POLITECNICO DI TORINO

MASTER's Degree in Engineering and Management

MASTER's Degree Thesis

Analysis of Quality Determinants in the Car-sharing Sector

Supervisors

Prof. LUCA MASTROGIACOMO

Prof.ssa BIANCA MARIA COLOSIMO

Candidate

GIORGIO SCHEMBARI

October 2021

Abstract

A recent trend in the automotive industry is related to the switch of more and more customers towards vehicles' rental, rather than ownership. According to this, the car-sharing sector is rapidly expanding, favoured also by the circular economy wave, as well as by complementary factors (wide internet access, advanced level of IT, good customer acceptance). Car-sharing can be classified as a *product-service system* (PSS), i.e., a bundle of a product (in this case the car) and a service (the rental). To assess the quality of a PSS no standard methodologies are diffused. Recent studies apply Topic Modelling algorithms to the users' reviews to grasp the quality determinants, represented by the discussion topics. However, understanding how these affect the overall customers' perception requires further investigations. In this study we use the factor analysis method to group the topics extracted from a database of reviews (downloaded using web-scraper tools). Through this approach we aim at detecting general determinants of quality that are independent from the specific service considered. In order to categorize the relations between these determinants and the customers' satisfaction a *"Kano-like framework"* is used. This framework associates the distributions of rankings within topics (or determinants) to Kano categories and then prioritize them. Determinants linked to the rental process and the documentation and fees are identified as the most critical for users, while determinants linked to support activities (software and customer services) seem to have a lower impact on the overall quality. These criticalities do not vary significantly when the analysis is focused on a specific sharing scheme (*free-floating* or *station based*) and are equally not influenced by the geographical market considered. The last part of the study is dedicated to the benchmarking of the competitors considered with respect to the quality of the service offered (according to the determinants identified). Some providers are, in general, associated with a higher quality perception, due to better performances in all the determinants. However, when focusing only on a specific scheme (or market) the rankings are different.

Table of Contents

List of Tables

List of Figures

Acronyms

PSS
: product-service system

UGC
: User Generated Content

EFA
: Explorative Factor Analysis

KMO
: Kaiser-Meyer-Olkin

STM
: Structured Topic Modelling

Chapter 1

Introduction

Car-sharing is a relatively old concept, dating as far back as the second post-war period [1]. However, the last decades saw a significant increase of car-sharing users that will be as much as 58.9 million by 2025 [2]. It can be included in the broader cluster of product-service systems (PSS), i.e. bundles of products and services, provided jointly by the same firm to fulfil specific users' needs. The PSS business models fit well in the realm of a global transition towards circular economy and resources sharing [3]. Other factors, such as diffused internet accessibility, maturity of information technology and a good acceptance by customers, contribute to the success of PSS businesses [4]. Despite this wide diffusion, evaluating the customer satisfaction of a PSS is definitely not a simple task. The main reason for that is the complexity of a PSS that encompasses both product-related and service features [5].

To integrate the evaluation of the two aspects there are no standard tools, but User Generated Content (UGC) can represent a valid alternative. UGC "*happens when previous buyers share their experiences online, which allows others including the potential buyers to read*" [6]. Through the analysis of UGC, then the voice of the customer can be integrated into the design and monitoring of quality of a PSS. Besides being a cheap solution, UGC has another important advantage. In fact, unlike wise traditional ways of assessing quality (e.g., questionnaires, surveys, etc.) that are criticizes for their stillness [7], UGC is constantly updated and adapted to most recent users' requirements. On the other hand, UGC requires specific methodologies to overcome the limitations due to the fact that it is usually an unstructured source of information.

Besides presenting a way to extract the main determinants of quality for the car-sharing sector, this study proposes a possible approach to assign a criticality level to each of them. This is aimed at revealing if some aspects of the PSS have a larger impact on customer satisfaction with respect to others. However, since car-sharing encompasses several types of different systems, the approach used is to aggregate the determinants on a macro-level which should be independent from the specific system considered. The results of this analysis can then be used to compare the performance of the different players in the market.

The structure of this document is organized as follows. Chapter 2 describes the way in which UGC is processed and how the topics for quality assessment are extracted. Chapter 3 contains a factor analysis aimed at grouping the topics into macro-determinants of quality. Chapter 4 deals with the assignment of criticality levels to each of the determinants. In chapter 5 a benchmarking of competitors is presented, according to the model previously proposed. Finally, in chapter 6, the main conclusions and implications of the analysis are discussed.

Chapter 2

Topic Modelling

UGC is a valuable source of information to analyse users' quality perception. However, since UGC comes as unstructured data, dedicated methodologies, like the one proposed in [8], must be developed. In this research, a topic modelling algorithm has been used. This chapter describes the way data have been collected and processed in order to identify the main topics of discussion.

2.1 Database

The basic input of a topic modelling method is a dataset containing the contents generated by users, together with what are called metadata or "*data about data*" [9]. To build such a database, web scraping tools have been used. In fact, many online platforms (e.g., *Yelp!, TrustPilot, etc.*) are aimed at gathering customers' review about a specific service (or PSS in this case). In particular, two software packages (*Data Miner* and *Web Scraper*) have been adopted to download an adequate number of reviews. These data have then been integrated into an already existing database, used for similar scopes in [10]. The overall number of reviews composing the database is 18,000, covering a time range of approximately 15 years (from 2006 until today). The other information associated with each review are the country where the service is provided, the car-sharing scheme, the provider, and the rating score.

Two main geographical areas have been considered, i.e., United States and United

Kingdom. Besides these, the dataset contains some reviews from the Australian and Canadian markets and a large number of reviews from unspecified countries (due to the lack of the geographical information in some sources utilized). The car-sharing scheme refers to the way the service is offered, that is if central hubs (for car delivery and pick-up) exist. If this is the case, the service will be classified as *station based*; if instead users can directly access the cars with their phones the service will be classified as *free-floating*. The provider is simply the company offering the service and, as such, responsible for the quality delivered. Sixteen different providers have been analysed, even though they cannot be considered all as competitors because they offer different schemes, or they are present in different markets. Finally, the rating score is what objectively quantify the satisfaction level of users, regardless of the specific issues discussed in the review. As such, this is a fundamental information that will be exploited in the following steps of this study.

The table 2.1 below offers an example of the database, as it has been described.

Source	Country	Provider	Type	Date	Rating	Review
TrustPilot	United Kingdom	Car2go	Free-floating	01/01/2017	5	...
TrustPilot	United States	Hertz	Station based	27/03/2020	1	...

Table 2.1: Example of Data-set Entries

2.2 Application of the Method

The topic modelling approach is organized into several sequential steps [11]. After the database has been consolidated, a pre-processing phase is necessary, both to increase the efficiency of the algorithm and to select the optimal number of topics to extract. The next step encompasses the core of data modelling, i.e., the application of the Structured Topic Modelling function ([12]) and the labelling of topics. Results should then be validated "*manually*", as explained in [10] so to be correctly interpreted. In this case the validation phase has not been performed as the task had already been performed on a similar database in [10] with positive results.

The R software has been used to carry out the analysis presented [13].

2.2.1 Pre-processing and Number of Topics Selection

The pre-processing phase, as explained in [14], aims at easing the topics extraction by making some adjustments to the reviews' text, according to the following criteria:

- Conversion to lower case
- Stop words and punctuation removal
- Removal of too short or too long words
- Removal of words with very low frequency
- Removal of words that do not provide particular topic information
- Application of a stemming process aimed at reducing derived words [15]
- Substitution of co-occurring words with single terms [16]

An important parameter for the application of the STM function is the number of topics to be extracted. Several criteria can be used to come up with this value [17]. The general approach is anyway to apply iteratively the model with different values and evaluate the performance at each iteration. Such evaluation can be done through the *held-out likelihood*, which can be thought as a measure of the proportion of variability of the text content explained by the model [18]. As such, we want to identify the number of topics at which this proportion is maximized. The R-software automatically plots the results of this analysis (figure 2.1 below):

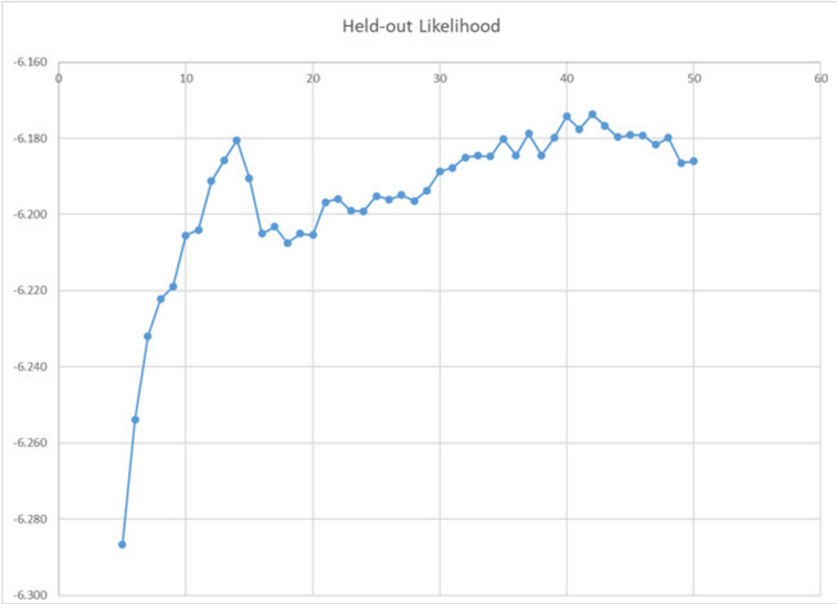

Figure 2.1: Number of topics vs *Held-out likelihood*

We can observe as the *held-out likelihood* steeply increases when the number of topics goes from 1 to 14 and then decreases. The actual maximum value is obtained with 42 topics. However, considering the marginal increase with respect to the value obtained with 14 topics, the optimal number of topics has been fixed at 14. This is a reasonable choice to clearly distinguish among the different discussion areas.

2.2.2 Data Modelling

The topic modelling algorithm (specifically the STM method) belongs to the category of machine-learning algorithms that aim at identifying latent topics within an unstructured textual content. In doing so, it associates to each of them a list of keywords. The STM has a probabilistic approach, in the realm of probabilistic models like, for instance, Latent Dirichlet Allocation [19] or Correlated Topic Models [20]. In fact, it will assign to each line of the database (and thus to each review) a probability of belonging to each of the topics extracted. The main advantages of such a technique are the possibility of making associations with the related data (rating, provider, etc.) and the relation between a specific word and a topic. This last feature actually requires the human intervention to be insightful. In fact, the labelling operation, which eventually leads to the topics expression, must be carried out by the researcher looking at the relevant textual information [21]. These include:

- **Highest Probability**: words with high probability of presence within a topic
- **FREX**: words that are contemporarily frequent and exclusice
- **Score**: words with high LDA score
- **Lift**: a score obtained considering the word-topic distribution and the overall word count distribution

The analysis of such factors, have led to the following list of topics:

1. **App Reliability**
   - Highest Prob: app, time, try, error, use, open, log, crash, load, work, fix, keep
   - FREX: log, crash, login, password, load, uninstal, open, error, useless, constant, screen, reinstal
   - Lift: exhaust, username, pixel, uninstal, credenti, reinstal, login, everytim, password, log, reset, blank
   - Score: app, exhaust, crash, log, load, password, login, buggi, reinstal, open, error, map
2. **Customer Service Support**
   - Highest Prob: help, issue, call, support, phone, custom, problem, servic, team, understand, staff, experience
   - FREX: help, staff, support, team, resolv, issu, reach, happi, understand, solv, answer, experienc
   - Lift: jam, team, english, script, shout, staff, accident, solv, help, adjus, helplin, resolv
   - Score: jam, help, issu, call, support, team, staff, resolv, custom, answer, happi, phone
3. **Rental Fees**
   - Highest Prob: car, price, use, conveni, drive, citi, rate, around, hour, cost, cheaper, expense
   - FREX: cheaper, price, conveni, citi, own, rate, expens, van, cheap, compar, smart, occasion

- Lift: reassur, environment, downsid, pricey, perk, cute, cheaper, varieti, cheapest, freedom, brilliant, zippi
- Score: reassur, price, conveni, cheaper, citi, car, insur, rate, expens, drive, own, cost

4. **Parking Area**
   - Highest Prob: park, find, area, lot, walk, spot, home, garag, car, block, locat, street
   - FREX: park, spot, space, area, street, garag, walk, anywher, zone, home, block, lot
   - Lift: ave, space, street, park, spot, underground, zone, meter, rack, borough, metro, honk
   - Score: park, ave, spot, area, garag, space, walk, street, home, find, block, ticket

5. **Car Reservation**
   - Highest Prob: time, reserv, hour, minut, book, call, cancel, anoth, wait, trip, end, hold
   - FREX: cancel, min, anoth, wast, minut, hold, hour, spent, wait, reserv, arriv, ruin
   - Lift: rob, rebook, min, ruin, fourth, car, wast, rip, disast, cancel, spent, doctor
   - Score: rob, cancel, hour, book, reserv, call, minut, wait, anoth, refund, time, hold

6. **User Registration**
   - Highest Prob: account, card, sign, email, website, credit, licens, inform, phone, day, payment, driver
   - FREX: licens, payment, regist, sign, verifi, registr, info, valid, account, card, applic, approv
   - Lift: licenc, licens, laptop, selfi, verif, registr, verifi, account, valid, regist, passport, expir
   - Score: applic, account, licens, card, email, sign, credit, regist, payment, info, registr, verifi

7. **Payment Management**
   - Highest Prob: compani, charg, email, receiv, money, call, account, pay, month, refund, day, contact
   - FREX: refus, receiv, scam, suspend, lie, drivi, depar, disput, money, collect, paid, email
   - Lift: stole, debt, crook, money, lawyer, right, bureau, court, uneth, suspend, harass, dishonest

- Score: stole, email, charg, compani, receiv, account, refund, money, pay, ticket, call, scam

8. **Car Availability**

   - Highest Prob: car, app, location, available, book, trip, reservation, time, find, see, option, show
   - FREX: availability, search, list, select, date, car, wish, option, navig, accuracy, reliability, view
   - Lift: tight, userfriend, accuracy, lockunlock, search, default, popup, scroll, navigate, select, browser, availability
   - Score: tight, app, car, availability, vehicle, book, wish, search, see, show, select, find

9. **Car Condition**

   - Highest Prob: damage, report, rent, owner, renter, dirty, clean, tire, drive, smell, driver, smoke
   - FREX: tire, smoke, damage, report, smell, renter, scratch, dirty, seat, repair, interior, safety
   - Lift: income, paint, vacuum, wear, carpet, crumb, stain, interior, marijuana, wiper, dirty, dash
   - Score: income, damage, tire, renter, report, dirty, owner, claim, clean, photo, rent, scratch

10. **Fuel Policy**

   - Highest Prob: gas, hour, call, late, pick, card, minute, start, return, tank, fill, wait
   - FREX: gas, fill, station, tank, truck, battery, office, late, receipt, fuel, return, remote
   - Lift: procedure, gallon, roadside, station, die, pack, refuel, bridge, fill, freak, truck, gas
   - Score: procedure, gas, tank, late, station, call, truck, roadside, fill, card, battery, return

11. **User Interface**

   - Highest Prob: app, work, update, map, improve, slow, features, use, function, version, fix, please
   - FREX: version, interface, function, improve, update, radar, features, connect, release, develop, latest, feedback
   - Lift: caution, tune, stable, layout, stabily, thirdparty, slower, version, glitch, network, radar, wifi

- Score: app, caution, update, bug, version, release, map, featur, connect, function, improv, feedback

12. **User Experience**

- Highest Prob: user, experience, host, time, recommend, rent, definit, clean, trip, pick, process, friend
- FREX: definit, awesom, host, amaz, excel, high, comunication, efficient, simple, recommended, seamless, accommod
- Lift: easiest, ease, vega, happier, breez, awesome, beautiful, immacul, amaz, high, definit, excel
- Score: high, host, experience, definit, awesome, clean, excel, amazing, recommend, rent, owner, use

13. **Subscription Fees**

- Highest Prob: servic, custom, fee, charge, use, month, problem, year, membership, company, care, call
- FREX: custom, servic, fee, membership, hidden, subscript, year, rude, loyal, month, annual, care
- Lift: scammer, hidden, annual, loyalti, overprice, service, greedy, execut, subscript, fallen, custom, dimension
- Score: custom, service, scammer, fee, charge, terrible, membership, month, year, care, company, cancel

14. **Efficacy**

- Highest Prob: donate, use, year, life, actual, time, now, thing, expect, probably, get, work
- FREX: life, expect, communiti, program, donat, chanc, actual, world, certain, real, cycle, work
- Lift: saver, life, community, relationship, cycle, profit, revenue, world, reality, guest, toward, program
- Score: saver, life, bill, corporate, community, probable, actual, donate, profit, expect, plan, program

2.2.3 Analysis of Results

Some preliminary analyses can be done in light of the topics extracted through the STM algorithm. First of all, it can be analysed the overall prevalence of certain topics within the considered dataset. To this scope, the probability of assignment to a certain topic can be considered, as reported in figure 2.2 below (the horizontal axis indeed shows the average probability for each topic).

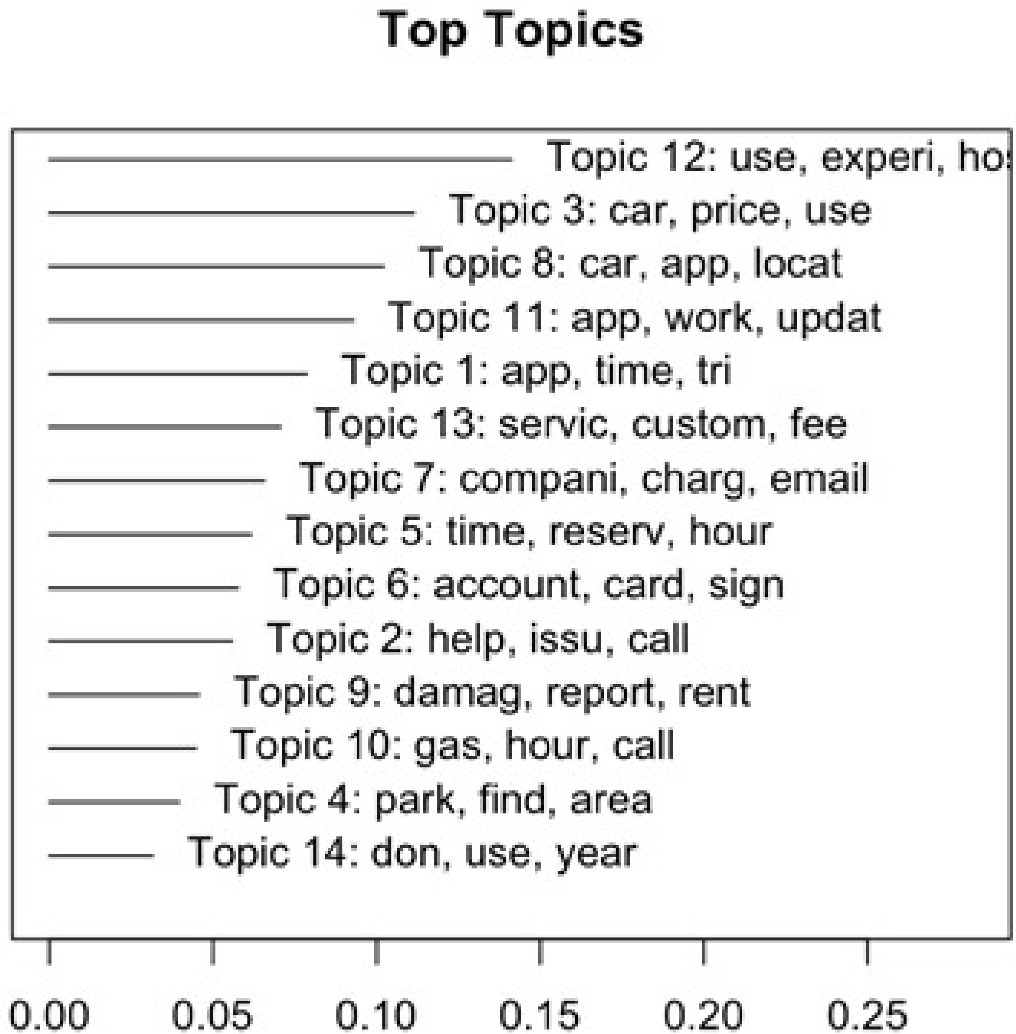

Figure 2.2: Discussion Frequency of Topics

Topic 12 (*User Experience*) is the most discussed topic, according to this analysis. This is quite in line with the fact that it treats the car-sharing under a more general perspective of overall perception with respect to the other topics. Other prevalent topics include *Rental fees* and *Car Availability*, while *Efficacy* is the less discussed one.

The overall ratings follow a U-shaped distribution, as shown in figure 2.3 below, while the relation among topics and scores will be deepened in chapter 4.

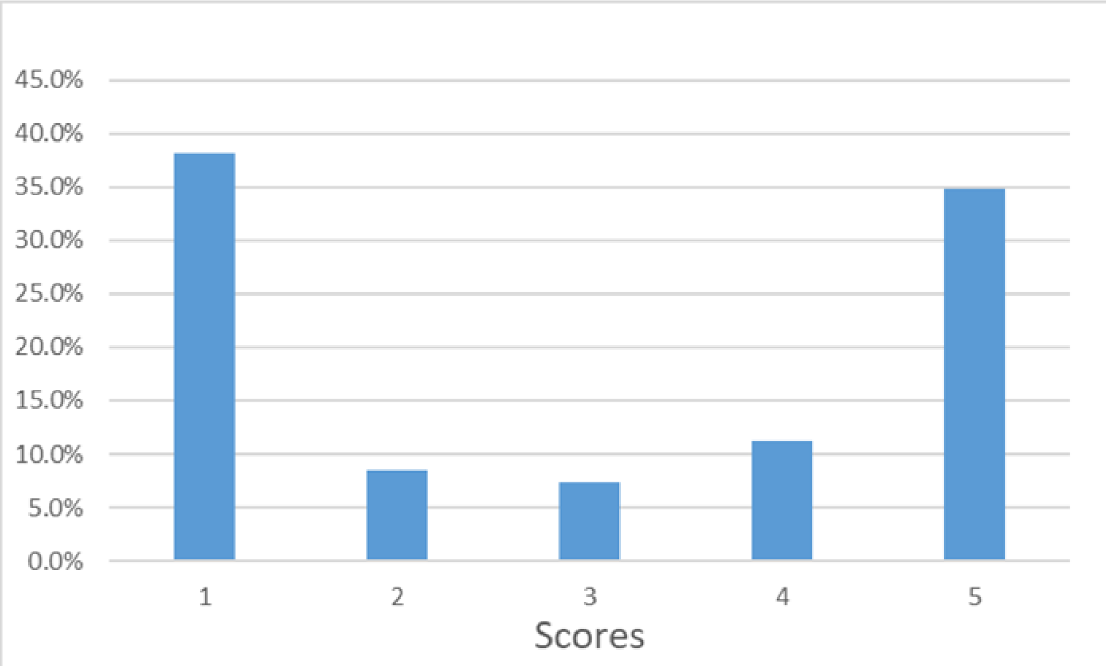

Figure 2.3: Distribution of Scores

Chapter 3

Factor Analysis

The extraction of the topics provides a solid framework for the analysis of the main quality drivers. However, considering the heterogeneity of the data involved (in terms of market, type of service, provider, etc.), using more general clusters would enable the creation of a general scheme for the analysis of the service offered. To do so, a factor analysis has been performed with the objective of detecting possible correlations among the topics and identify the clusters. The same criterium is used in [10] but the extraction of aggregation factors is not explored in detail. In this chapter we present the theoretical foundations of the factor analysis method together with the results obtained. To perform the factor analysis the SPSS software [22] has been used.

3.1 Theoretical Framework

Factor analysis can be generically thought of as "the search for latent variables starting from some observed variables ". An "observed variable" is a variable that has been actually measured, while a "latent variable" (either hidden or underlying) is a type of variable which has not been measured, or perhaps is not even measurable directly and therefore it is hypothesized and "analysed" through its effects. The influence that one latent variable has on other measurable variables becomes a way to trace this hidden variable. In this case, the observed variables will be represented by the topics extracted with the topic modelling algorithm and the measures will be the probability of each review of belonging to the topics. Contrary to most data analyses (those commonly called "inferential") the AFE (exploratory factor analysis) does not use hypothesis testing (that is, it does not have a hypothesis nothing and an alternative) even if (internally) it can use inferential tests to make certain decisions less random. In fact, in conducting an AFE, various arbitrary decisions must be taken, and such decisions are sometimes guided by theory, practice or by some inferential tests. The starting point of this technique is a matrix of the correlations between the variables. A correlation index informs us about the concomitant trend of two variables, but it is not possible to say that if A correlates with B, then A causes B or that B causes A. Usually the correlation relationship is graphically represented as reported in figure 3.1 below:

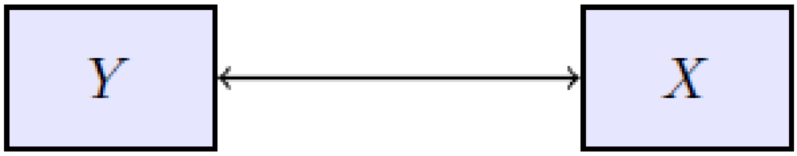

Figure 3.1: Graphical Representation of Correlation

Where rectangles indicate variables and the double-headed arrow indicates co-relationship (in this case a correlation, but it could also indicate a covariance). A high correlation index allows us to understand that when one varies, it varies simultaneously the other too. Intuitively, correlations between the topics will be expressed by similar profiles of probability values across the reviews.

It is impossible to say whether one of the two is responsible for varying the second or whether both are linked to a third (unknown) variable that is responsible of their concomitant variation; this situation can be graphically represented as follows:

in which the dashed circle represents a hypothesized variable (i.e., which has not been measured) and the dotted arrows indicate the direction of influence.

[23], using the concept of "tetrad" (i.e., three interrelated variables), hypothesized the existence of a latent variable (called "factor") which should be responsible of the concomitant trend of the variables. This same reasoning can be extended to four or more variables, all of them highly related. One of these can be responsible for varying the others, or there might be an additional variable to which attribute

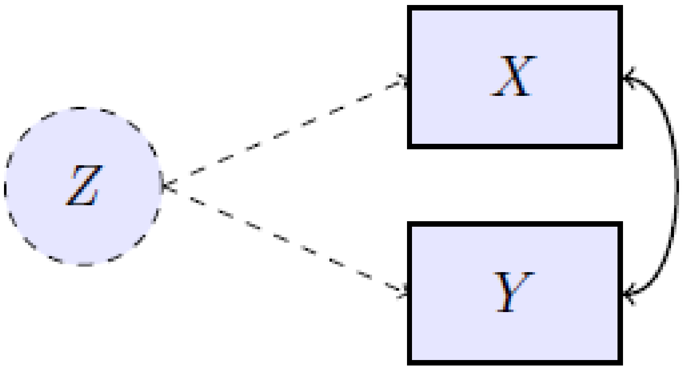

Figure 3.2: Graphical Representation of Latent Variable

the varying concord of all.

Factor Analysis starts precisely from the hypothesis that this additional variable exists and that somehow it influences and acts on a group of variables (which therefore result highly related among them). This underlying variable (defined as a factor or "Latent" variable) obviously acts on a particular "trait" common to all the others. Factor analysis, then, assumes the task of identifying the factor or factors, that is, the variables underlying a group of other variables. For this reason, in interpreting the factors, it is necessary to find the common meaning of the variables that converge in a factor, taking into account that these variables do not have the same weight in determining the significance of this factor. In fact, based on the mathematical calculations (that we will not treat in much detail), a value, called "loading" (weight) is assigned to each variable, indicating the importance of that variable in determining the meaning of the factor. Therefore, a variable of great importance in a factor, i.e., with a high saturation in that factor, in the interpretation phase, will have a larger impact with respect to a variable with lower saturation.

We can therefore say that the overriding purpose of factor analysis is to reduce a several measurements or variables, through factor-variables that are fewer in number. These should then explain all (or almost all) the correlations of the variables of that grouping. This is particularly relevant for the purpose of this research as it would reveal the existence of macro-determinants for the quality of the service offered.

3.2 Sample Selection

In carrying out an exploratory factor analysis, the data to be used as input must be carefully evaluated. The main verifications include:

- The measurement levels of the variables (interval or ratio for EFA)
- Data normality and linearity
- Presence of "outliers"
- The number of variables to be used
- The number of factors expected to be found

The aspects to consider when choosing the sample are its breadth with respect to the features measured and its representativeness with respect to the characteristics that are assumed to be correlated with the factors. If the purpose of the research is simply the identification of factors in a new area research, a very large sample is preferable. However, if the results are to be generalized to an accurately defined population [24], the sample must be representative of the characteristics studied. To this end, it is extremely important to decide on the heterogeneity or homogeneity of the sample with respect to the variables to be studied. For example, if the study includes variables specific to a particular geographical area, the sample to be examined should be representative of that region. As such, in the selection of the sample it will be necessary to respect the proportion existing in the population referred to multiple important variables with respect to the specific variables studied. If, on the other hand, the overall goal is to determine the possible existence of common factors, the heterogeneity of the sample must be pursued as much as possible in order to eliminate the importance of individual differences attributable to small groups of subjects.

3.2.1 From Data to Correlation Matrix

The first step in a factor analysis is the transition from the data to the correlation matrix. A correlation measure can be used to quantify the degree of association of variables. In general, Pearson's product-moment correlation is used, as it satisfies the linearity criterion which is one of the presuppositions of factorial theories. However, it is possible to use other types of correlation measures and in particular Spearman's rho coefficient, without particularly affecting the calculations [25]. The latest techniques also use association matrices based on tetrachoric correlations (two dichotomous), polyserial (one dichotomous and one interval) or polycoric (two Likert ordinals).

As said, the starting point of a factor analysis is the matrix of correlations. Often, in this matrix, values called "commonalities" can be inserted along the main diagonal. These are identified with particular mathematical calculation procedures, but they cannot be calculated precisely (except at the end of the analysis) and it is therefore necessary to make an estimate. In practice, since factorial analysis is generally carried out with the aid of processors, the choice of the estimate of commonality, is not always necessary.

In order to be processed through a Factor analysis, the correlation matrix must be positively definite. If this condition is not met, in fact, the principal extraction methods used by SPSS software will not lead to any result. The correlation matrix can be non-positively defined due to the existence of linear dependencies among the variables. Since the variables used in this study are probabilities and their sum is always 1, a linear dependency exists. To overcome this problem, a transformation has been done using a logarithmic function that would break the linear dependency among the variables, while keeping the same relations among them.

3.2.2 Analysis of Correlation Matrix

In order for a factor analysis to produce relevant factors, the matrix of correlation should contain high values alongside with low values. A first check is then to look at the correlation matrix to see if there are any correlations higher than 0.30, but it is not easy if the number of variables is high.

The determinant of the correlation matrix is a first index that can be used (but with poor results). If it is null, an AFE cannot be performed (very rare event). When it is high, we can say that the correlations are generally low and vice versa (if all correlations were equal to zero, the determinant would be 1). Therefore, a low determinant value would be needed (which would indicate many high correlations) but non-zero. Often, a determinant lower than 0.00001 [26] is considered too low (because it would indicate that there are too many multicollinear variables or too many variables that are too correlated with each other). However, it is not that easy to establish "how good" a certain value of the determinant is.

A second possibility is using the Bartlett's Sphericity Test which tries to verify the null hypothesis that the correlation matrix R is an identity matrix (*H0*: R = I). That is to say, it tests if the values outside the main diagonal are zero and those along the main diagonal are 1. It is based on the value of the determinant and is distributed as a chi-square (see Appendix A). If it is significant, it means that R has sufficiently high correlations not to be comparable to 0; if it is not significant, the correlations are low and are not distinguished from 0. However, this test depends on the number of variables and the sample size, so it tends to be significant as the sample and the number of variables increase, even if there are low correlations.

A third indication is the Kaiser-Meyer-Olkin Sample Adequacy Test (KMO). It is based on the correlation of each variable with each other, partialized on all the others. If there are variables related to each other (the basis for hypothesizing a common factor), their "Real" correlation without the influences of others should be very low. According to [27], a KMO value greater than 0.90, is excellent; a value between 0.80 and 0.90 is good; a value between 0.70 and 0.80 is acceptable; a value between 0.60 and 0.70 is mediocre, while a value lower than 0.60 would indicate that it is better not to do the analysis. A KMO value greater than 0.60 is generally considered to be an indication that it is possible carry out an AFE with a certain probability of obtaining results. Despite this test, the expression "sample adequacy" has nothing to do with the sample (see Appendix A).

The table 3.1 below shows the results of both KMO and Bartlett's tests with respect to the correlation matrix used as input. Since the KMO indicator is acceptable and the null hypothesis of Bartlett's test is rejected (as significance level is very low), we can conclude that factor analysis may be useful with the input data considered.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.776
Bartlett's Test of Sphericity	Approx. Chi-Square	126789.003
	df	91
	Sig.	0.000

Table 3.1: KMO and Bartlett's Test

3.3 Factors Extraction

The extraction of factors is a critical step of the EFA. After the optimal number of factors has been established, an extraction method must be selected according to the peculiarities of the research. Finally, a rotation of the loading matrix can be performed to highlight the correlation between variables and factors.

3.3.1 Number of Factors

As the extraction is done using a software, it is necessary to know in advance the number of factors to be extracted or provide the software with a criterion to stop the extraction of factors. [28] already considered it necessary to carry out more analyses, to study the various solutions and take into consideration those factors that remain fairly stable in the various solutions. Since for our research the number of factors could not defined a priori, it had to be identified through a theoretical or analytic method.

The theoretical methods are usually based on previous similar research, on the characteristics of the variables' scale or on the *"5 to 1 rule of thumb"* (which associates one factor to each five variables) [29]. Analytic criteria are instead used by almost all software (e.g. SPSS) to perform a purely explorative analysis and obtain a factorial matrix for evaluation.

A first criterion is the one proposed by [30],[31], which extracts as many factors as the eigenvalues greater than or equal to a number (which is generally 1). The logic of this criterion depends on the fact that the eigenvalues correspond to the variance of the factors and that, starting from a correlation matrix in which all values are standardized (therefore with variance equal to 1), the extractable factors must collect more variance than a single variable would. This is the choice adopted, automatically in most software (including SPSS). The use of this criterion, however, might lead to the extraction of a large number of factors which are generally considered excessive in relation to the number of variables analysed.

Still based on the eigenvalues, [32] proposed a graphical method, called scree test. The eigenvalues (in ordinate) relative to each factor (on the abscissa) are represented on a Cartesian plane with points that will then be connected by a line. In correspondence of the point where the curve stops falling and tends to become more like a straight line, the limit of the factors to be extracted is set, and it will probably be significant. The logic of this method is to select those factors whose eigenvalues imply a certain quantity of variance and in which a subsequent factor does not explain too little variance compared to the previous one (so the graphical representation does not tend to become flat). In more mathematical terms, the number of factors should coincide with the inflection point of the curve; [32],[33] propose to choose the factor immediately preceding the inflection point. Since it is a visual criterion, the risk is to extract fewer factors than those that could be significant. A second risk is related to the scale represented in the graph; in fact, depending on the unit you choose to distance the factors, the line it will become flat more or less quickly [34].

Figure 3.3 below shows the eigenvalues for each of the 14 possible factors analysed. Following the criteria proposed above, the optimal number of factors should be four. However, looking at the curve, this might be questionable, and three factors could also represent a correct choice (the inflection point for instance seems to occur at the third component).

To overcome the risks associated with the previous criteria, an option is to check the cumulative proportion of the total variance and ask for a number of factors such as to reach at least 60/75%. This criterion is insightful when the correlation matrix contains many high values, while it is totally useless when correlation values tend to be generally low. In this case, in fact, many factors are needed in order to reach 75% of the total variance and most of these factors explains a very small part of the variance. The risk of this method is to extract more valid factors than it

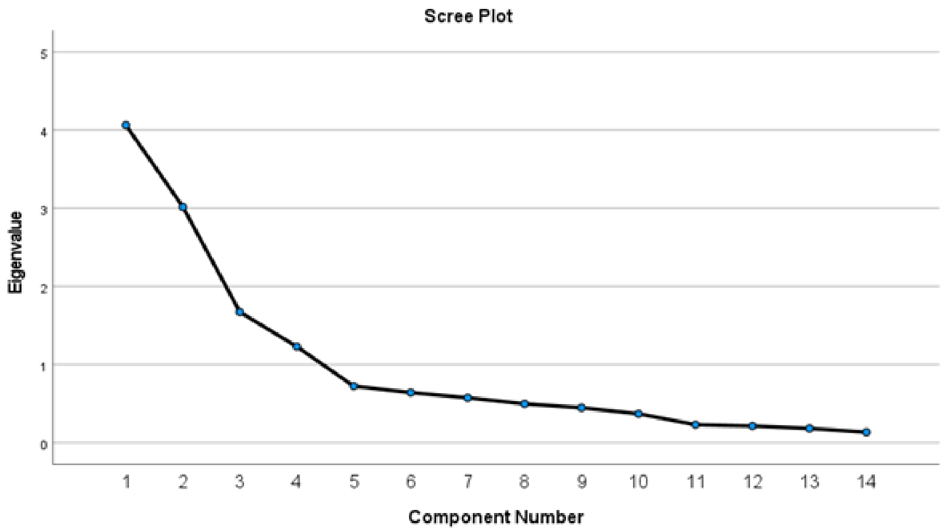

Figure 3.3: Scree Plot

would be actually significant. The table 3.2 below shows the cumulative variance explained by the increasing number of factors.

Component	**Initial Eigenvalues**			**Extraction Sums of Squared Loadings**		
	Total	% of Variance	Cumulative%	Total	% of Variance	Cumulative%
1	4.063	29.022	29.022	4.063	29.022	29.022
2	3.017	21.547	50.569	3.017	21.547	50.569
3	1.672	11.942	62.511	1.672	11.942	62.511
4	1.231	8.790	71.301	1.231	8.790	71.301
5	0.723	5.167	76.468			
6	0.641	4.581	81.049			
7	0.574	4.101	85.149			
8	0.497	3.550	88.699			
9	0.448	3.197	91.896			
10	0.3716	2.650	94.546			
11	0.231	1.650	96.196			
12	0.214	1.531	97.727			
13	0.183	1.308	99.036			
14	0.135	0.964	100.000			

Table 3.2: Total Variance Explained

What proposed by the eigenvalues criteria is confirmed. Three factors explain more than 60% of the total variance and adding another factor makes this value increase by an additional 10%. As a result, the final number of factors has been fixed at four.

3.3.2 Extraction of Factors

Once the number of factors has been established, the next step is to obtain a first factorial solution, called the non-rotated factorial matrix. There are several methods to obtain the extraction of the factors, and each of them has some particular features, advantages and disadvantages. The choice of the method is related to the reasons of the specific research, the possibility of using automatic calculation methods, the number of the variables that make up the research, the characteristics of the correlation matrix [29]. The principal methods available in SPSS include:

- *Principal component and principal axis*

  The basic property of these factor extraction method is that each factor extracted tries to be as explanatory as possible with respect to the starting data. Beyond the mathematical calculations this means that the first factor extracted will have the utmost importance, as it "explains" the higher percentage of variability of the data, compared to the other factors. However, it does not mean that it will have higher loadings (although this is often the case). The second factor extracted explains the maximum possible variance of how much is left after the first factor and so on up to the last factor extracted.

- *Maximum likelihood factor*

  Thurstone's multifactorial theory assumes that the matrix of correlations among the variables is calculated on the entire population while it is instead calculated on a sample. This method, on the contrary, is well aware of using measurements made on a sample and therefore tries to calculate an estimate of the correlations on the population. To this end, it uses a typically mathematical procedure, called “maximum likelihood" [35].

- *Image factoring*

  This method makes use of the “theory of the image ", which does not consider the matrix of correlations between variables, but a matrix which contains the "projections" of each variable onto all the others. This matrix is called “matrix image "because it contains the image that one variable projects onto the others. According to Guttman [30], the image matrix is the closest one to the matrix of correlations between variables, once the weight of specific factors has been eliminated.

- *Alpha factoring*

  This method tries to obtain factors that have the maximum value of "Generalizability". This value is measured using the Kuder-Richardson fidelity coefficient or the Cronbach's alpha coefficient [36].

The principal axis method, according to [37] allows to obtain the best factorial solution among all those obtainable with other methods, with the same factors extracted, because each factor accounts for the maximum possible percentage of variance. For this reason, it has been selected as extraction method for our analysis.

3.3.3 Rotation of Factors

Once the first factorial solution (non-rotated factorial matrix) has been obtained, it is possible to proceed with the factor rotation phase. Rotations are operations that computers perform to search for alternative factor solutions to the one identified, as long as they satisfy, both mathematically and logically, to the criterion of the simple structure [37].

The reason why the factor matrix is rotated lays in the fact that each variable should belong to a single common factor, that is, it should be very saturated in one factor and weakly or not at all saturated in all the others. Graphically, the factors can be represented as axis and the loading matrix values would be coordinates in this cartesian plane. Rotation is then aimed at reducing variables' distances from a certain axis (i.e., increasing the loadings with respect to the corresponding factor). However, when the factors identified are more than three, such a graphical representation is visually impossible. Below a representation map with only three of the factors is shown:

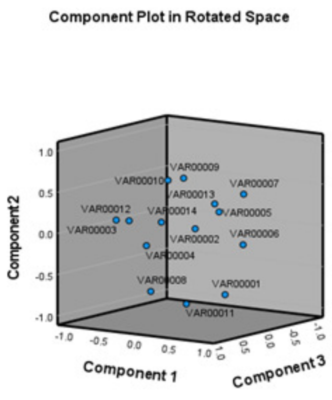

Figure 3.4: Component Plot in Rotated Space

Rotation techniques can be of two main types: orthogonal and obliques. The former relies on the hypothesis that no correlation exists between the factors (graphically expressed by a right angle). The latter instead assumes that this correlation is between 0 and 1. As such, the choice of rotation method must be guided by the hypotheses that it is possible to formulate on variables [38]. Since the goal of this EFA is to identify the main quality determinants for car-sharing sector (imagined as separated blocks), it has been hypothesized that factors are not correlated. Of course, this is not necessarily the case and further investigations could be done in order to spot potential dependencies between the factors.

Within the orthogonal methods we can distinguish several rotation techniques:

- *Varimax:* this technique tries to maximize high saturations while minimizing low ones, within the individual factors. It is recommended if you want to achieve a clear separation between the factors or if you do not have precise criteria to follow. By default, it should be noted that it favours the first factor.

- *Quartimax:* this technique works by trying to spread the variance within the single variables, but it actually tends to favour the first factor. This should make reading the variables easier and should not produce general factors. However, its efficacy is not robust.

- *Equamax:* this technique works equally on variables and factors while holding constant the variance explained by the entire solution. It often fails to get the simple solution.

To avoid possible failures, a conservative choice has been made and the *Varimax* technique has been selected. The table 3.3 below shows the rotated component matrix obtained as final output.

Topic	**F1**	**F2**	**F3**	**F4**
T1	-0.558	-0.723	0.786	-0.081
T2	-0.006	-0.009	-0.111	0.835
T3	0.776	0.093	0.396	0.078
T4	-0.051	0.637	0.517	-0.175
T5	-0.631	0.422	0.414	0.160
T6	0.674	-0.134	-0.113	0.328
T7	0.740	0.498	-0.031	0.256
T8	-0.294	0.467	0.382	-0.082
T9	0.084	0.668	0.254	0.069
T10	0.005	0.663	0.458	0.099
T11	0.013	-0.889	0.795	-0.030
T12	-0.191	0.315	-0.061	0.293
T13	0.583	0.357	0.054	0.387
T14	-0.005	0.371	0.079	0.328

Table 3.3: Rotated Component Matrix

3.4 Interpretation of Results

The rotated matrix must then be interpreted to come up with the final clusters. Since a statistic test to verify the significance level of the loadings does not exist, the experience of the researcher is still very important to grasp the meaning of the variables merged into a factor. Since several factors (i.e., the choice of the extraction method, the number of factors to be extracted and that of the rotation method) make the interpretation of a single factorial solution very arbitrary, some authors [39] suggest to perform several analysis and then select the one that best fits the scopes of the research.

3.4.1 Criteria for the Interpretation

Once the rotated loadings matrix is obtained, some general guidelines enable its interpretation. They can be summarized in the following mains steps:

1. A threshold for the loadings must be chosen. It will indicate the minimum correlation value that will be considered as significant. This threshold has been fixed at 0.4, according to the indications contained in [29].
2. Loadings must be sorted in descending order and values below the threshold must be removed.
3. The denomination of the variables with values above the threshold must be reported under each factor.
4. Common traits among the grouped variables must be detected and a denomination for each factor can thus be chosen.

It is also important to note that:

– Negative loadings indicate negative correlations of variables with a factor.

– In case of multiple assignments (i.e., when at least two loadings for the same topic were above the threshold), the general criterion used was to assign the topic to the factor entailing the highest correlation. However, exceptions were admitted in case of negligible differences and the assignment was made according to logical evidence.

– Topics with no loadings above the threshold have been excluded from the clustering.

3.4.2 Clusters

Following the steps listed in 3.4.1. the clusters in table 3.4 have been identified.

It can immediately be observed that two topics have not been assigned to any determinant (name by which from now on we will refer to the factors extracted) as no loadings were above the threshold. Another important remark is that the third and fourth determinants include fewer topics than the first two (the last is

Topic	Determinant
User Registration	Documents and Fees
Payment Management	Documents and Fees
Rental Fees	Documents and Fees
Subscription Fees	Documents and Fees
Car Condition	Car Rental
Fuel Policy	Car Rental
Car Reservation	Car Rental
Parking Area	Car Rental
Car Availability	Car Rental
App Reliability	Software
User Interface	Software
Customer Service Support	Support
Efficacy	-
User Experience	-

Table 3.4: Clusters of Topics - Determinants

actually composed of a single topic). However, this is consistent with the choices made concerning the extraction methods [29].

The rationale for the denominations of the determinants can be explained as follows:

– *Documents and fees:* all the topics associated to this determinant are related to the charges for the car-sharing service or to exchanges of documents (i.e., payments and registration). The implicit quality-related assumption is that users want a simple and effective processing of documents and low tariffs.

– *Car rental:* all the topics related to the rental process converge in this determinant. They include mere procedural aspects (for instance car reservation) and product-oriented issues like car condition.

– *Software:* as nowadays no car-sharing service is imaginable without an associated software support (app, website, etc.), this determinant tries to reproduce the need for a well-functioning IT tool.

- *Support:* this determinant is simply associated with the customer assistance which in turn would act on all the other determinants. Its logic can be expressed by "how well the staff is able to provide effective solutions to the users?".

It is important to specify that alternative clustering schemes were possible. However, for our research scopes the clusters identified are assumed to explain quite well the relations among the gathered data and, as such, they will be used as starting point for further analyses contained in the next chapters.

Chapter 4

Analysis of Quality Determinants

Once the main topics of discussion have been detected and then grouped into four main quality determinants, we want to answer the following question: *"Which determinants have a larger impact on the quality of the service offered?"*. Of course, there is not a trivial and unique solution to this problem. In this chapter we present a possible method to assign a criticality index (a weight) to each determinant and we analyse the results obtained by applying it to our dataset.

4.1 Kano Quality Framework

It has already been said that car-sharing's business model can be classified as a PSS. As such, it encompasses both traits of a service and of a product. If the analysis of UGC can be a way to overcome traditional methods (like questionnaires, surveys, etc.) to find the quality determinants [40], other techniques are needed to find a way to prioritize such determinants. One possible choice is to adapt the Kano quality framework [41] to the peculiar scopes of this research. The Kano's Model of customer satisfaction is usually associated with quality function deployment and anyway with physical product improvement. However, recent studies ([42],[43]) apply the framework in different service-related contexts. In [44], the Quality Function Deployment for a PSS is integrated with the Kano model. Through the application of the model, it will be possible to categorize the different topics extracted, according to the different perceptions of customers. Then, in 4.2., a method to obtain a criticality index from this information will be proposed.

4.1.1 Kano Model

The Kano model [45] is based on the assumption that the attributes of a system can affect customer satisfaction according to five different categories. The categories, even though associated with various names, can be expressed as follows:

- **Must-have:** these are basic characteristics (with respect to the system analysed) and, as such, are taken for granted by customers. If the associated performance is poor, the users will be unsatisfied, while a good performance would simply make the users neutral.

- **One-dimensional:** the more these features are done well, the higher will be the customer satisfaction level and vice versa. They represent the main ground for competition as they can have large impact on customers' perception of quality.

- **Attractive or Delighters:** these features provide satisfaction when a good performance is achieved and make customers neutral when performance is not so good. Their presence can provide companies with a competitive advantage, but it is not necessary to stay in the market.

- **Indifferent:** these features do not result neither in customer satisfaction nor dissatisfaction. As such, they can be performed in a way that minimizes the costs.

- **Reverse:** the higher the achievement of these features, the lower the customer satisfaction level.

Figure 4.1 shows a graphical representation of the Kano categories.

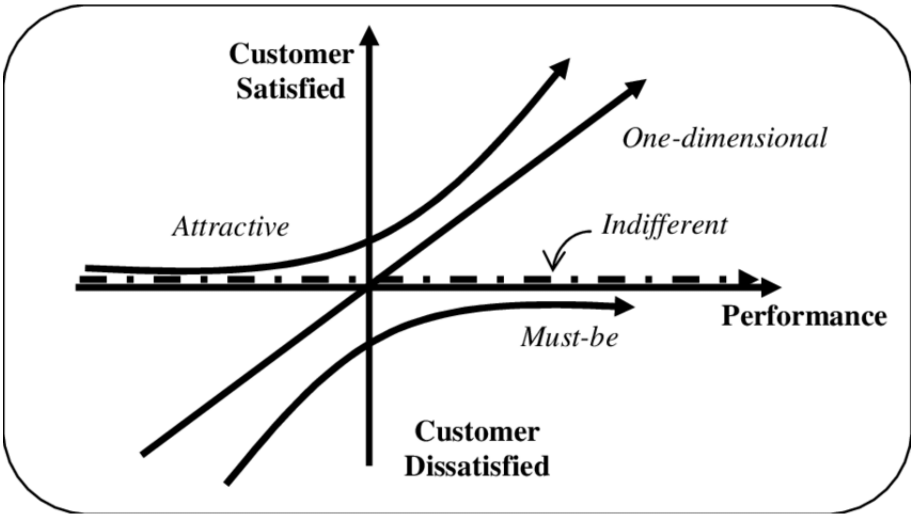

Figure 4.1: Kano Attributes - Graphical Representation

4.1.2 Hypotheses

The application of this model to the car-sharing topics requires some preventive considerations. First of all, it must be noted that topics are not exactly features, but, in a sense, an association exists. In fact, a certain degree of performance can be related to all the topics. As an example, the more robust the application will be, the better can be considered the *App Reliability* performance. Likewise, the lower the tariffs, the better the *Rental Fees* performance will be.

Another consideration regards the distinction between reverse and one-dimensional categories. If we assume that the customers direction of preference is homogeneous, then the difference between the two categories lays in the direction of proportionality relation among performance and satisfaction. This can be arbitrarily set as, for instance, we can consider that lower rates imply a better performance and as such a higher satisfaction (for all customers).

The most critical assumption concerns the way in which a certain topic is classified according to one of the five categories. The basic intuition is that, since the dataset contains a large number of customers' feedbacks (in turn referring to a large set of providers from different markets), the real performances (experienced by customers) are homogeneous. Therefore, in principle, for each topic, performance levels are evenly distributed, and we exclude the possibility that performance of some topics is always good or bad. As such, eventual differences in ratings frequency can be attributed to the different perception of the topics and not to performance profiles defined a priori. That is to say that the shape of frequency with respect to the rating provides the necessary information to categorize the topic. It must be said that this might not always be the case. In fact, some topics could systematically be performed well (or poorly), due to specific reasons (for instance previous criticality analyses) and then, the frequency of rating would result unbalanced for structural reasons. However, even if such situation would occur, they would not significantly alter the interpretation of results as it will be clarified in 4.1.3.

A final remark is concerned with the frequency quantification. Since a review is not univocally assigned to a specific topic, the topic prevalence (i.e., the probability of each review of belonging to a topic) is used to quantify the frequencies. This implies that a certain degree of noise is included in the analysis. In fact, all the reviews have a probability (greater than zero) of belonging to all the topics (even if they do not contain any reference to the topic) and these probabilities will be considered as well. However, this effect does not affect particularly the frequency shapes. We can in fact report that the proportion of significant values of probability (at least 10%) account, on average, for the 80% of the sum of probabilities of belonging to a specific topic.

4.1.3 Topics Profiles

Taking into consideration the premises expressed in 4.1.2., we can therefore find the general frequency profiles associated with the four Kano categories considered. *Must-have* profiles should follow a J-shaped distribution with a high frequency on low rating and decreasing frequency on higher ratings. That is to say that these topics are discussed only if the performance is not satisfying, while a good performance is not worth a review (because it was considered as a basic requirement). On the contrary, *delighters* profiles should have increasing frequency with respect to the rating (with a peak on the highest value). As such, they are discussed when the performance is above the average and are not mentioned when a poor performance is provided. *One-dimensional* profiles should instead follow a U-shaped distribution with peaks on high and low ratings. This shape would represent a condition in which a poor performance implies a low rating, and a good performance implies a high rating. Finally, *Indifferent* profiles are represented by flat frequency distributions. The figure 4.2 below reproduces the typical profiles for each of the categories considered.

It can thus be explained why the structural assumption in 4.1.2. would not heavily influence the results. If a topic is systematically badly performed (and as such will receive negative ratings), probably it needs a structural improvement and as such it seems correct to classify it as a must-have within the Kano framework. A topic that is systematically performed well could instead lead to misleading conclusions (it will not necessarily be an attractive), but, since it is already performed at high level, it will not affect particularly the overall assignments of weights.

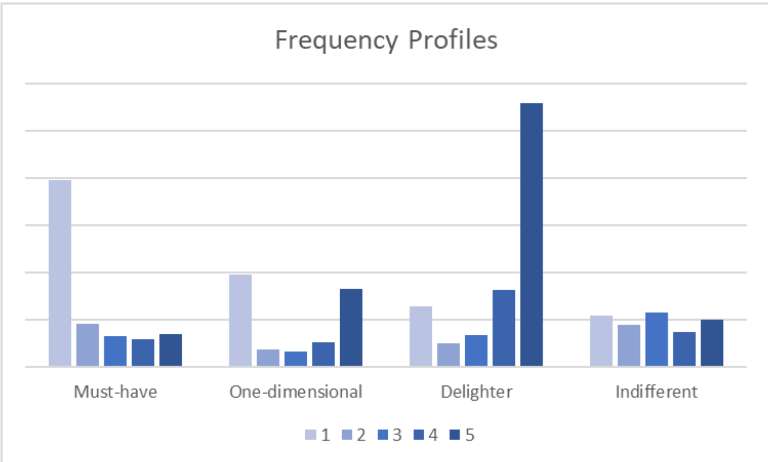

Figure 4.2: Frequency Profiles - Kano Categories

4.1.4 Topics Classification Procedure

It is clear that the assignment of a topic to a certain category of the Kano model can be done by comparing its frequency profile with the typical profiles depicted above. However, to this scope an analytic algorithm has also been built. The aim of such model is to automatically reproduce the profiles' comparison through the evaluation of the three following criteria:

1. *Low rating quota:* the proportion of frequency associated to the lowest rating

value (1).

2. *High rating quota:* the proportion of frequency associated to the highest rating value (5).

3. *Inter-quartile range:* the difference between the rating associated with a cumulative frequency of 75% and that associated with a cumulative frequency of 25%.

Through these parameters, it is possible to build a table like 4.1 below that associates specific values to a certain category.

Parameter	KANO FRAMEWORK			
Interquartile Range	low/medium	high	low/medium	low
Low Rating Quota	high	medium	low	low
High Rating Quota	low	medium	high	low
Kano-category	**Must-have (M)**	**One-dimensional (O)**	**Delighter(A)**	**Indifferent (I)**

Table 4.1: Classification Parameters - Kano Framework

In order to classify a parameter as low, medium or high the two following legends have been used. Of course, these represent an arbitrary choice among many possible others and, to have a clear understanding of the impact of a threshold change, a sensitivity analysis could be performed.

Interquartile Range	
0	very low
1	low
2	medium
3	high
4	very high

Table 4.2: Legend - Interquartile Range

Quota Thresholds	
<20%	low
20-50%	medium
>50%	high

Table 4.3: Legend - Quota Thresholds

4.1.5 Non – satisfaction Index

The model proposed so far refers only to the topics. To include the quality determinants in the analysis, a relation between the categories of the topics and a criticality indicator must be identified. In [46], a hierarchy of priorities is proposed. This follows the MOAI criterion, according to which the attributes' criticality level is assigned as follows:

Must-have > One-dimensional > Attractive > Indifferent

The rationale for this sequence is that a *must-have* attribute has a larger impact on customer dissatisfaction with respect to the *one-dimensional* that in turn has a larger impact with respect to the *delighter* and so on. The prioritization rule is thus based on avoiding dissatisfaction, rather than favouring satisfaction. Of course, this is not the unique solution possible and alternatives could also be evaluated.

In [46] the author also proposes a way to express the criticality of a certain product (or component) through the evaluation of the attributes of which it is composed. This is done through a *non-satisfaction index* that evaluates the proportion of the two most critical types of attributes (*must-have* and *one-dimensional*) with respect to the total of attributes. Therefore, in our context, the non-satisfaction index can be calculated for each determinant as follows:

$NSI = \frac{M+O}{M+O+A+I}$

Where M, O, A, I represent respectively the number of *must-have*, *one-dimensional*, *delighter* and *indifferent* topics within each determinant.

4.2 Analysis of Results

Section 4.1. points out a way to assign a certain weight to each determinant, based on the intrinsic characteristics of the topics contained in that determinant, according to the Kano model. In this section we deepen this aspect to come up with a final prioritization model and present the results obtained for different subsets of the original database.

4.2.1 Prioritization Method and Assumptions

The classification of topics provides an insightful way to look at the determinants' criticality. However, other criteria could be considered. One of these is the determinant's prevalence of discussion, that is to say how much a certain topic is discussed. A proxy for this measure will again be given by the sum of the probability values associated with all the topics linked to a determinant. It must be noted that, in general, a higher discussion frequency does not necessarily express a higher criticality. However, some assumptions can be done to sustain this choice, similarly to what done in 4.1.2.

Since the data considered are quite heterogeneous, we can in fact assume that, ideally, all the topics could be treated with same frequency and the differences related to the dataset creation are negligible. Furthermore, topic modelling errors cannot be considered monodirectional, which means that, theoretically, any topic benefits of a frequency increase due to the *"noise"* of the algorithm. As such, eventual differences between the discussion frequencies can be attributed exclusively to the intrinsic nature of the topics. In turn, frequency differences between the determinants indicate that users are more *"sensible"* to certain determinants than they are to others. Hence, for each determinant, we can compute a *frequency index*, given by:

$$FrequencyIndex = \frac{\sum_i FrequencyOfTopic_i}{TF}$$

Where index i indicates all the topics belonging to the determinant and *TF* the total frequency observed.

As a result, the *"final weight"* of each determinant can be expressed as the combination of two components. The first is linked to the Kano categories assigned to the topics composing the determinant, while the second is based on the discussion frequency of the determinant itself. Finding a way to combine these two inputs is a tough task for which several techniques could be used. MCDA methods [47] could represent a valid alternative, as well as an educate guess by experts (as some recent literature would suggest [48]). For the scopes of this research, a simple solution has been adopted. The *final weight* will be given by the average of the two indicators, i.e., the weight deriving from the *non-satisfaction index* and the *frequency index*.

This solution presents two main limitations. The first is due to the fact that the comparability of the two indexes cannot be guaranteed (since they come from different analyses). The second is instead connected to the high sensibility of the resulting *final weight* with respect to the number of topics that compose each determinant. Determinants made of a few topics will in fact result in lower *final weights*. Despite these limitations, this model offers a very simple overview of the criticality if determinants. Moreover, replacing the arithmetic average with a weighted average can provide more customized results that better fits the needs of a specific research.

4.2.2 General Results

The proposed methodology has been applied to the dataset according to different configurations of type of service and market considered. The rationale for this choice lays in the fact that criticalities of determinants might change when we move from a station based to a free-floating service or when we consider different geographical markets.

Table 4.4 below shows the Kano framework referred to the whole database, i.e., when no filters are applied.

Rating	1	2	3	4	5
App Reliability	790	186	131	120	140
Customer Service Support	393	77	66	104	330
Rental Fees	257	100	137	329	1115
Parking Area	240	70	71	101	209
Car Reservation	672	118	70	74	139
User Registration	609	103	74	80	138
Payment Management	913	95	45	35	56
Car Availability	428	166	195	313	675
Car Condition	411	82	62	80	161
Fuel Policy	338	75	57	91	219
User Interface	572	180	174	248	439
User Experience	116	48	70	223	1999
Subscription Fees	693	109	71	95	261
Efficacy	210	52	46	67	174

Rating	Determinant	IQ Range	Low Quota	High Quota	Category
App Reliability	Software	LOW	58%	10%	**M**
Customer Service Support	Support	HIGH	40%	34%	**O**
Rental Fees	Documents and Fees	MEDIUM	13%	58%	**A**
Parking Area	Car Rental	HIGH	35%	30%	**O**
Car Reservation	Car Rental	LOW	63%	13%	**M**
User Registration	Documents and Fees	MEDIUM	61%	14%	**M**
Payment Management	Documents and Fees	VERY LOW	80%	5%	**M**
Car Availability	Car Rental	HIGH	24%	38%	**O**
Car Condition	Car Rental	HIGH	52%	20%	**O**
Fuel Policy	Car Rental	HIGH	43%	28%	**O**
User Interface	Software	HIGH	35%	27%	**O**
User Experience	-	LOW	5%	81%	**A**
Subscription Fees	Documents and Fees	HIGH	56%	21%	**O**
Efficacy	-	HIGH	38%	32%	**O**

Table 4.4: General Results - Kano Framework

The assignment of a Kano category has been made according to the criteria explained in 4.1. In order to have a visual confirmation, it is possible to compare the frequency profiles obtained through the data contained in the table 4.4 (in figure 4.3) with the theoretical category profiles depicted in 4.1.3.

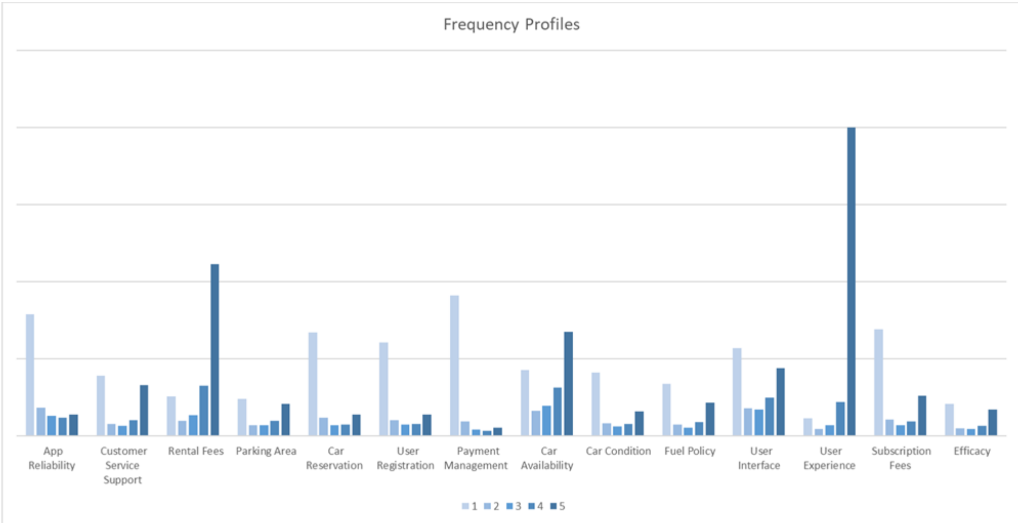

Figure 4.3: Kano Profiles Results

The graphical representation shown above confirms the analytical results. Most of the profiles correspond to one of the typical shapes, even though no *indifferent* topics have been detected.

In light of the categories identified and, considering the clusters (as per chapter 3) the following *non-satisfaction coefficients* have been calculated:

Determinant	A	M	O	I	Total	Non-Satisfaction Coefficient	Weight
Car Rental	0	1	4	0	5	1	27%
Documents and Fees	1	2	1	0	4	0.75	20%
Software	0	1	1	0	2	1	27%
Support	0	0	1	0	1	1	27%
Total	**1**	**4**	**7**	**0**	**12**	**3.8**	**100%**

Table 4.5: Non-satisfaction Weights

At the same time, the analysis of frequencies shows the following figures:

Determinant	Discussion Frequency	Weight
Car Rental	5,116	36%
Documents and Fees	5,314	37%
Software	2,980	21%
Support	970	7%
Total	14,381	**100%**

Table 4.6: Frequency Weights

The combination of the two weights, leads to the final weights as follows:

Determinant	**Final Weight**
Car Rental	31%
Documents and Fees	28%
Software	24%
Support	17%
Total	**100%**

Table 4.7: Final Weights

We can thus conclude that the most critical driver of quality is the *car rental* process, followed by the *documents and fees* category. Despite the two determinants have almost the same discussion frequency, the presence of an attractive topic lowers the overall critical level of the second determinant. *Software* and *support* determinants are less critical, due to lower discussion frequencies. As already said, these results rely on the assumptions expressed above and are subject to changes when thresholds and weights assignments change. Anyway, they appear reasonable, in light of the typical characteristics of a car-sharing system and would be useful to guide the bench-marking of competitors in chapter 5.

4.2.3 Station Based vs Free-floating

If we consider only the reviews associated with a specific scheme of car-sharing service, we could have a deeper view of the specific critical level of determinants. However, as shown in the figures below, the topics' profiles do not vary significantly.

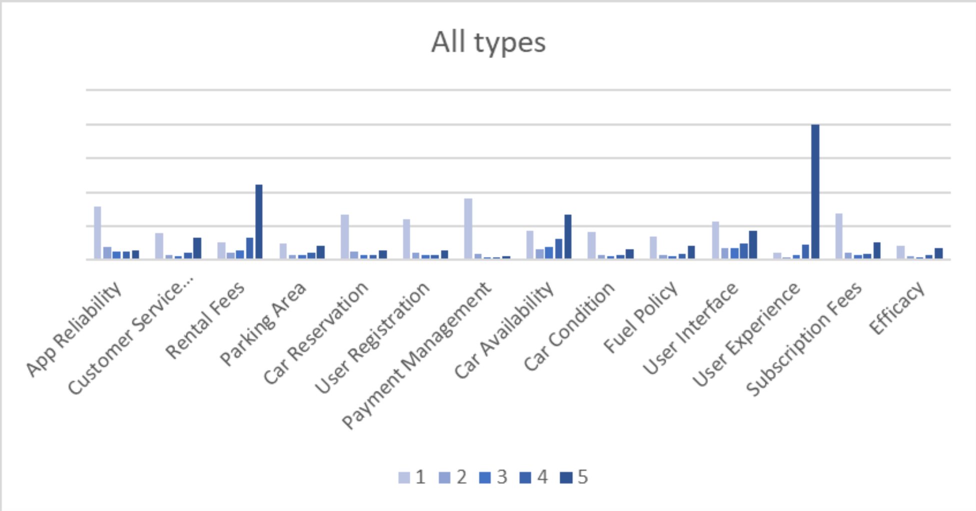

Figure 4.4: Frequency Profiles - All Types of Schemes

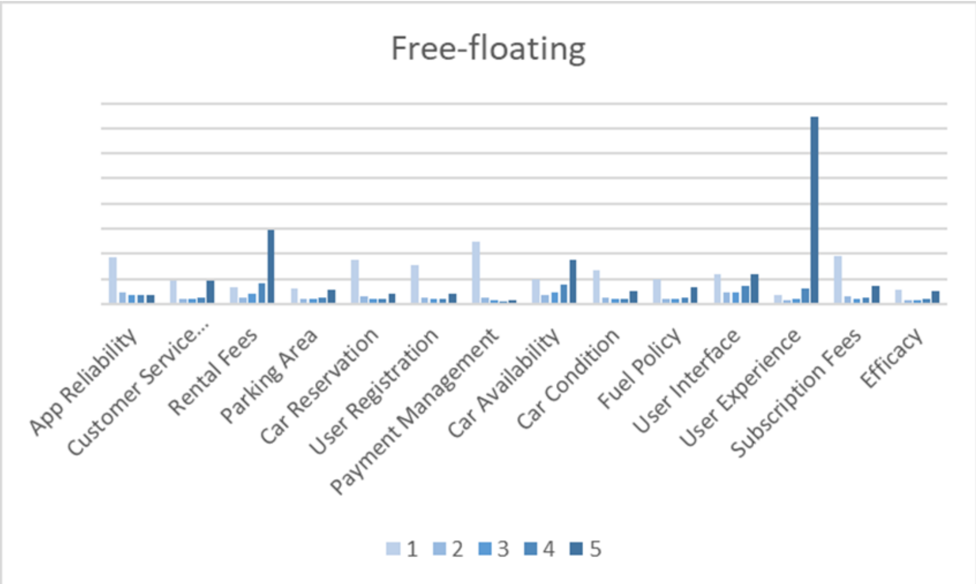

Figure 4.5: Frequency Profiles - Free-Floating

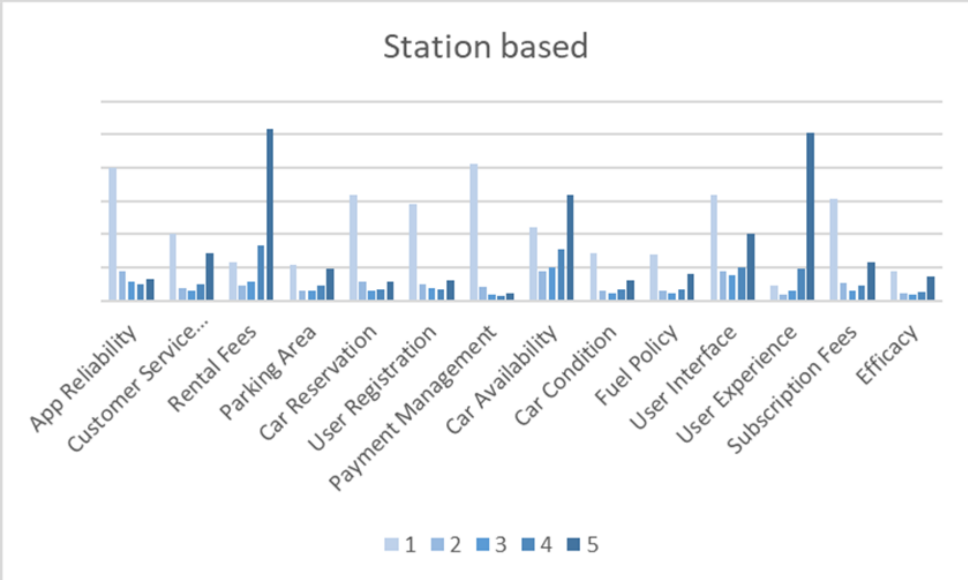

Figure 4.6: Frequency Profiles - Station Based

The overall discussion frequencies confirm the absence of particular differences among the two schemes, as reported below:

Scheme	**Free-floating**		**Station Based**	
Determinant	**Discussion Frequency**	**Weight**	**Discussion Frequency**	**Weight**
Car Rental	2,773	37%	2,301	35%
Documents and Fees	2,834	37%	2,435	37%
Software	1,475	19%	1,459	22%
Support	498	7%	465	7%
Total	**7,580**	**100%**	**6,659**	**100%**

Table 4.8: Frequency Comparison - Schemes

Therefore, the *final weights* when considering only one of the car-sharing schemes do not present significant differences (also with respect to the general results), as highlighted in table below:

Determinant	All Types	Free-floating	Station Based
Car Rental	31%	32%	31%
Documents and Fees	28%	29%	28%
Software	24%	23%	24%
Support	17%	17%	17%
Total	**100%**	**100%**	**100%**

Table 4.9: Weights Comparison - Schemes

We can therefore conclude that the car-sharing scheme does not have a significant influence on the critical level of quality drivers.

4.2.4 United States vs United Kingdom

The second factor analysed is the reference market. One could expect that the user's priorities might vary depending on the geographical area considered. The figures below show the profiles related to the market considered and, again, no particular discrepancies can be observed.

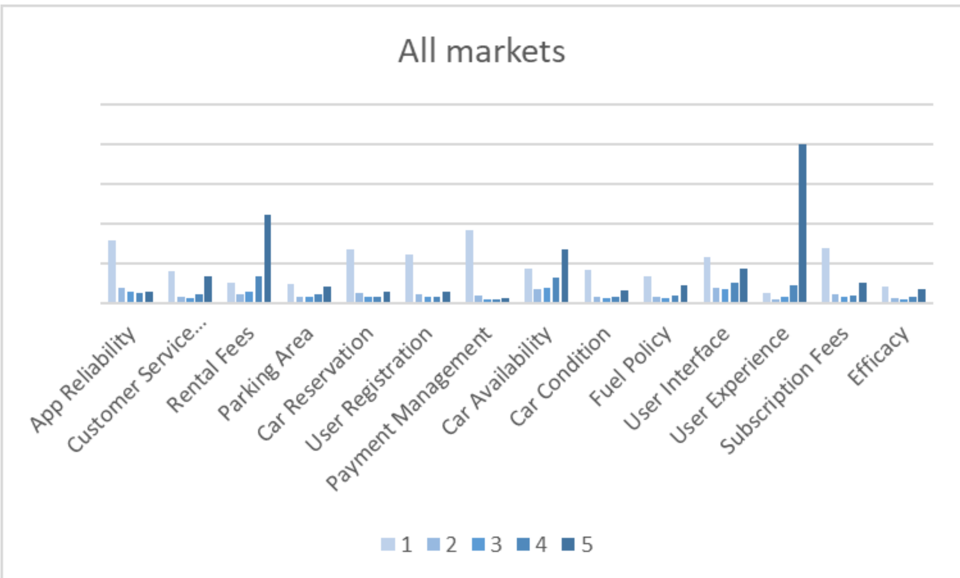

Figure 4.7: Frequency Profiles - All Markets

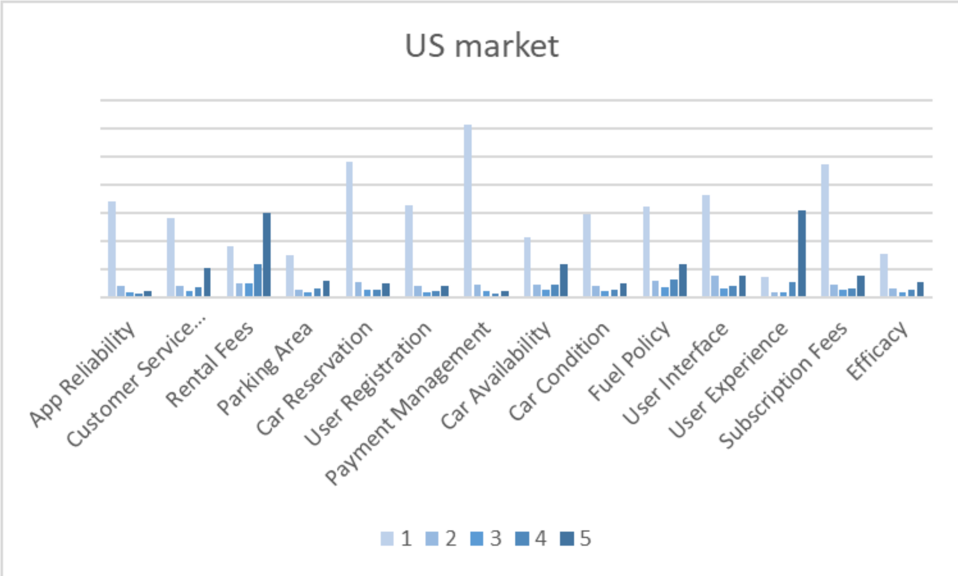

Figure 4.8: Frequency Profiles - United States

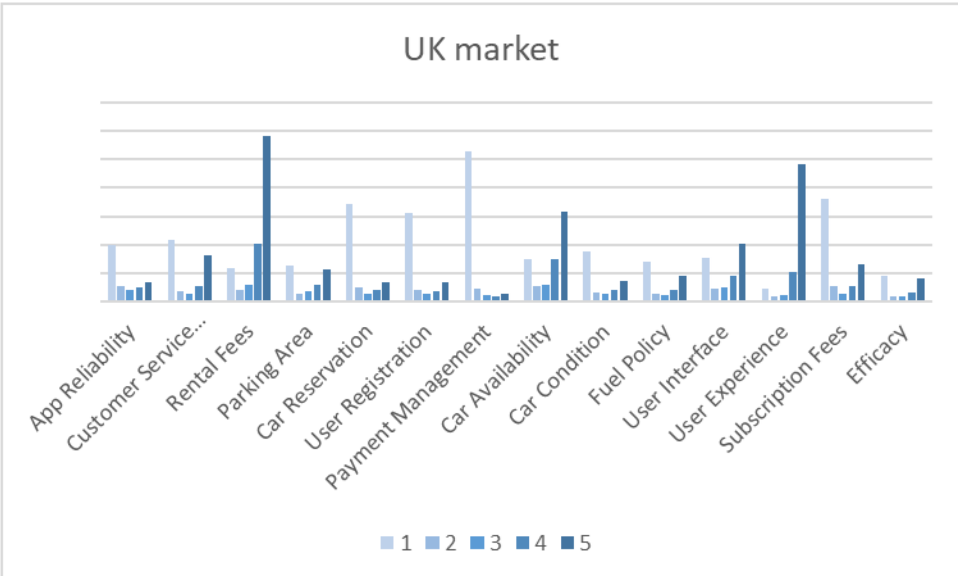

Figure 4.9: Frequency Profiles - United Kingdom

The discussion frequencies related to the different markets are reported below:

Scheme	**US**		**UK**	
Determinant	**Discussion Frequency**	**Weight**	**Discussion Frequency**	**Weight**
Car Rental	1,212	37%	1,128	35%
Documents and Fees	1,264	39%	1,371	43%
Software	515	16%	469	15%
Support	243	8%	245	8%
Total	**3,234**	**100%**	**3,213**	**100%**

Table 4.10: Frequency Comparison - Markets

As a result, we obtain the following final weights:

Determinant	**All Types**	**Free-floating**	**Station Based**
Car Rental	31%	31%	29%
Documents and Fees	28%	32%	32%
Software	24%	20%	21%
Support	17%	16%	18%
Total	**100%**	**100%**	**100%**

Table 4.11: Weights Comparison - Markets

In the two specific markets considered, the critical level of *software* decreases, while *documents and fees* have a larger impact on users' quality perception.

Chapter 5

Benchmarking of Competitors

This chapter proposes an evaluation method to compare the performance of the different competitors in the car-sharing industry. This is done taking into account the critical weights analysed in chapter 4. The crucial level for the performance evaluation is the user score linked to each review. As already said, the companies in the car-sharing industry are actually quite differentiated in terms of service offered and geographical market. As such, specific comparisons can be done, filtering the whole list by sharing scheme and country. The next sections describe the criteria used for the comparisons and the main results obtained.

5.1 Evaluation Method

In order to provide an evaluation of the companies' performance several approaches are possible. A first hypothesis is to observe the score distributions related to each of the determinants identified. This method enables to observe the proportion of each score with respect to a certain topic (or determinant). If there is a prevalence of high scores, we can conclude that the company in general deals well with the topic (or determinant) and vice versa. However, the interpretation is less simple when a u-shaped distribution is observed. In fact, it could be hypothesized that the company used to perform poorly in the past and some improvements have been done afterwards, or the other way around. However, it could be also assumed that the evaluation of that topic by customers is not homogeneous, that is, some customers perceive a good performance and some others a poor performance.

To overcome the limitations due to arbitrary interpretations, a simplified analytical model has been used. The model calculates a weighted score for each of the determinants and for each competitor. Of course, by condensing the information in such an indicator, no insights can be actually deducted on the specific performance (for instance if it has improved or worsened with time). However, it allows to have a macro-view on the overall performance levels.

As a last step, we can weight the score obtained by the providers for each determinant with the *final weights* as calculated in chapter 4 and obtain an overall score. Even though this cannot be considered as a definitive evaluation, it certainly provides a ground for a preliminary analysis. A ranking can in fact be computed and it is possible to understand which companies are generally performing better and which are instead lagging behind. It would then be necessary to get back to the causes and deep dive on the analysis of determinants to detect the roots of such general perceptions.

5.2 Benchmarking

The method explained above has been applied to the data, taking into considerations different two main distinctions: the sharing scheme (station based and free-floating) and the principal markets (United States and United Kingdom). This means that a ranking has been generated for each of the two schemes (with no market distinction) and for each of the two markets (with no scheme distinction). The general aim is to perform an evaluation that takes into account that the weights of determinants might change when the scheme or the market considered change.

5.2.1 General Benchmarking

When looking at the distribution of scores, no particular assumptions are needed. As an example, the figure 5.1 below shows the profiles of one provider (i.e., *SnappCar*) with respect to the four determinants:

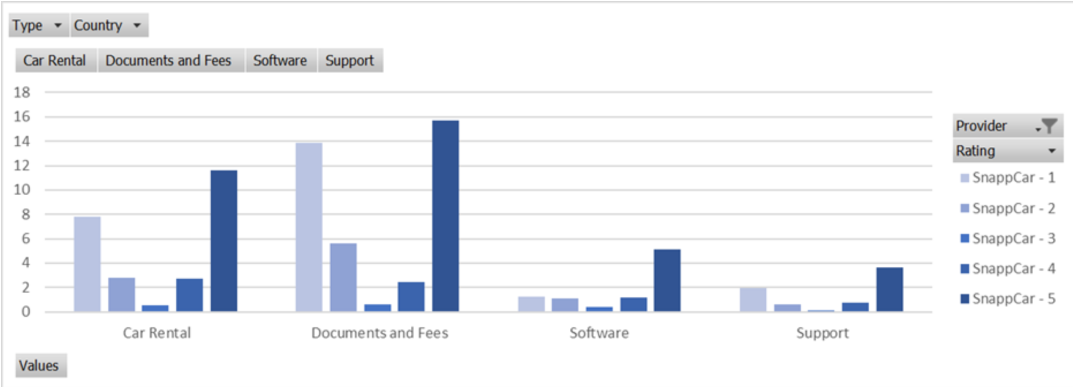

Figure 5.1: Example of Provider's Frequency Profiles

We can note that the perception of software performance is generally good, while for the other determinants it is more complex to formulate accurate considerations. We could for instance assume that, within these determinants, some topics are generally performed well, while others not. But it is also possible that the performance has worsened (or improved) with time.

If we apply the aforementioned analytical evaluation process to the whole data-set, we obtain the following results:

		weights					
		31%	28%	24%	17%		
Provider	**Frequency**	**Car Rental**	**Documents and Fees**	**Software**	**Support**	**Total**	**Ranking**
Car2go	2118	3	2.7	2.8	2.9	2.9	4
DriveNow	558	2.7	2.4	2.5	2.8	2.6	8
EnterpriceCarShare	420	2.8	2.7	2.2	2.9	2.6	7
EvoCarShare	1040	1.6	1.7	1.5	1.6	1.6	16
Getaround	1285	2.5	2.5	2.9	3	2.7	6
GoGet Car Share	240	2.8	2.9	2.3	3	2.7	5
Hertz	266	2	2	1.9	2.6	2.1	14
Hertz 24	135	2.3	2.2	1.9	2.6	2.2	10
Maven	164	1.6	1.7	1.6	1.9	1.7	15
piccolo	141	2.2	2.1	1.8	2.6	2.1	13
Turo	1554	3.7	3.8	4.3	4.1	3.9	1
Ubeeqo	213	2.2	2.1	2	2.4	2.2	12
zip car	4727	2.6	2.5	2.5	2.6	2.5	9
SHARENOW	1164	3.5	3.2	3.1	3.2	3.3	3
SnappCar	80	3.3	3	3.9	3.5	3.4	2
sixt	276	1.9	1.9	2.4	2.9	2.2	11

Table 5.1: General Benchmarking

In the previous table the weights correspond to the *final weights* calculated in 4.2.2. We can understand their impact by looking at the performance of the last provider (i.e. *Sixt*). Despite the average performance in *software* and *support* the low scores in the most critical determinants, lead to an overall low ranking. The best-in-class provider seems to be *Turo*, followed by *SnappCar* (even though it has very low discussion frequency) and *SHARENOW*. The worst performance, instead, are those provided by *Evo Car Share* and*Maven*.

5.2.2 Specific Benchmarking

When we restrict the analysis to a subset of the data, not only it is easier to compare the results (due to a lower number of providers involved) but it is also more meaningful. If we consider only the providers competing in the free-floating scheme, the overall number boils down to seven, while it reduces to ten, if we consider only station-based providers. The tables 5.2 and 5.3 below show the results related to the two schemes (using the respective weights calculated in 4.2.3.).

Free-floating		weights					
		32%	29%	23%	17%		
Provider	**Frequency**	**Car Rental**	**Documents and Fees**	**Software**	**Support**	**Total**	**Ranking**
Car2go	2118	3.0	2.7	2.8	2.9	2.9	2
DriveNow	558	2.7	2.4	2.5	2.8	2.6	4
Evo Car Share	515	1.7	1.8	1.5	2.0	1.7	6
Getaround	1285	2.5	2.5	2.9	3.0	2.7	3
Maven	164	1.6	1.7	1.6	1.9	1.7	7
Turo	1554	3.7	3.8	4.3	4.1	3.9	1
zip car	1386	2.1	2.0	1.9	2.0	2.0	5

Table 5.2: Benchmarking - Free-floating

Station based		weights					
		31%	28%	24%	17%		
Provider	**Frequency**	**Car Rental**	**Documents and Fees**	**Software**	**Support**	**Total**	**Ranking**
EnterpriceCarShare	420	2.8	2.7	2.2	2.9	2.4	5
Evo Car Share	525	1.6	1.6	1.5	1.5	1.4	10
GoGet Car Share	240	2.8	2.9	2.3	3.0	2.5	4
Hertz	266	2.0	2.0	1.9	2.6	1.9	9
Hertz 24	135	2.3	2.2	1.9	2.6	2.0	6
Ubeeqo	213	2.2	2.1	2.0	2.4	2.0	7
zip car	3341	2.8	2.8	2.5	2.9	2.5	3
SHARENOW	1164	3.5	3.2	3.1	3.2	3.0	2
SnappCar	80	3.3	3.0	3.9	3.5	3.0	1
sixt	276	1.9	1.9	2.4	2.9	1.9	8

Table 5.3: Benchmarking - Station based

It can be observed as some competitors, not positioned at first places in the general ranking, are actually among the best providers within their scheme. For instance, this is the case for *zipcar*: evaluated only as ninth best provider overall, it is actually the third in the station-based category.

Similar tables can be constructed using United States and United Kingdom only data, as shown below:

United States		weights					
		31%	32%	20%	17%		
Provider	**Frequency**	**Car Rental**	**Documents and Fees**	**Software**	**Support**	**Total**	**Ranking**
Car2go	160	2.1	1.6	2.0	1.9	1.9	7
DriveNow	4	2.4	2.2	2.1	2.7	2.3	2
Enterprice Car Share	102	2.4	2.4	1.9	2.2	2.3	4
Evo Car Share	525	1.6	1.6	1.5	1.5	1.5	8
Getaround	646	2.5	2.5	2.8	3.0	2.6	1
GoGet Car Share	1	1.0	1.0	1.0	1.0	1.0	9
Hertz	200	2.3	2.3	1.9	2.9	2.3	3
zip car	1321	2.1	2.0	1.9	2.0	2.0	6
sixt	276	1.9	1.9	2.4	2.9	2.2	5

Table 5.4: Benchmarking - United States

United Kingdom		weights					
		29%	32%	21%	18%		
Provider	**Frequency**	**Car Rental**	**Documents and Fees**	**Software**	**Support**	**Total**	**Ranking**
Car2go	42	1.8	1.5	1.6	1.6	1.6	8
DriveNow	93	2.3	2.1	2.2	2.2	2.2	6
Enterprice Car Share	98	1.6	1.6	1.6	2.0	1.7	7
GoGet Car Share	1	5.0	5.0	5.0	5.0	5.0	1
Hertz	66	1.3	1.2	1.1	1.2	1.2	9
piccolo	33	2.0	2.1	1.9	3.2	2.2	5
Ubeeqo	174	2.3	2.3	2.4	2.6	2.4	4
zip car	1542	2.6	2.6	2.6	2.7	2.7	3
SHARENOW	1164	3.5	3.2	3.1	3.2	3.3	2

Table 5.5: Benchmarking - United Kingdom

In this case it is interesting to note that the same provider can have a different perception of performance, depending on the country considered. For instance, *zipcar* presents an overall score of 2 in the United States and it reaches only the sixth position in the US ranking. In United Kingdom the score increases to almost 3 and the provider is the third best. Taking into consideration that the differences (besides small) in the weights of the determinants do not affect the evaluation, the causes of this different perception might be structural. The service, indeed, might not be tailored to the requirements of each specific market.

Chapter 6

Conclusions

This study proposes a comprehensive framework to evaluate the quality determinants of a PSS and analyses in detail the car-sharing case. UGC represents an interesting choice to dynamically retrieve users' feedbacks and quality perception. At the same time, as expressed in [10], Topic Modelling can transform it into useful insights for quality analysts, but also for companies.

The main elements of novelty contained in the study can be summarized as follows:

- The results obtained on UGC with a STM algorithm can be further analysed to spot potential correlations among the topics extracted (through statistic techniques, such as Factor Analysis).
- The analysis of discussion frequency profiles (with respect to the ratings) can be used to assign a category of the Kano model to the quality determinants.
- The Kano categories, together with the discussion frequency, can be used to prioritize the quality determinants (assign to each of them a certain weight).
- A dynamic prioritization can be performed. That is, different weights can be extracted when specific clusters of reviews are considered.
- The weights calculated following the steps above can be used to benchmark specific groups of competitors.

When identifying the determinants, the peculiarities of each service must be taken into account. However, by building quality clusters, it is possible to create a general ground for comparison (since all the systems need to deal with the primary aspects). This can represent a starting point, rather than a final result. In fact, the observation of macro quality trends and differences among different providers, can trigger a reverse process aimed at detecting the real causes. In doing so, the application of a Kano-like model is an interesting choice, especially for engineering design as it allows to understand how specific issues should be dealt with.

The results obtained with the car-sharing data tell us that this PSS revolves around four main quality determinants. The most critical ones are represented by the rental process and the documents and fees management (with almost the same impact on overall satisfaction). The other two determinants are related to supporting services, i.e., the software tools used to access the service and the customer service. The first two should be considered as the pillars of the PSS; if performed well they can be drivers of users' satisfaction, while a poor performance might induce customers to switch to a competitor or simply not use the service.

As said, the models proposed rely on several assumptions and their robustness is yet to be tested. Additional investigations might be aimed at comparing these results with results obtained with other models. Moreover, a sensitivity analysis could be performed to evaluate the impact of arbitrary parameters on the final considerations.

Appendix A

Formulas

- **Bartlett's Sphericity Test**

$\chi^2 = -[N - 1 - \frac{1}{6} * (2p + 5)] * \ln |R|$

with $(p^2 - p)/2$ degrees of freedom; where $|R|$ is the determinant of the correlation matrix, N is the sample size, and p indicates the number of variables.

- **Kaiser-Meyer-Olkin sample adequacy test**

$KMO = \frac{\sum_i \sum_j r_{ij}^2}{\sum_i \sum_j r_{ij}^2 + \sum_i \sum_j p_{ij}^2}$

where r_{ij} are the correlations and p_{ij} the partialized correlations on all the others.

Bibliography

[1] Daniel Sperling Susan Shaheen and Conrad Wagner. «A Short History of Carsharing in the 90's». In: *The Journal of World Transport Policy and Practice* 5 (Sept. 1999), p. 20 (cit. on p. 1).

[2] Statista. *Car-sharing*. www.statista.com. 2020 (cit. on p. 1).

[3] Janaina M.H. Costa Aldo R. Ometto Gustavo Michelini Renato N. Moraes Renata N.Cunha. «From Linear to Circular Economy: PSS Conducting the Transition». In: *Procedia CIRP* 64 (Mar. 2017), pp. 2–6 (cit. on p. 1).

[4] T. Dyllick and Z. Rost. «Towards true product sustainability». In: *Journal of Cleaner Production* 162 (2017), pp. 346–360 (cit. on p. 1).

[5] Beuren F. H.& Gomes Ferreira M. G. & Cauchick Miguel P. A. «Product-service systems: A literature review on integrated products and services». In: *Journal of Cleaner Production* 47 (2013) (cit. on p. 1).

[6] Mazzini Muda Azlin Zanariah Bahtar. «The Impact of User – Generated Content (UGC) on Product Reviews towards Online Purchasing – A Conceptual Framework». In: *Journal of Cleaner ProductionProcedia Economics and Finance* 37 (2015) (cit. on p. 1).

[7] LaValle S. & Lesser E. & Shockley R. & Hopkins & M. S. and Kruschwitz N. «Big data, analytics and the path from insights to value». In: *MIT sloan management review* 52 (2011) (cit. on p. 1).

[8] Jose Ramon Saura and Dag R. Bennett. «A Three-Stage method for Data Text Mining: Using UGC in Business Intelligence Analysis». In: *Symmetry* 11 (2019) (cit. on p. 3).

[9] Murtha Baca. *Introduction to Metadata*. The Getty Resarch Institute, 2016 (cit. on p. 3).

[10] Luca Mastrogiacomo & Federico Barravecchia & Fiorenzo Franceschini & Frederic Marimon. «Mining quality determinants of product-service systems from user-generated contents». In: *Quality Engineering* 33 (2020) (cit. on pp. 3, 4, 13, 51).

[11] Janet R. McColl-Kennedy Mohamed Zaki. «Text mining analysis roadmap (TMAR) for service research». In: *Journal of Services Marketing* (2020) (cit. on p. 4).

[12] Margaret Roberts & Brandon Stewart & Dustin Tingley & Kenneth Benoit. *Package 'stm'*. http://www.structuraltopicmodel.com/. 2020 (cit. on p. 4).

[13] PBC RStudio. https://www.rstudio.com/ (cit. on p. 4).

[14] I. Meyer D. & Hornik K.& Feinerer. «Text mining infrastructure in R». In: *Journal of statistical software* 25 (2008) (cit. on p. 5).

[15] A. G. Jivani. «A comparative study of stemming algorithms». In: *International Journal of Computer Applications in Technology* 2 (2011) (cit. on p. 5).

[16] Durrani N.& Schmid H. & Fraser A. & Koehn P. & Schütz H. «The operation sequence model—combining N-gram-based and phrase-based statistical machine translation». In: *Computational Linguistics* 41 (2015) (cit. on p. 5).

[17] Roberts M. E. & Stewart B. M. & Tingley D. & Lucas C. & Leder-Luis J. & Gadarian S. K. & Albertson B. & Rand D. G. «Structural topic models for open-ended survey responses». In: *American Journal of Political Science* 58.4 (2014) (cit. on p. 5).

[18] J. Scott and J. Baldridge. «A recursive estimate for the predictive likelihood in a topic model». In: *Journal of Machine Learning Research* 31 (2013) (cit. on p. 5).

[19] Blei D. M. & Ng A. Y. & Jordan M. I. «Latent dirichlet allocation». In: *Journal of machine Learning research* 3 (2003) (cit. on p. 6).

[20] D. M. Blei and J. D. Lafferty. «A correlated topic model of science». In: *The Annals of Applied Statistics* 1 (2007) (cit. on p. 6).

[21] Roberts M. E. & Stewart B. M. & Tingley D. «STM: R package for structural topic models». In: *Journal of Statistical Software* 91 (2019) (cit. on p. 7).

[22] *IBM SPSS software*. https://www.ibm.com/analytics/spss-statistics-software (cit. on p. 13).

[23] C. Spearman. «General intelligence objectively determined and measured». In: *American Journal of Psychology* 15 (1904) (cit. on p. 14).

[24] B. Fruchter. «Introduction to factor analysis». In: (1954) (cit. on p. 16).

[25] R. L. Gorsuch. «Factor Analysis». In: (1974) (cit. on p. 17).

[26] A. Field. «Discovering statistics using Spss». In: (2009) (cit. on p. 18).

[27] H. F. Kaiser. «A second generation little jiffy». In: *Psichometrika* 35 (1970) (cit. on p. 18).

[28] R. L. Gorsuch. «Factor Analysis». In: (1983) (cit. on p. 19).

[29] Germano Rossi. «Appunti di analisi fattoriale». In: (2018) (cit. on pp. 19, 22, 26, 27).

[30] L Guttman. «A new approach to factor analysis: the Radex». In: (1954) (cit. on pp. 19, 23).

[31] H. F. Kaiser. «The application of electronic computers to factor analysis». In: *Educational and Psychological Measurement* 20 (1960) (cit. on p. 19).

[32] R. B. Cattell. «The scree-test for number of factors». In: (1966) (cit. on p. 20).

[33] H. H. Harman. *Modern factor analysis*. 1967 (cit. on p. 20).

[34] Runyon R. P. Haber A. *Fundamentals of behavioral statistics (3rd ed.)* 1976 (cit. on p. 20).

[35] K.G. Joreskog. «SOME CONTRIBUTIONS TO MAXIMUM LIKELIHOOD FACTOR ANALYSIS». In: *Psychometrika* 32 (1967) (cit. on p. 22).

[36] Kaiser H. F. Caffry J. «Alpha factor analysis». In: *Psichometrika* (1965) (cit. on p. 23).

[37] L.L. Thurstone. «Multiple factor analysis: A development and expansion of vectors of the mind». In: *University of Chicago Press* (1947) (cit. on p. 23).

[38] M. Reuchlin. «Methodes d'analyse factorielle a l'usage des psychologues». In: *Presses Universitaire de France* (1964) (cit. on p. 24).

[39] S. Sadocchi. «Manuale di analisi statistica multivariata per le scienze sociali». In: (1980) (cit. on p. 25).

[40] Sui Z. Allen T. T. and Akbari K. «Exploratory text data analysis for quality hypothesis generation». In: *Quality Engineering* 30 (2018) (cit. on p. 29).

[41] Hans Hinterhuber Elmar Sauerwein & Kurt Matzler & Franz Bailom. «The Kano Model: How to Delight Your Customers». In: *International Working Seminar on Production Economics*. Insbruck Austria, 1996 (cit. on p. 29).

[42] Wei-Jaw Deng Yeng-Feng Kuo Jing-Yu Chen. «IPA–Kano model: A new tool for categorising and diagnosing service quality attributes». In: *Total Quality Management Business Excellence* 23 (2012) (cit. on p. 29).

[43] I-Ching Yang Mu-Chen Chen Kuo-Chien Chang Chia-Lin Hsu. «Understanding the relationship between service convenience and customer satisfaction in home delivery by Kano model». In: *Asia Pacific Journal of Marketing and Logistics* 23 (2011) (cit. on p. 29).

[44] Nicolas Haber, Mario Fargnoli, and Tomohiko Sakao. «Integrating QFD for product-service systems with the Kano model and fuzzy AHP». In: *Total Quality Management & Business Excellence* 31 (2020) (cit. on p. 29).

[45] F. Takahashi Kano N. N. Seraku and S. Tsuji. «Attractive Quality and Must-be Quality». In: *The Journal of the Japanese Society for Quality Control* (1984) (cit. on p. 30).

[46] Cuomo M.T. *La customer satisfaction: vantaggio competitive e creazione di valore*. CEDAM, 2000 (cit. on p. 35).

[47] Andrea De Montis & Pasquale De Toro & Bert Droste-Frank & Ines Omann & Sigrid Stagl. «Criteria for quality assessment of MCDA methods». In: Vienna, 2000 (cit. on p. 37).

[48] Amorim P. *O poder da intuição*. https://www.publico.pt/2021/06/15/opiniao/opiniao/intuic
1966522. 2021 (cit. on p. 37).