safety, (ix) easy-of-use, (x) digital accessibility, and (xi) payments. It was developed using a bottom-up approach, with the definition of quality determinants based on the analysis of extensive sets of textual digital Voice-of-Customers. This approach allows *MOBI-Qual* to be grounded in the actual experiences and opinions of shared mobility users, providing a deeper insight of the factors that influence the perceived quality of these services. In addition, *MOBI-Qual* was created by comparing the quality determinants of the most prevalent shared mobility modes, resulting in a common framework that is applicable to a wide range of shared mobility services.

Overall, the *MOBI-Qual* framework offers a robust and reliable approach for understanding the quality determinants of shared mobility and is a valuable tool for providers of these services looking to enhance the user experience.

The shared mobility sector is undergoing significant changes due to technological advances and shifts in consumer preferences. As a result, new and innovative personal transportation systems are expected to emerge and play a role in the sector evolution. The *MOBI-Qual* framework can be a valuable resource to support the design of these new forms of shared mobility. By considering the various quality determinants identified in the framework, operators can develop systems taking into account the customers needs and expectations.

The *MOBI-Qual* framework offers a useful tool for regulators and policy makers to evaluate the quality of shared mobility services and identify areas for improvement. By recognizing the factors that influence the perceived quality of shared mobility, policy makers may develop targeted policies and regulations to enhance the user experience and support the sustainability of these services.

Overall, this study makes several original contributions: (i) it defines the quality determinants specific to the three prevalent modes of shared mobility (car sharing, bike sharing, and e-scooter sharing); (ii) it is the first framework to define a set of quality determinants that can be applied across different modes of shared mobility; (iii) *MOBI-Qual* can be used for a range of practical purposes, including monitoring the quality of shared mobility using traditional assessment methods (such as questionnaires and interviews) and redesigning shared mobility services to enhance their quality; (iv) The procedure used to define the *MOBI-Qual* framework provides a practical approach to consolidate different frameworks for determining quality.

One limitation of the study is that it only examined explicit customer needs. More research is needed to determine whether implicit needs are also included in the identified quality determinants. Additionally, further research is required to fully understand how the released period of UGC can influence the development of the framework.

The model proposed in this study offers potential openings for further validation, especially by analyzing digital VoC datasets using alternative text mining approaches, notably BERT or other Large Language Model (LLM).

Appendix 1

In this study, a topic modelling algorithm developed in the R programming language was implemented to extract key quality determinants from three digital Voice of Customer (VoC) datasets related to car sharing, bike sharing, and e-scooter sharing services. The analytical procedure predominantly relies on the Structural Topic Model (STM) library (Roberts et al. 2019a, b), which offers a powerful suite of functions for detailed topic modelling. A summary of R code used for this analysis follows:

```
library(stm)
data <- read.csv("Dataset.csv")
processed <- textProcessor(data$Review, metadata = data, verbose=TRUE)
out <- prepDocuments(processed$documents, processed$vocab, processed$meta, lower.thresh=15, verbose=TRUE )
docs <- out$Review
vocab <- out$vocab
meta <-out$meta
searchK(out$documents, out$vocab, (5:50), data = meta)
Model <- stm(documents=out$documents, vocab=out$vocab,K=k , data=out$meta, init.type="Spectral")
```

Appendix 2

Tables 6, 7, and 8 respectively provide detailed descriptions of the quality determinants and associated keywords for bike sharing, car sharing and e-scooter sharing.

Table 6 Quality determinants of bike sharing

No	Label	Highest probability keywords	Description
1	Battery issues	End, start, stop, trip, use, battery, journey, electric	Users often experience problems finding bikes whose batteries are flat, making them unusable, or because the battery drains too quickly, forcing them to stop renting
2	Short distance commuting	Convenience, commuter, town, short, far, especially, faster, local	Users point out that bike sharing services are ideal for covering short distances, replacing walking, driving or other transportation
3	Bike condition	Broken, report, gear, seat, brake, heavy, break, fact	Users describe the condition of the bicycles and any damage found
4	Registration / login issues	Phone, code, number, tri, sign, registration, download, log	Users report problems encountered while registering or accessing the app, e.g. app crashes, errors during the two processes, failure to send confirmation codes for phone number registration
5	Sightseeing benefits	Way, city, help, change, live, program, share, navigator	Bike sharing services are not only perceived as useful, but they also have collateral benefits to be considered, in particular users consider bike sharing a useful way to enjoy the beauty of their city and to explore the cities they are visiting
6	Economic convenience	Min, transport, car, take, longer, public, cheaper, taxi	Users choose and continue to use bike sharing services based on their cost-effectiveness compared to other mobility services
7	Use rates	Charge, hour, minute, day, fee, pass, read, clear	Users discusses about fees charged by bike sharing services
8	Dock proximity	Check, minute, rack, station, kiosk, pick, drop, code	The location of the docks is one of the factors that determines whether users choose to use a bike sharing service or not
9	App bugs	App, work, time, hire, open, problem, bug, use	Users reports bugs and malfunctions that emerge when using bike sharing service applications
10	Notification system	Email, ask, contact, receive, multiple, response, active, provider	Effectiveness and actual usefulness of push notifications or email received from the shared mobility services they use

Table 6 (continued)

No	Label	Highest probability keywords	Description
11	Membership	Year, membership, month, week, key, annual, paid, day	Users reports the possibility of subscribing a membership, the cost, and the actual convenience of long-term or short-term subscriptions to bike sharing services
12	Ease of use	Easy, quick, fast, convenient, access, set, reliable, city	Users rate the simplicity, straightforwardness, and intuitiveness of using the services of bike sharing
13	Use areas	Park, area, place, zone, spot, outside, allow, warn	Bike sharing services provide for the rental and parking of shared bicycles which is possible only within limited areas
14	Bike and docks availability	Station, dock, find, avail, full, location, plan, empty	Users evaluate both whether and how many bicycles are available for use within the docks and whether and how much space is available in the docks where bicycles can be stationed
15	Map features	Map, update, point, feature, improv, old, location, version	Since the location of docks and bikes depends on a map available on the apps of bike sharing services, its characteristics are discussed by the users
16	Safety	Street, miss, big, requirements, road, helmet, cycle, lane	Users describe problems they have encountered while using bicycles in the context of bicycle safety on the road and evaluate whether the state of the bicycle is safe
17	Unlock issues	Unlock, location, try, time, second, charge, lock, attempt	The moment of release of the bicycles is critical for their use, in fact problems encountered at the moment of the start of the rental are decisive in the choice of users to use or not the service
18	App reliability	Crash, fix, update, user, slow, location, load, screen	The app is considered reliable by users if it doesn't show slowdowns and crashes (unexpected closures), in the presence of which it becomes complex to use the service
19	Charges & fees	Price, cost, expense, minute, less, quit, drive, concept	When choosing which mobility service to adopt, users evaluate its cost competitiveness
20	Payment	Card, account, money, credit, payment, bank, detail, pay	Payment methods available for bike sharing services and whether or not they work properly

Table 6 (continued)

No	Label	Highest probability keywords	Description
21	Alternative transportation comparison	Walk, mile, bus, travel, speed, save, easier, expect	Users compare bike sharing services and other available methods of travel. In order to be chosen, bike sharing services must obviously have advantages over other services
22	Customer service	Service, custom, call, support, issue, company, refund, help	Users describe and rate interactions with customer service

Table 7 Quality determinants of e-scooter sharing provided

No	Label	Highest probability keywords	Description
1	Passes and programs	Time, ride, experience, day, pass, month, today, program	Users discusses the loyalty programs available to use an e-scooter sharing service on an extended basis at an advantageous price
2	Scooter location	Find, location, map, battery, available, gps, die, low	Precise location on the map of loaded e-scooters is important so that users can find a scooter near them to use
3	Licence validation	Drive, ask, wait, long, license, sign, complete, driver	Given the lack of regulation with respect to the use of scooters, services may require a license to enable the user to use the service. The license is validated within a certain period of time
4	Ease of use	Easy, around, city, set, convenient, town, electric, downtown	Users rate the simplicity, straightforwardness, and intuitiveness of using e-scooter sharing services
5	Start-up / scan issues	Scan, code, error, message, say, fail, uninstall, enter	Shared scooters must be unlocked in order to be used. Users describe any problems in the unlocking process, often possible by scanning code
6	Use rates	Price, min, hour, cost, half, less, fee, buy	Hourly rates charged by providers of e-scooter sharing services
7	Use and parking areas	Park, area, zone, place, spot, outside, design, warn	The use and parking of shared scooters is only possible within defined zones of use and parking
8	Phone login issues	Phone, rent, call, number, sign, log, stand, guess	Users describe issues encountered when accessing the service application, particularly if done via phone number
9	Customer service	Service, custom, help, user, response, buggy, improve, application	Users describe and rate customer service interactions
10	Convenience	Transport, use, near, especial, share, mode, later, concept	Users choose and continue to use e-scooter sharing services based on their convenience compared to other mobility services
11	Speed limits and management	Slow, expense, speed, faster, cheaper, limit, mph, compare	Given the lack of regulation on e-scooters, the sharing services impose speed limits on shared vehicles for safety reasons

Table 7 (continued)

No	Label	Highest probability keywords	Description
12	App reliability	App, update, load, fix, connect, open, crash, unable	The app is considered reliable by users if it doesn't show slowdowns and crashes (unexpected closures), in the presence of which it becomes complex to use the service
13	Safety	Street, road, rider, provide, helmet, offer, danger, avoid	Users describe problems encountered while using scooters in the context of scooter safety on the road and rate whether the condition of the scooters and the equipment provided are sufficient to make them safe to use
14	Experience pleasantness	Quick, system, access, cheap, year, simple, operator, old	E-scooter sharing services are not only perceived as useful for travel but are also evaluated with respect to the pleasantness of the experience, i.e. if the system is easy to use and is also pleasant during use
15	Riding experience	Fast, power, point, safe, smooth, expect, quit, paus	Experience of users when using e-scooters for moving. Users evaluate if the service was useful to cover the chosen route without encountering problems
16	Recharging mode	Company, charger, left, pick, drop, wrong, notification, release	E-scooter sharing services allow users to also register as recharging scooters
17	Alternative transportation comparison	Walk, mile, away, block, bus, reserve, destination, miss	Users compare e-scooter sharing services with other available methods to make their trips. In order to be chosen, the e-scooter sharing services must obviously have advantages over other services
18	Payment	Card, pay, account, credit, payment, option, add, balance	Payment methods available for e-scooter sharing services and whether or not they work properly
19	Scooter condition	Broken, brake, report, button, accelerator, vehicle, break, damage	Users describe the condition the scooters are in and any damage found
20	Charging policy	Work, charge, unlock, money, dollar, refund, move, differ	Users describe and comment on the pricing policies applied by providers of e-scooter sharing services in the event that the scooters are activated and are not working

Table 7 (continued)

No	Label	Highest probability keywords	Description
21	Customer service responsiveness	Issue, support, problem, contact, email, review, refund, week	Users describe the proactivity and speed of customer service in responding to problems they report
22	App download issues	Run, download, annoy, close, front, trouble, forever, wonder	Problems encountered while downloading the application of the selected service
23	Use rates issues	End, minute, lock, start, tri, stop, charge, extra	Users describe problems that have arisen in the application by providers of hourly rates, particularly after the rental has ended
24	App bugs	Actual, check, rental, stuck, basic, app, screen, correct	Users describe bugs encountered while using the app

Table 8 Quality determinants of car sharing

No	Label	Highest probability keywords	Description
1	Customer service (physical office)	Help, phone, call, person, office, answer, number	Users describe and rate interactions with customer service
2	Accident & damages	Damage, report, accident, fault, member, enterprise, claim	Users have particular concern and interest in the accident and damage management when they occur during the rental period
3	Registration process	Sign, process, website, license, drive, driver, registration	Users report problems encountered while registering or accessing the app/website. Some common issues may include app crashes, errors during the two processes, failure to send confirmation codes for phone number registration, failure in uploading and validate the licence of the driver
4	Charges & fees	Charge, fee, late, return, time, pay, hour	When choosing which mobility service to adopt, users evaluate its cost competitiveness
5	Parking areas	Park, lot, spot, find, ticket, street, space	The parking of shared car is possible basically in any existing parking spot within defined zones of use, and the pickup takes place from the point of release by the previous user. This can also bring some disadvantages with respect to other sharing services due to the lack of free parking spots in some areas or in certain periods
6	App reliability	App, work, update, book, map, reserve, time	The app is considered reliable by users if it doesn't show slowdowns and crashes (unexpected closures), in the presence of which it becomes complex to use the service. Moreover, the technology enabling the service must be accurate and reliable
7	End trip issues	Trip, end, time, make, actual, take, system	Users report issue that arose during the phase of release of the rented car at the end of the trip
8	Car condition	Gas, dirty, rent, clean, tank, card, tire	Users describe the condition of the cars in the moment they pickup it and any damage found
9	Convenience	Need, convenient, quick, recommend, awesome, clean, perfect	Users choose and continue to use car sharing services based on their convenience compared to other mobility services
10	Use rates	Hour, price, rate, cost, expense, mile, cheaper	Hourly or daily rates charged by providers of car sharing services for the rental

Table 8 (continued)

No	Label	Highest probability keywords	Description
11	Car proximity	Minute, reservation, walk, wait, home, time, away	The proximity of the vehicle's location is one of the factors that determines whether users choose to use a car sharing service or not
12	Car availability	Car, available, location, vehicle, area, change, time	Users evaluate how many cars are typically available for use in their area of interest and the process of searching, choosing and selecting the vehicle. A common complaint against the car sharing services is that vehicles aren't available when needed
13	Efficacy	Use, time, now, far, user, review, star	Users choice to move from car-ownership-based model to one more oriented towards sharing is due to the efficacy of the service, which allows to change transportation systems, on a case-by-case basis, according to one's travel needs, since the car can be effectively located even for a few minutes and a few kilometres
14	Sharing benefits	City, year, insurance, member, gas, need, month	Users identify the most common benefits of using car sharing, e.g. it enables to avoid the fixed overheads of car ownership, insurance and maintenance
15	Customer service responsiveness	Service, custom, issue, company, terrible, problem, experience	Users describe the proactivity and speed of customer service in responding to problems they report
16	Intermodal transportation	Way, drive, little, take, get, town, bus	Users provide their experience about the benefit of car sharing service as intermodal transportation, typically mixed with the use of bus o bike
17	Car start-up issues	Time, start, location, turn, lock, pick, key	Shared cars must be unlocked in order to be used. Users describe any problems in the unlocking process, usually possible through the providers app
18	Customer service courtesy	Call, member, cancel, ask, rep, refund, manage	Users describe the proactivity and courtesy of customer service in responding to problems they report; in particular some users report negative experiences with employees that prove to be rude and unpleasant

Table 8 (continued)

No	Label	Highest probability keywords	Description
19	Billing and membership	Account, card, email, credit, month, day, membership	Users discusses about the possibility of subscribing a membership, the cost, and the actual convenience of long-term or short-term subscriptions to bike sharing services. Moreover, they also evaluate the payment methods which sometimes require the use of credit card, especially for station-based car sharing scheme
20	Car reservation	Reservation, plan, time, need, book, cancel, advance	Users talk about the reservation process through which they can book or cancel the vehicle, and in particular the possibility to reserve it in advance

		Human topic assignment ***(true condition)***			
		T_i existence	*T_i non-existence*	*Accuracy* $\frac{\sum_{i=1}^{n} tp_i + \sum_{i=1}^{n} tn_i}{\sum_{i=1}^{n} tp_i + \sum_{i=1}^{n} tn_i + \sum_{i=1}^{n} fp_i + \sum_{i=1}^{n} fn_i}$	
Automatic topic assignment	*T_i existence*	**True Positive ($\boldsymbol{tp}$)** Correct inference	**False Positive ($\boldsymbol{fp}$)** Type I error	*Precision* $\frac{\sum_{i=1}^{n} tp_i}{\sum_{i=1}^{n} tp_i + \sum_{i=1}^{n} fp_i}$	*False discovery rate* $\frac{\sum_{i=1}^{n} fp_i}{\sum_{i=1}^{n} tp_i + \sum_{i=1}^{n} fp_i}$
	T_i non-existence	**False Negative ($\boldsymbol{fn}$)** Type II error	**True Negative ($\boldsymbol{tn}$)** Correct inference	*False omission rate* $\frac{\sum_{i=1}^{n} fn_i}{\sum_{i=1}^{n} fn_i + \sum_{i=1}^{n} tn_i}$	*Negative predictive value* $\frac{\sum_{i=1}^{n} tn_i}{\sum_{i=1}^{n} fn_i + \sum_{i=1}^{n} tn_i}$
		Recall $\frac{\sum_{i=1}^{n} tp_i}{\sum_{i=1}^{n} tp_i + \sum_{i=1}^{n} tn_i}$	*Fall-out* $\frac{\sum_{i=1}^{n} fp_i}{\sum_{i=1}^{n} fp_i + \sum_{i=1}^{n} tn_i}$	*F_1 Score* $2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$	
		Miss rate $\frac{\sum_{i=1}^{n} fn_i}{\sum_{i=1}^{n} tp_i + \sum_{i=1}^{n} fn_i}$	*Specificity* $\frac{\sum_{i=1}^{n} tn_i}{\sum_{i=1}^{n} fp_i + \sum_{i=1}^{n} tn_i}$		

Fig. 7 Quality metrics for topic model validation. $\sum_{i=1}^{n} tp_i$, $\sum_{i=1}^{n} tn_i$, $\sum_{i=1}^{n} fp_i$, $\sum_{i=1}^{n} fn_i$ indicate respectively the total amount of true positives, true negatives, false positives, and false negatives observed when comparing human and automatic topic assignments. *n* is the sample size of the analysed records. (Zaki and McColl-Kennedy 2020; Barravecchia et al. 2022)

Appendix 3

Full details on the validation procedure of the results of topic modelling algorithms applied to digital VoC analysis are provided in Barravecchia et al. (2022). Figure 7 shows the formulas for calculating the validation indicators.

Appendix 4

See Table 9.

Table 9 Clustering of the quality determinants of the three shared mobility services (bike sharing, e-scooter sharing and car sharing) on the basis of keyword similarity

Cluster	Shared mobility mode	No.	Quality determinant label	Highest probability keywords
1	Bike sharing	22	Customer service	Service, custom, call, support, issue, company, refund, help
	E-scooter sharing	9	Customer service	Service, custom, help, user, response, buggy, improve, application
	Car sharing	15	Customer service responsiveness	Service, custom, issue, company, terrible, problem, experience
2	Bike sharing	9	App bugs	App, work, time, hire, open, problem, bug, use
	Bike sharing	15	Map features	Map, update, point, feature, improv, old, location, version
	E-scooter sharing	12	App reliability	App, update, load, fix, connect, open, crash, unable
	Car sharing	6	App reliability	App, work, update, book, map, reserve, time
3	Bike sharing	7	Use rates	Charge, hour, minute, day, fee, pass, read, clear
	Bike sharing	19	Charges & fees	Price, cost, expense, minute, less, quit, drive, concept
	E-scooter sharing	6	Use rates	Price, min, hour, cost, half, less, fee, buy
	Car sharing	4	Charges & fees	Charge, fee, late, return, time, pay, hour
	Car sharing	10	Use rates	Hour, price, rate, cost, expense, mile, cheaper
4	Bike sharing	3	Bike condition	Broken, report, gear, seat, brake, heavy, break, fact
	E-scooter sharing	19	Scooter condition	Broken, brake, report, button, accelerator, vehicle, break, damage
5	Bike sharing	21	Alternative transportation comparison	Walk, mile, bus, travel, speed, save, easier, expect
	Car sharing	16	Intermodal transportation	Way, drive, little, take, get, town, bus
6	E-scooter sharing	2	Scooter location	Find, location, map, battery, avail, gps, die, low
	Car sharing	12	Car availability	Car, available, location, vehicle, area, change, time
7	Car sharing	11	Car proximity	Minute, reservation, walk, wait, home, time, away
	Car sharing	20	Car reservation	Reservation, plan, time, need, book, cancel, advance

Table 9 (continued)

Cluster	Shared mobility mode	No.	Quality determinant label	Highest probability keywords
8	Bike sharing	13	Use areas	Park, area, place, zone, spot, outside, allow, warn
	Car sharing	5	Parking areas	Park, lot, spot, find, ticket, street, space
	E-scooter sharing	7	Use and parking areas	Park, area, zone, place, spot, outside, design, warn
9	Bike sharing	16	Safety	Street, miss, big, requirements, road, helmet, cycle, lane
	E-scooter sharing	13	Safety	Street, road, rider, provide, helmet, offer, danger, avoid
10	Bike sharing	12	Ease of use	Easy, quick, fast, convenient, access, set, reliable, city
	E-scooter sharing	4	Ease of use	Easy, around, city, set, convenient, town, electric, downtown
11	Bike sharing	17	Unlock issues	Unlock, location, try, time, second, charge, lock, attempt
	Car sharing	17	Car start-up issues	Time, start, location, turn, lock, pick, key
12	E-scooter sharing	3	Licence validation	Drive, ask, wait, long, license, sign, complete, driver
	Car sharing	3	Registration process	Sign, process, website, license, drive, driver, registration
13	Bike sharing	20	Payment	Card, account, money, credit, payment, bank, detail, pay
	E-scooter sharing	18	Payment	Card, pay, account, credit, payment, option, add, balance
	Car sharing	19	Billing and membership	Account, card, email, credit, month, day, membership

Degree of similarity threshold = 0.4

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

Funding Open access funding provided by Politecnico di Torino within the CRUI-CARE Agreement. There is no funding for this research.

Data availability Not applicable.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval The authors respect the Ethical Guidelines of the Journal.

References

Almars A, Li X, Zhao X (2019) Modelling user attitudes using hierarchical sentiment-topic model. Data Knowl Eng 119:139–149

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. Int J Qual Reliab Manag 40(4):990–1008

Ashqar HI, Elhenawy M, Rakha HA, House L (2022) Quality of service measure for bike sharing systems. IEEE Trans Intell Transp Syst 23(9):15841–15849

Barravecchia F, Mastrogiacomo L, Franceschini F (2020a) Categorizing quality determinants mining user-generated contents. Sustainability 12(23):9944

Barravecchia F, Mastrogiacomo L, Franceschini F (2022) Digital voice-of-customer processing by topic modelling algorithms: insights to validate empirical results. Int J Qual Reliab Manag 39(6):1453–1470

Barravecchia F, Mastrogiacomo L, Franceschini F, Zaki M (2021) Research on product-service systems: topic landscape and future trends. J Manuf Technol Manag 32(8):208–238

Barravecchia F (2023) Dataset: digita5l voice-of-customer on sharing mobility services. 10.7910/DVN/JXK3Z8

Barravecchia F, Mastrogiacomo L, Franceschini F (2020b) Identifying car-sharing quality determinants: a data-driven approach to improve engineering design. In: International conference on quality engineering and management, Braga, Portugal, pp 125–140

Beirigo BA, Negenborn RR, Alonso-Mora J, Schulte F (2022) A business class for autonomous mobility-on-demand: modelling service quality contracts in dynamic ridesharing systems. Transp Res Part C Emerg Technol 136:103520

Bharadiya J (2023) A comprehensive survey of deep learning techniques natural language processing. Eur J Technol 7(1):58–66

Bordagaray M, Ibeas A, dell'Olio L (2012) Modelling user perception of public bicycle services. Proc Soc Behav Sci 54:1308–1316

Castellanos S, Grant-Muller S, Wright K (2022) Technology, transport, and the sharing economy: towards a working taxonomy for shared mobility. Transp Rev 42(3):318–336

Catelli R, Fujita H, De Pietro G, Esposito M (2022) Deceptive reviews and sentiment polarity: effective link by exploiting BERT. Expert Syst Appl 209:118290

Chang J, Gerrish S, Wang C, Boyd-Graber JL, Blei DM (2009) Reading tea leaves: How humans interpret topic models. In: Advances in neural information processing systems, pp 288–296
Devlin J, Chang MW, Lee K, Toutanova K (2018) Bert: pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805
Ding K, Choo WC, Ng KY, Ng SI (2020) Employing structural topic modelling to explore perceived service quality attributes in Airbnb accommodation. Int J Hosp Manag 91:102676
Diouf R, Sarr EN, Sall O, Birregah B, Bousso M, Mbaye SN (2019) Web scraping: state-of-the-art and areas of application. In: 2019 IEEE international conference on big data (big data), IEEE, pp 6040–6042
Ferrero F, Perboli G, Rosano M, Vesco A (2018) Car-sharing services: an annotated review. Sustain Cities Soc 37:501–518
Fikar C, & Hirsch P (2018) Evaluation of trip and car sharing concepts for home health care services. Flex Serv Manuf J 30:78–97
Garvin D (1987) Competing on the eight dimensions of quality. Harvard business review 1987, pp 101–109
Hamerska M, Ziółko M, Stawiarski P (2022) Assessment of the quality of shared micromobility services on the example of the electric scooter market in poland. Int J Qual Res 16(1):19–34
Hennig-Thurau T, Malthouse EC, Friege C, Gensler S, Lobschat L, Rangaswamy A, Skiera B (2010) The impact of new media on customer relationships. J Serv Res 13(3):311–330
Hensher DA, Mulley C, Ho C, Wong Y, Smith G, Nelson JD (2020) Understanding Mobility as a Service (MaaS): past, present and future. Elsevier, Cambridge
Hickman L, Thapa S, Tay L, Cao M, Srinivasan P (2022) Text preprocessing for text mining in organizational research: review and recommendations. Organ Res Methods 25(1):114–146
Hsu C-C, Liou JJH, Lo H-W, Wang Y-C (2018) Using a hybrid method for evaluating and improving the service quality of public bike-sharing systems. J Clean Prod 202:1131–1144
Jelodar H, Wang Y, Yuan C, Feng X, Jiang X, Li Y, Zhao L (2019) Latent Dirichlet allocation (LDA) and topic modelling: models, applications, a survey. Multimed Tools Appl 78:15169–15211
Kim JH, Jang J, Kim Y, Nan D (2022) A structural topic model for exploring user satisfaction with mobile payments. Comput Mater Contin 73(2):3815–3826
Kumar A, Gupta A, Parida M, Chauhan V (2022) Service quality assessment of ride-sourcing services: a distinction between ride-hailing and ride-sharing services. Transp Policy 117:61–79
Kühl N, Mühlthaler M, Goutier M (2020) Supporting customer-oriented marketing with artificial intelligence: automatically quantifying customer needs from social media. Electron Mark 30:351–367
Lee H, Baek K, Chung J-H, Kim J (2021) Factors affecting heterogeneity in willingness to use e-scooter sharing services. Transp Res Part D Transp Environ 92:102751
Lock O, Pettit C (2020) Social media as passive geo-participation in transportation planning–how effective are topic modelling & sentiment analysis in comparison with citizen surveys? Geo-Spat Inf Sci 23(4):275–292
Ma F, Shi W, Yuen KF, Sun Q, Guo Y (2019) Multi-stakeholders' assessment of bike sharing service quality based on DEMATEL–VIKOR method. Int J Log Res Appl 22(5):449–472
Machado CAS, de Salles Hue NPM, Berssaneti FT, Quintanilha JA (2018) An overview of shared mobility. Sustainability 10(12):4342
Maslowska E, Malthouse EC, Viswanathan V (2017) 'Do customer reviews drive purchase decisions? The moderating roles of review exposure and price. Decis Support Syst 98:1–9
Mastrogiacomo L, Barravecchia F, Franceschini F, Marimon F (2021a) Mining quality determinants of product-service systems from user-generated contents. Qual Eng 33(3):425–442
Mattia G, Mugion RG, Principato L (2019) Shared mobility as a driver for sustainable consumptions: the intention to re-use free-floating car sharing. J Clean Prod 237:117404
Morton C (2018) Appraising the market for bicycle sharing schemes: perceived service quality, satisfaction, and behavioural intention in London. Case Stud Transp Policy 6(1):102–111
Mugion RG, Toni M, di Pietro L, Pasca MG, Renzi MF (2019) Understanding the antecedents of car sharing usage: an empirical study in Italy. Int J Qual Serv Sci 11(4):523–541
Octopus Data Inc (2023) Software octoparse. Available at: https://www.octoparse.com/
Otero I, Nieuwenhuijsen MJ, Rojas-Rueda D (2018) Health impacts of bike sharing systems in Europe. Environ Int 115:387–394
Özdağoğlu G, Kapucugil-İkiz A, Çelik AF (2018) Topic modelling-based decision framework for analysing digital voice of the customer. Total Qual Manag Bus Excell 29(13–14):1545–1562

Palese B, Usai A (2018) The relative importance of service quality dimensions in E-commerce experiences. Int J Inf Manag 40:132–140
Papadia G, Pacella M, Giliberti V (2022) Topic modelling for automatic analysis of natural language: a case study in an Italian customer support center. Algorithms 15(6):204
Parasuraman A, Zeithaml VA, Berry LL (1988) Servqual: A multiple-item scale for measuring consumer perceptions of service quality. J Retail 64(1):12–40
Park E, Chae B, Kwon J, Kim W-H (2020) The effects of green restaurant attributes on customer satisfaction using the structural topic model on online customer reviews. Sustainability 12(7):2843
Prencipe LP, van Essen JT, Caggiani L, Ottomanelli M, de Almeida Correia GH (2022) A mathematical programming model for optimal fleet management of electric car-sharing systems with vehicle-to-grid operations. J Clean Prod 368:133147
Putranto Y, Sartono B, Djuraidah A (2021) Topic modelling and hotel rating prediction based on customer review in Indonesia. Int J Manag Decis Mak 20(3):282–307
Qi J, Zhang Z, Jeon S, Zhou Y (2016) Mining customer requirements from online reviews: a product improvement perspective. Inf Manag 53(8):951–963
Qian L, Pang Z, Soopramanien D (2022) Influences of car sharing and car license plate lottery policy on consumer preference and accessibility in urban mobility system: a stated choice experiment in Beijing. J Clean Prod 362:132505
Qiu LY, He LY (2018) Bike sharing and the economy, the environment, and health-related externalities. Sustainability 10(4):1145
Roberts ME, Stewart BM, Tingley D (2019b) STM: R package for structural topic models. J Stat Softw 91(2):1–40
Roberts ME, Stewart BM, Tingley D, Lucas C, Leder-Luis J, Gadarian SK, Albertson B, Rand DG (2014) Structural topic models for open-ended survey responses. Am J Political Sci 58(4):1064–1082
Roberts M, Stewart B, Tingley D, Benoit K (2019) stm: An R Package for Structural Topic Models. R Package Version 1.3.6.1. Retrieved from cran.r-project.org
dos Santos MLB (2021) The "so-called" UGC: an updated definition of user-generated content in the age of social media. Online Inf Rev 46(1):95–113
Sbalchiero S, & Eder M (2020) Topic modeling, long texts and the best number of topics. Some Problems and solutions. Qual & Quant 54:1095–1108
Schlagwein D, Schoder D, Spindeldreher K (2020) Consolidated, systemic conceptualization, and definition of the "sharing economy." J Am Soc Inf Sci 71(7):817–838
Shaheen S, Cohen A, Chan N, Bansal A (2020) Sharing strategies: carsharing, shared micromobility (bikesharing and scooter sharing), transportation network companies, microtransit, and other innovative mobility modes. Transportation, land use, and environmental planning. Elsevier, Amsterdam, pp 237–262
Shang Z, Luo JM, Kong A (2022) Topic modelling for Ski resorts: an analysis of experience attributes and seasonality. Sustainability 14(6):3533
Siegfried P (2022) Digital mobility business concepts. Digitalisation in mobility service industry. Springer, New York, pp 33–45
Statista (2021) Worldwide - statista market forecast, 2021. Available: https://www.statista.com/outlook/mmo/shared-mobility/
Subhashini L, Li Y, Zhang J, Atukorale AS, Wu Y (2021) Mining and classifying customer reviews: a survey. Artif Intell Rev. https://doi.org/10.1007/s10462-021-09955-5
Trenz M, Berger B (2013) Analyzing online customer reviews-an interdisciplinary literature review and research agenda. In: ECIS 2013 completed research, p 83
Ullah A, Khan K, Khan A, Ullah S (2023) Understanding quality of products from customers attitude using advanced machine learning methods. Computers 12(3):49
Uysal AK, Gunal S (2014) The impact of preprocessing on text classification. Inf Process Manag 50(1):104–112
Wallach HM, Murray I, Salakhutdinov R, & Mimno D (2009) Evaluation methods for topic models. In Proceedings of the 26th annual international conference on machine learning (pp. 1105–1112)
Wang M, Zhou X (2017) Bike-sharing systems and congestion: evidence from US cities. J Transp Geogr 65:147–154
Wanganoo L, Shukla V, Mohan V (2022) Intelligent micro-mobility e-scooter: revolutionizing urban transport. Trust-based communication systems for internet of things applications. Wiley, Hoboken, pp 267–290

Yang Z, Fang X (2004) Online service quality dimensions and their relationships with satisfaction: a content analysis of customer reviews of securities brokerage services. Int J Serv Ind Manag 15(3):302–326

Yi X, & Allan J (2008) Evaluating topic models for information retrieval. In Proceedings of the 17th ACM conference on Information and knowledge management (pp. 1431–1432)

Zaki M, & McColl-Kennedy JR (2020) Text mining analysis roadmap (TMAR) for service research. J Serv Mark 34(1):30–47

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Federico Barravecchia is an Assistant Professor at at Politecnico di Torino (Italy) – Department of Management and Production Engineering, where he also earned his doctorate, specializing in management, production, and design. He is the author or co-author of papers published in scientific journals and international conference proceedings on the topics of quality and collaborative robotics.

Luca Mastrogiacomo is a Full Professor of Quality Engineering and Manufacturing Systems at Politecnico di Torino (Italy). He received a doctorate in management, production and design from Politecnico di Torino. He is the author or co-author of many published papers in scientific journals and international conference proceedings.

Martí Casadesús Fa is a Full Professor in the department of business administration at the University of Girona in Spain. He received a doctorate in industrial engineering from the University of Girona. Casadesús is co-author of Impact of ISO 9001 Standard: An Empirical Study (Documenta Universitaria, May 2014).

Fiorenzo Franceschini is a Full Professor of Quality Engineering at Politecnico di Torino (Italy) – Department of Management and Production Engineering. He is the author or coauthor of 9 books and more than 300 published papers in prestigious scientific journals, and international conference proceedings. His current research interests are in the areas of Quality Engineering, Performance Measurements Systems and Service Quality. Franceschini may be contacted at fiorenzo.franceschini@polito.it.