



HAL
open science

Customer satisfaction and natural language processing

Yolande Piris, Anne-Cécile Gay

► **To cite this version:**

Yolande Piris, Anne-Cécile Gay. Customer satisfaction and natural language processing. *Journal of Business Research*, 2021, 124, pp.264-271. 10.1016/j.jbusres.2020.11.065 . hal-03110702

HAL Id: hal-03110702

<https://hal.science/hal-03110702v1>

Submitted on 15 Dec 2022

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution - NonCommercial 4.0 International License

Customer satisfaction and natural language processing (NLP)

Yolande PIRIS*

University Bretagne Sud – LEGO EA 2652
Campus de Tohannic - BP 573
56017 Vannes
France
yolande.piris@univ-ubs.fr
[+33\(0\)6 85 30 26 33](tel:+330685302633)

Anne-Cécile GAY

University Bretagne Sud Foundation
Campus de Tohannic - BP 573
56017 Vannes
France
annececile.gay@gmail.com

***Corresponding author**

Acknowledgements

The authors would like to thank the Bred for making the data available. They would also like to thank the different members of the DCC Chair (Data and customer knowledge). They also thank Nicole Geslin for the translation.

Customer satisfaction and natural language processing

1. Introduction

As early as 1999, Pine and Gilmore viewed the evolution of the economy as a pyramid showing the reduction of goods and services and the centralization of experiences. More recently, Klaus and Maklan (2013) have shown that the customer experience is a better predictor of loyalty or recommendations to third parties than satisfaction measures. Customer delight is now considered alongside satisfaction to best understand consumers' judgment of an entire consumption experience, which can engender loyalty if positive (Ahrholdt et al., 2019). Understanding the customer journey and fostering a positive and memorable experience constitute major challenges for companies, but important ones especially given the positive link between loyalty programs and financial performance (Lee et al., 2014). Essential to meeting these challenges are data and data marketing, as the Adobe and eConsultancy (2019) digital trends report shows. The report indicates that 24% of respondents prioritize customer data ahead of customer experience optimization (19%).

At the same time, the development of the Internet and the emergence of e-commerce have considerably expanded the customer journey. The number of contact points between customers and companies has increased, as have the opportunities for customers to air their views. This situation encourages both the development of omni-channel strategies (Verhoef et al., 2015) and the proliferation of customer data, which brings up questions about measuring and processing customer satisfaction. Satisfaction is closely linked to customer experience, but it is also influenced by the omni-channel context in which customers operate. Both issues of customer experience, understood as the cognitive and affective treatment of the direct and indirect links between companies and their customers (Klaus & Maklan, 2013; Verhoef et al., 2009), and customer satisfaction are commonly dealt with from a quantitative perspective. Customer satisfaction is measured as the gap between preexisting expectations and actual experience (Anderson, 1973); in contrast, experience is not measured directly as a performance gap but in a more holistic way (Verhoef et al., 2009).

Hence, this study brings into question the limitations of quantitative approaches to measure and process customers' experience and satisfaction. As the customer journey has become increasingly complex, and experiences become increasingly globalized, it is necessary to use qualitative data and natural language processing (NLP) methods to handle them. In this study, we used a bank's customer database of over 12,300 respondents, which enabled us to investigate over 6,800 qualitative answers and Net Promoter Score (NPS) indicators. This controlled database (as opposed to diverse data

collected on the Internet) shows the need to use qualitative data for mass processing through NLP in order to better reveal the factors influencing customer satisfaction and to provide both automatic and individualized processing.

2. Theoretical framework

2.1. Customer experience and satisfaction

Very early, the literature recognized the need to foster a strong and positive customer experience (Pine & Gilmore, 1998; Hogan et al., 2002), to which is now added the need to take into account the multiplication of contact points (Lemon & Verhoef, 2016). As defined by Schmitt (1999) as a multidimensional variable, experience involves five dimensions: sensorial, affective, cognitive, physical, and identity-related. Meyer and Schwager (2007) indicate that experience has become so globalized that it needs to incorporate all direct and indirect contacts (e.g. advertising, services, uses) with customers.

In their review article on the customer experience, Lemon and Verhoef (2016) propose a literature review and a synthetic model showing the complexity of the customer experience. The authors detail the habitual stages of the purchasing process and identify for each of them four possible “touch points”: brand-owned touch points, controlled and initiated by the brands; partner-owned touch points, partly controlled by the brands with their partners (e.g. distributors); customer-owned touch points, controlled by neither brands nor their partners and resulting from consumers’ decisions; and social/external touch points, also controlled by neither brands nor partners, but created by role players in the social environment of consumers.

Distinguishing these different contact points is all the more important as consumers operate in an omni-channel context. Numerous studies have focused upon the development of consumer behaviors in the present environment, in which virtual spaces (e.g. Internet sites, e-commerce) are added to the traditional purchasing process (Avery et al., 2012; Verhoef et al., 2017) and the customer journey is influenced by new strategies for information search and purchasing (Grewal et al., 2013; Verhoef et al., 2007). In this context, Collin-Lachaud and Vanheems (2016) show an absence of fragmentation; consumers switch between real and virtual spaces without any apparent difficulty and view their purchasing experience as a whole, despite its blending very diverse aspects. Consumers may search for information on a range of websites or on social media (Bronner & de Hoog, 2014) and may be interrupted by popup ads, flash sales, e-mail alerts, and so on, while keeping contact with the brand or company and retrieving information. Exchanges with other consumers may sometimes impact on the journey (Leeflang et al., 2013; Libai et al., 2010). Even individuals’ future time perspective may affect the link between satisfaction and loyalty (Kuppelwieser & Sarstedt, 2014). All these elements modify

the process and complexity of the customer journey (Grant et al., 2013) as well as consumers' overall experience (Schmitt et al., 2015).

The increasing attention paid to the customer experience is due to its increasing complexity and its major role in consumer satisfaction (Fornell, 1992). The customer experience is viewed as preceding satisfaction (Shankar et al., 2003), which is a determining factor explaining loyalty, number of purchases, average amount spent, and company growth (Anderson & Sullivan, 1993; Anderson & Mittal, 2000) as well as recommendations (Hosany & Prayag, 2013). Satisfaction is defined on two levels: horizontal and vertical (Oliver, 1997); whereas the former refers to satisfaction arising from a given action (e.g. a transaction), the latter refers to the accumulation of experiences associated with a brand or company. Thus, transaction-specific satisfaction needs to be distinguished from relational satisfaction involving a synthetic evaluation.

Relational satisfaction, just like the customer experience, is influenced by customer journeys that are increasingly dense and complex. Brands cannot control all the contact points or, hence, the overall customer experience (Lemon & Verhoef, 2016), but they still have to ensure their customers' satisfaction, all the more so as consumer satisfaction is a determining variable companies may act upon (Ho et al., 2006). It is thus useful to investigate existing approaches to knowledge of and processing of customer satisfaction.

2.2. Analysis and processing of customer satisfaction

The complexity of the customer journey is reflected in the numerous theoretical approaches to it, which have been interweaving and following each other for several years (Lemon & Verhoef, 2016). Consumer data processing is known to be a complex and dynamic task (Davenport & Klahr, 1998). Central to this type of work is the literature on satisfaction, viewed as essential to apprehend the consumer experience, and loyalty (Kumar et al., 2013; Wu, 2016; Yoo & Park, 2016).

Work on satisfaction measurement is extensive (e.g. Hubbert et al., 1995; Oliver, 1997). However, in light of the context detailed in the preceding section, it is difficult to expect that consumers may provide anything else than a very general evaluation, more or less influenced, depending upon the situation and the moment, by the horizontal and/or vertical elements. Llosa (1997) distinguishes between different product attributes to increase understanding of satisfaction, identifying four families of attributes that correspond to various combinations of contributions to satisfaction and consumer perception:

- The “basic” elements contribute to customer dissatisfaction and are not determining factors of satisfaction;
- The “plus” elements influence only customers' overall satisfaction and do not influence their dissatisfaction;

- The “key” elements strongly influence the degree of satisfaction, regardless of the customers’ evaluation of satisfaction, and they are always determining factors;
- The “secondary” elements do not play a role in overall customer satisfaction and are never determining factors.

Customers’ journeys and experiences are dotted with numerous contact points of various natures, and a traditional approach based upon attributes appears to be rather complex: how can one isolate and take into account the elements arising from consumers’ actions (customer-owned touch points) or their environment (social/external touch points) (Lemon & Verhoef, 2016)? Satisfaction reflects judgments that capture an entire consumption experience (Ahrholdt et al., 2019). This also explains interest in delight, a key emotional response (Finn, 2012) that also matters for the understanding of loyalty (Ahrholdt et al., 2019).

Furthermore, these approaches entail measures that aim either at identifying problematic attributes (Anderson & Mittal, 2000) or at understanding satisfaction level from a general perspective through indirect measures such as the NPS (Reichheld, 2003). The former are limited by the non-symmetrical and non-linear nature of the relationship between attributes and consumer satisfaction (Anderson & Mittal, 2000). It is difficult to generalize quantitative approaches since, depending upon the situation (e.g. type of company, sector), some attributes may contribute to maintaining satisfaction without necessarily fostering it and others vice versa (Anderson & Mittal, 2000). The NPS could be the main indicator to show the link between satisfaction (as measured by the propensity to recommend the brand) and company growth. Although companies use this indicator to assess overall satisfaction, its capacity to predict growth has been called into question (Keiningham et al., 2007). In short, traditional approaches do not yield generalizable and transferable quantitative tools or operational solutions for satisfaction assessment.

Lemon and Verhoef (2016) have also pointed out the limitations of traditional approaches to customer experience, and after reviewing the main trends relating to knowledge of customer experience, particularly concerning satisfaction, have suggested exploring the potential of big data. The goal of such an approach would be to collect numerous sources of information to take into account the complexity, dynamism, and specific characteristics of the customer experience. Indeed, we contend that masses of qualitative data, used alone or combined with other measures, could account for all the determining factors from the perspective of consumers, and that experiences have become so globalized that a qualitative approach giving free run to consumers’ views could help reveal both horizontal and vertical aspects of satisfaction, which we believe are linked rather than independent. In addition, this approach could allow automatic customized processing, in contrast to the current approaches using general or even non-existent processing, especially since we know the importance of recovery efforts after complaining evaluations by consumers (Maxham & Netemeyer, 2002).

3. Design of the study and methodology

The first goal of this study is the automatic exploration of customer voices based on identification of the main themes mentioned by customers. In contrast to traditional approaches focusing upon either a horizontal or a vertical approach (Oliver, 1997), we contend that the customer experience is made of an optimal blending of vertical and horizontal elements. Hence, we used an NLP method, Latent Dirichlet Allocation, which is a probability model that can categorize documents using themes whose number has been determined beforehand. NLP combines linguistic, computing, and artificial intelligence resources with a view to conducting specific processing of customers' qualitative discourse.

The second goal of this study is to link this analysis to NPS results so as to generate automatic processing of satisfaction. To do this, we tested different hypotheses in order to 1) understand whether the number of themes evoked by the respondents is different according to their NPS score and 2) explore whether the nature of topics evoked is different according to the respondent's NPS score.

To do so, we formulated, for different couples (three populations corresponding to "promoters", "neutral", and "detractors") of NPS scores and for the different topics revealed by NLP, the following hypotheses:

1) For each population:

H0: average number of topic (population 1) \leq average number of topic (population 2)

H1: average number of topic (population 1) $>$ average number of topic (population 2)

2) For each population and each topic:

H0: proportion of topic (topic 1) (population 1) \leq proportion of topic (topic 1) (population 2)

H1: proportion of topic (topic 1) (population 1) $>$ proportion of topic (topic 1) (population 2)

3.1. Data collection

The data used for this analysis stem from a controlled satisfaction survey sent by a bank to its customers on a random basis (10% of total customers), to ensure internal validity (Campbell & Stanley, 1966). Customers may not be asked more than once a year to answer a questionnaire, and they were all questioned in the same short period of time without any interaction between them.

This controlled data collection, as distinct from diverse data collected on the Internet, ensures homogeneity in the customers' response topics and prevents collection from contaminating information. Customers provided two simple items of information that were used in the study:

- **A recommendation score** ranging from 0 to 10, used to calculate the NPS;
- **Free comments** explaining the score (optional field).

Over 12,000 customer feedback answers were analyzed, among which over 6,800 (i.e. 55%) included qualitative comments concerning the respondents' intention to recommend the brand or not.

3.1.1. Data pre-processing

Data pre-processing constitutes an essential and systematic step in any text modeling. Its purpose is to facilitate algorithmic processes by decreasing noisy data and optimize computation time by reducing vocabulary size upstream.

3.1.2. Identification of multi-word items

The first data pre-processing step involves defining a list of multi-word items that form meaningful and inseparable units. In addition to compound words (e.g., credit crunch, give up) and fixed expressions (e.g., arriving after the battle, in the medium term), the list contains the specific and technical vocabulary pertaining to the banking domain (e.g., bank card, *Livret A* [French savings account], *plan d'épargne logement* [French housing savings plan]).

3.1.3. Segmentation (or tokenization)

Segmentation (also called tokenization) involves cutting up text into units composed of single words and multi-word items in order to facilitate the next pre-processing step. Punctuation and capitals are deleted.

3.1.4. Filtering out (removing) the stop words

Stop words are common words bringing little contextual information, such as articles, pronouns, and prepositions. Their frequency of occurrence is high, and removing them can reduce considerably the volume of data before modeling, with little loss of information. There are dictionaries of stop words that can be completed by the specificities of each corpus of documents. For the study, we used the list of stop words in the natural language toolkit (NLTK) in Python.

3.1.5. Stemming

Finally, we used stemming to reduce the complexity of the corpus vocabulary. This step involves removing the prefix and/or suffix of each word to reduce it to its stem, to factor in words belonging to the same stem or lemma (e.g. "retrieval", "retrieved", and "retrieves" reduce to the stem "retrieve").

We used the Snowball stemming algorithm developed by Martin Porter and implemented in NLTK in Python (Table 1).

3.2. Data representation

3.2.1. Bag-of-words representation

Machine learning algorithms use digital data rather than text; to use these algorithms, it is thus necessary to transform a textual corpus into numbers. A technique widely used in NLP employs the bag-of-words (BoW) method: the textual corpus is represented by an “items/documents” matrix containing the customer comments in rows and the words used in columns.

Each cell c_{ij} of the BoW matrix shows the number of occurrences of item j in comment i (Figure 1).

Figure 2 shows an illustration of a BoW transformation of a customer corpus:

Comment 1: “*Extremely satisfied!*”

Comment 2: “*Excellent services, extremely happy*”

Comment 3: “*Response time too long*”

After the implementation of the comment pre-processing stage (segmenting, removing stop words, stemming), the corpus of comments may be represented in the BoW matrix (Figure 1).

3.2.2. Term Frequency - Inverse Document Frequency weighting

To increase document differentiation, a Term Frequency-Inverse Document Frequency (TF-IDF) statistical measure is applied to the items/documents matrix. The purpose of this analysis is to under-weight items that appear in most documents and thus bring little information upon each occurrence while over-weighting rare words that appear in few documents and are informative.

Hence, in a corpus composed of D documents, the TF-IDF weighting of the word w_i in the document d_j is calculated as follows:

$$\text{TF-IDF}(w_i, d_j) = \text{TF}(w_i, d_j) \times \text{IDF}(w_i),$$

with $\text{TF}(w_i, d_j)$ =frequency of use of the word w_i in document d_j

and $\text{IDF}(w_i) = \log\left(\frac{D}{n_i}\right)$ with n_i the number of documents containing word w_i .

3.3. Identifying the corpus topics: Latent Dirichlet Allocation modeling

3.3.1. Probabilistic methods for thematic identification

Document topic modeling is a major issue in text mining. Different NLP techniques have been developed to automatically identify the main topics present in large document corpora and the words that characterize these topics. Probabilistic methods are those that use probability theory to identify topics.

Probabilistic methods of topic identification are based upon the following assumptions:

- Each document is a probabilistic mixture of topics among a set of k topics. This mixture uses a multinomial law. Thus, given a document \mathbf{d} , the topic \mathbf{z} is present in this document with the probability $\mathbf{P}(\mathbf{z}|\mathbf{d})$.
- Each topic is a probabilistic mixture of words. This mixture also follows a multinomial law. Given a topic \mathbf{z} , the word \mathbf{w} is present in this topic with the probability $\mathbf{P}(\mathbf{w}|\mathbf{z})$.

3.3.2. Latent Dirichlet Allocation modeling

Latent Dirichlet Allocation (LDA) is a common probabilistic model for topic identification. LDA modeling is a generative probabilistic modeling approach (i.e. the model can infer topics on any new document) proposed by Blei et al. (2003). It is a non-supervised method that can model the contents of a document using a set of topics previously unobserved. These topics are defined by word similarities. The method works as follows.

It is supposed that the document corpus is constituted of k topics. The number k is fixed ahead of the algorithmic process using expert advice and/or a posteriori validation of the consistency of the links between topics and words.

We assume the following:

- Each document is a mixture of topics among a set of k topics. This mixture follows a Dirichlet parameter law α ;
- Each topic is a mixture of words. This mixture follows a Dirichlet parameter law β .

The purpose of LDA is to learn the topics present in each document and the words associated with these topics. It is an iterative algorithm:

- Initialization: for each verbatim statement, a set of topics is identified following a Dirichlet parameter distribution α . For each topic, a set of words is identified following a Dirichlet parameter distribution β . The resulting model at this stage is rather improbable because randomly generated.
- Learning: Modeling involves finding the topic and word distributions that have generated answers with the highest probability.

Each word of each document is viewed, and its related topic is updated. This new topic is the one that would have the highest probability of generating the word in this document. Hence, the assumption is that all topics are correct except for the word in question.

Thus, for each word \mathbf{w} of each document \mathbf{d} , the calculation is:

$\mathbf{P}(\text{topic } \mathbf{z} \mid \text{document } \mathbf{d}) = \text{probability that the document } \mathbf{d} \text{ is concerned by the topic } \mathbf{z};$

$\mathbf{P}(\text{word } \mathbf{w} \mid \text{topic } \mathbf{z}) = \text{probability that the topic } \mathbf{z} \text{ in the corpus is assigned to the word } \mathbf{w}.$

The new topic z is then chosen with the following probability:

$P(\text{topic } z \mid \text{document } \mathbf{d}) * P(\text{word } \mathbf{w} \mid \text{topic } z) = \text{probability that the topic } z \text{ will generate the word } \mathbf{w} \text{ in the document } \mathbf{d}.$

These steps are repeated until stabilization of the estimates.

These different steps give rise to the mixture of topics present in each document by counting each representation of a topic associated with the words in the document and to the words associated with each topic by counting the words associated with it in the corpus.

Hence, LDA models document words through a set of topics and topics through a set of words.

4. Results

The first outcome of the analysis is that writing a comment, over and above giving a recommendation score, indicates a lower level of customer satisfaction: whereas the ratio of promoters remains relatively constant, the ratio of detractors is significantly higher when a verbatim statement is entered (Table 2).

4.1. Analysis of the corpus topics

Eight major topics emerge from the qualitative data analysis (Table 3). To interpret these topics, we use the notion of relevance as presented by Sievert and Shirley (2014).

With V the number of words composing the vocabulary of the corpus.

With \mathbf{w} a word in the corpus ($\mathbf{w} \in \{1, \dots, V\}$).

We observe $\Phi_{z\mathbf{w}}$ the probability of occurrence of the word \mathbf{w} in topic z .

We observe \mathbf{p}_w the probability of occurrence of the word \mathbf{w} in the corpus.

The relevance of the word \mathbf{w} in topic z given the parameter λ ($0 \leq \lambda \leq 1$) is written:

$$r(\mathbf{w}, z \mid \lambda) = \log(\Phi_{z\mathbf{w}}) + (1 - \lambda) \log(\Phi_{z\mathbf{w}} / \mathbf{p}_w),$$

with λ the weighting attributed to the probability of occurrence of the word \mathbf{w} in topic z in relation to its frequency of occurrence in the whole corpus.

Thus, if $\lambda=1$, the relevance of the word indicates its presence in topic z , regardless of its presence in the rest of the corpus. High relevance shows high presence of the word in topic z , without analyzing its presence in the rest of the corpus.

If $\lambda=0$, the relevance of the word indicates the difference in frequency of occurrence of the word between topic k and the rest of the corpus; high relevance shows a much higher presence of the word in topic z than in the rest of the corpus.

4.2. Topics and NPS: Five families of elements accounting for satisfaction

Although the ability of the NPS to predict company growth has been called into question (Keiningham et al., 2007), this score remains a good overall evaluation of customer satisfaction level. The links between the different topics and the NPS are used to determine whether some topics are significantly associated with a greater number of detractors or promoters; hence, we observe that the analysis of the NPS shows large disparities depending upon the topics mentioned by the customers (Table 4).

A detailed analysis of the significant differences shows that all topics do not appear to play the same role in customer satisfaction, which is congruent with the work of Llosa (1997) on categories of attributes and their impact upon satisfaction. Four categories of topics may be slotted into the four families of attributes identified by Llosa:

1. “Basic” topics, significantly associated with more detractors or fewer promoters, which contribute to customer dissatisfaction only and are not determining factors of satisfaction:
 - The relational and human dimension
 - The bank’s brick-and-mortar branches
2. “Key” topics, significantly associated with more promoters but also fewer detractors, which foster satisfaction:
 - The bank’s Internet site and mobile applications
 - Mortgages
3. One “plus” topic, significantly associated with more promoters, which plays a role in overall customer satisfaction only, and does not influence dissatisfaction:
 - Means of communication
4. “Secondary” topics, not significantly associated with more or fewer detractors or promoters, whose role does not appear to be a determining one:
 - Day-to-day operations of accounts and/or contracts
 - Pricing policy

Topic 5, which corresponds to the customers’ attitude elements, has not been categorized, inasmuch as it corresponds mainly with customers expressing their satisfaction or lack thereof.

4.3. NPS and average number of topics: Overall satisfaction

On average, customers mentioned 2.2 topics in their comments. The NPS analysis of the number of topics indicates that low satisfaction is significantly associated with a higher average number of topics.

Conversely, satisfaction is significantly associated with a lower average number of topics (Tables 5 and 6). These results come from unilateral tests, allowing us to test the non-inferiority of the average number of themes as a measure of low customer satisfaction (Table 6). These results are consistent with the notion that evaluation is vertical (Oliver, 1997), that is, general, rather than horizontal, that is, focused on one event only, and all the more so as customer satisfaction is low.

Hence, customers' free comments are general: more satisfied customers express fewer comments, or even none, as mentioned earlier, whereas less satisfied customers express more comments. Positive and negative comments are thus clearly distinct in terms of both content and form.

4.4. NPS and topics mentioned: The critical role of the relational or human dimension

Finally, the different unilateral tests were conducted; the analysis of the topics mostly mentioned in relation to the NPS, and hence to the satisfaction level, also reveals significant differences (Table 7).

We observe that topic 5, which focuses on the elements of attitude towards the bank, is significantly present for the promoters and the detractors, but not for neutral customers. This result indicates that customers express their opinion more readily when they are either satisfied or dissatisfied.

The promoters mention topic 1, relating to the Internet site and mobile applications, significantly more than the other customers, which confirms the "key" role of this topic in the construction of satisfaction. At the same time, promoters mention theme 3, relating to the relational and human dimension, significantly less. This result confirms the significant influence of the topic on dissatisfaction. The relational and human aspect appears to be expected by customers, but as something taken for granted. Hence, it tends to be detractors who mention the theme, and their frequent mention of it indicates considerable unmet expectations in this domain.

Finally, neutral customers mention topic 6 significantly more often; it corresponds to the brick-and-mortar branches, and was classified as a "plus", as it is positively correlated with satisfaction. This result might indicate comments relating to recommendations rather than negative opinions.

5. Discussion

The main contribution of this study lies in its methodology, which demonstrates the value of using NLP analysis to identify the nature of the attributes that influence consumer satisfaction and to overcome the limits of traditional approaches to reveal key elements of satisfaction and the nature of their impact (Anderson & Mittal, 2000). The messages of customer voices and the topics identified can be classified following Llosa's (1997) tetraclass model, which enhances the effectiveness of the method for the identification and analysis of the attributes contributing to consumer satisfaction level.

The study also provides a theoretical contribution in that it complements studies that contrast specific (horizontal) satisfaction and relational (vertical) satisfaction (Oliver, 1997) by drawing attention to the significant differences in the number and types of topics mentioned depending upon whether customers are promoters, detractors, or neutral. This study promotes considering satisfaction from that perspective of promotion/detraction/neutrality, which shows that satisfaction is not vertical or horizontal but may involve a more or less significant combination of topics. In the case of the data examined in this study, the lower the satisfaction level, the higher the number of topics mentioned. The study also calls into question the traditional approaches used to measure satisfaction, which do not distinguish between the discursive characteristics of satisfied and dissatisfied customers.

The main advantages of NLP lie in the spontaneous and exhaustive character of the data collected and processed, whereas traditional methods presuppose having identified beforehand the determining attributes based on a representative sample. These methods cannot be necessarily associated with any operational processing of satisfaction and/or dissatisfaction mentioned by the respondents. This is particularly the case with the NPS, which is nevertheless used extensively by companies. When customers indicate they would not recommend their bank, they are often met with silence, which can be disastrous and can worsen even further their dissatisfaction level. In contrast, combining NPS and qualitative data processed at both individual and mass levels makes it possible to devise a customized response that can properly address customers' satisfaction issues. In addition, the processing rapidity and automation of this method prove crucial to deal with some situations of dissatisfaction.

Hence, this study calls for the development of artificial intelligence tools for the automation of qualitative data processing and the establishment of models of response to customers. The method used in this study has identified critical topics, which require extensive processing and a high-value-added human response, and differentiated them from secondary topics that may be dealt with more automatically. Artificial intelligence may thus help provide a response to all customers while making the best use of the valuable—human—time of operational teams, whom it will allow to focus upon the more sensitive cases.

Furthermore, working on data arising from a controlled collection can generate customer knowledge and expertise that may lead to more effective processing of any other qualitative mass-generated materials, such as comments found on social networks or the Internet more generally. At a time of increasingly globalized and omni-channel consumers, these methods prove to be highly promising for customer knowledge. They could also reduce the risk of rupture in the customer journey, enhance the customer experience, and increase the company's profitability.

- Adobe and eConsultancy. (2019). Tendances digitales 2019. <https://www.lmcp.fr/wp-content/uploads/2019/03/Rapport-adobe-2019.pdf>
- Anderson, E. W., & Sullivan, M.W. (1993). The antecedents and consequences of customer satisfaction for firms. *Marketing Science*, 12(2), 125–143.
- Anderson, E. W., & Mittal, V. (2000). Strengthening the satisfaction profit chain, *Journal of Service Research*, 3(2), 107-120.
- Anderson, R.E. (1973). Consumer dissatisfaction: The effects of disconfirmed expectancy on perceived product performance. *Journal of Marketing Research*, 10, 38-44.
- Ahrholdt D.C., Gudergan S.P., & Ringle C.M. (2019). Enhancing loyalty: When improving consumer satisfaction and delight matters. *Journal of Business Research*, 94, 18-27.
- Avery J., Steenburgh, T.J., Deighton J., & Caravella, M. (2012). Adding bricks to clicks: Predicting the pattern of cross-channel elasticities over time. *Journal of Marketing*, 76(3), 96-111.
- Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent Dirichlet Allocation. *Journal of Machine Learning Research*, 3, 993–1022.
- Bronner, F., & de Hoog, R. (2014). Social media and consumer choice. *International Journal of Market Research*, 56(1), 51-71. <https://doi.org/10.2501/IJMR-2013-053>.
- Campbell D.T., & Stanley J.C. (1966). *Experimental and Quasi Ex-perimental Designs for Research*. Rand McNally College Publishing Company.
- Collin-Lachaud, I., & Vanheems, R. (2016). Navigating between real and virtual spaces: An exploration of the hybrid shopping experience. *Recherche et Applications en Marketing*, 31(2), 43-61.
- Davenport, T. H., & Klahr, P. (1998). Managing customer support knowledge. *California Management Review*, 40(3), 195–208.
- Finn, A. (2012). Customer delight: Distinct construct or zone of nonlinear response to customer satisfaction? *Journal of Service Research*, 15(1), 99–110.
- Fornell, C. (1992). A national customer satisfaction barometer: The Swedish experience. *Journal of Marketing*, 56(1), 6–21.
- Grant, R., Clarke, R.J., & Kyriakis, E. (2013). Modelling real-time online information needs: A new research approach for complex consumer behaviour. *Journal of Marketing Management*, 29(7-8), 950-972.

- Grewal, D., Roggeveen, A., & Runyan, R.C. (2013). Retailing in a connected world. *Journal of Marketing Management*, 29(3-4), 263-270.
- Ho, T.H., Park, Y.H., & Zhou, Y.P. (2006). Incorporating satisfaction into customer value analysis: Optimal investment in lifetime value. *Marketing Science*, 25(3), 260-277.
- Hogan, J. E., Lehmann, D. R., Merino, M., Srivastava, R. K., Thomas, J. S., & Verhoef, P. C. (2002). Linking customer assets to financial performance. *Journal of Service Research*, 5(1), 26-38.
- Hosany, S., & Prayag, G. (2013). Patterns of tourists' emotional responses, satisfaction and intention to recommend. *Journal of Business Research*, 66(6), 730-737.
- Hubbert, A.R., Garcia Sehorn, A. & Brown, S.W. (1995) Service expectations: The consumer versus the provider. *International Journal of Service Industry Management*, 6(1), 6-21.
- Keiningham, T. L., Cooil, B., Andreassen, T. W., & Aksoy, L. (2007). A longitudinal examination of net promoter and firm revenue growth. *Journal of Marketing*, 71(3), 39-51.
- Klaus, P., & Maklan, S. (2013). Towards a better measure of customer experience. *International Journal of Market Research*, 55(2), 227-246.
- Kumar, V., Pozza, I. D., & Ganesh, J. (2013). Revisiting the satisfaction-loyalty relationship: Empirical generalizations and directions for future research. *Journal of Retailing*, 89(3), 246-262.
- Kuppelwieser, V. G., & Sarstedt, M. (2014). Exploring the influence of customers' time horizon perspectives on the satisfaction-loyalty link. *Journal of Business Research*, 67(12), 2620-2627.
- Lee, J. J., Capella, M. L., Taylor, C. R., Luo, M., & Gabler, C. B. (2014). The financial impact of loyalty programs in the hotel industry: A social exchange theory perspective. *Journal of Business Research*, 67(10), 2139-2146.
- Leeflang, P.S.H., Spring, P.N., Van Doorn, J., & Wansbeek, T. (2013). Identifying the direct mail-prone consumer. *Journal of Global Scholars of Marketing Science*, 23(2), 175-95. <https://doi.org/10.1080/21639159.2012.760923>.
- Lemon, K.N., & Verhoef, P.C. (2016). Understanding customer experience throughout the customer journey. *Journal of Marketing*, 80(6), 69-96.
- Libai, B., Bolton, R.N., Bügel, M.S., de Ruyter, K. (2010). Customer-to-customer interactions: Broadening the scope of word of mouth research. *Journal of Service Research*, 13(3), 267-282.

- Lloso S. (1997), L'analyse de la contribution des éléments de service à la satisfaction : Un modèle tétraclasse, *Décisions Marketing*, 10, 81-88.
- Maxham, J.G. III, & Netemeyer, R.G. (2002). A longitudinal study of complaining customers' evaluations of multiple service failures and recovery efforts. *Journal of Marketing*, 66, 4, 57-71.
- Meyer, C. & Schwager, A. (2007). Understanding customer experience. *Harvard Business Review*, 85(2), 117–26.
- Oliver, R.L. (1997), *Satisfaction: On a behavioral perspective on the consumer*. New-York: McGraw-Hill.
- Pine, B.J. II, & Gilmore, J.H. (1998). *The experience economy: Work is theater and every business a stage*. Cambridge, MA: Harvard Business School Press.
- Reichheld, F.F. (2003). The one number you need to growth. *Harvard Business Review*, 81, 46-54.
- Schmitt, B.H. (1999). *Experiential marketing*. New York: The Free Press.
- Schmitt, B.H., Brakus, J. J, & Zarantonello L. (2015). From experiential psychology to consumer experience. *Journal of Consumer Psychology*, 25, 166–171.
- Shankar, V., Smith, A.K., & Rangaswamy, A. (2003) Customer satisfaction and loyalty in online and offline environments. *International Journal of Research in Marketing*, 20, 2, 153–175.
- Sievert, C., Shirley, K.E. (2014). LDAvis: A method for visualizing and interpreting topics. ACL Workshop on Interactive Language Learning, Visualization, and Interfaces, 2014.
- Verhoef, P.C., Neslin, S.A., & Vroomen, B. (2007). Multi-channel customer management: Understanding the research-shopper phenomenon. *International Journal of Research in Marketing*, 24(2), 129-148.
- Verhoef, P.C., Lemon, K., Parasuraman, A., Roggeveen, A., Tsiros, M., & Schlesinger, L. (2009). Customer experience creation: Determinants, dynamics and management strategies. *Journal of Retailing*, 85, 1, 31–41.
- Verhoef, P.C., Kannan, P.K. & Inman, J.J. (2015). From multi-channel retailing to omni-channel retailing: Introduction to the special issue on multi-channel retailing. *Journal of Retailing*, 9(2), 174–181.
- Verhoef, P. C., Stephen, A.T., Kannan, P.K., Luo, X., Abhishek, V., Andrews, M., . . . Zhang, Y. (2017). Consumer connectivity in a complex, technology-enabled, and mobile-oriented world with smart products. *Journal of Interactive Marketing*, 40, 1-8. <https://doi.org/10.1016/j.intmar.2017.06.001>.

Wu, C.-W. (2016). Destination loyalty modeling of the global tourism. *Journal of Business Research*, 69(6), 2213–2219.

Yoo, J., & Park, M. (2016). The effects of e-mass customization on consumer perceived value, satisfaction, and loyalty toward luxury brands. *Journal of Business Research*, 69(12), 5775–5784.

Fig. 1. Representation of a textual corpus using the bag- of-words method.

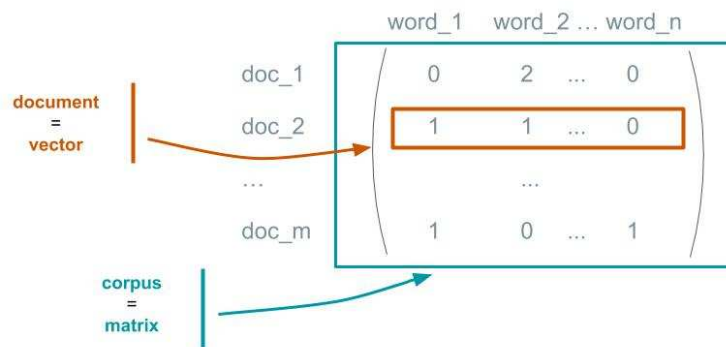


Fig. 2. Example of matrix items/documents from a corpus of customer comments

	extreme	satisfy	excel	service	time	response	too	long
doc_1	1	1	0	0	0	0	0	0
doc_2	1	0	1	1	0	0	0	0
doc_3	0	0	0	0	1	1	1	1

Table 1

Illustration of the different pre-processing steps for a text corpus.

Step	Example
1 - Acquiring customer comments	<i>Fast and useful answers given to customers' requests, advisors who know their products very well, particularly the different types of bank cards</i>
2 - Segmenting (tokenization)	<i>fast - and - useful - answers - given - to - customers - requests - advisors - who - know - their - products - very - well - particularly - the - different - types - of - bankcards</i>
3 - Removing stop words	<i>fast - useful - answers - given - customers - requests - advisors - know - products - well - particularly - different - types - bank cards</i>
4 - Stemming	<i>fast - use - answer - give - customer - request - advisor - know - product - well - particular - different - type - bank card</i>

Table 2

Ratio of promoter and detractor customers depending upon the verbatim statements entered.

Free verbatim statements	Ratio of promoter customers	Ratio of detractor customers
Verbatim statement not entered	25.1%	35.8%
Verbatim statement entered	27.6%	45.0%
Equality of proportions test (p-value)	0.109	<.00001

Table 3

Topics emerging from LDA modeling.

Topics		Frequent words ($\lambda=1$)	Frequent words in this topic only ($\lambda=0$)
1	Internet site and mobile applications	account, site, Internet, management, products, facilitate, mobile, propose	product, mobile, simplicity, transparency, informative, experience, service, tool, web
2	Day-to-day operations of the accounts and contracts	account, brand name, request, month, customer, card, fees, service, change, transfer	euros, closing, payment, salary, authorization, transfer, debit, opposition, incident
3	The relational and human dimension	customer, listening, advisor, reception, responsiveness, reactivity, availability, rapidity, solution, staff	listening, availability, rapidity, efficiency, access, friendly, efficient
4	Means of communication	consulting response, request email, telephone, contact, answer, quick	response, email, contact, answer, send impossibility, email, interview, urgent
5	Attitude towards the institution	brand name, bank, branch, consulting customer, recommend, problem	recommend, satisfied, dissatisfied, work, director, today, replace
6	The brick-and-mortar branch	branch, reception, opening hours, person, opening, midday, counter	opening hours, midday, counter, morning, hour, machine, Saturday
7	Mortgages	loan, real estate, rate, credit, request, project, file, manager, agreement	loan, real estate, manager, renegotiation, reduce, redemption, excessive
8	Pricing policy	tariff, high, expensive, reduction, cost, diminish, exorbitant, price	fees, tariff, too much, banking, high, expensive, less, management, reduction, more, card

Table 4

Link between topics and customer satisfaction.

Topic		Detractor customers		Promoter customers		NPS
		Rate	Significance	Rate	Significance	
1	Internet site and mobile applications	22%	0.001	58%	<0.00001	36
2	Day-to-day operations of the accounts and contracts	49%	0.219	19%	0.069	-29
3	The relational and human dimension	49%	0.014	25%	0.153	-24
4	Means of communication	42%	0.472	41%	0.001	-1
5	Attitude towards the institution	46%	0.490	26%	0.503	-20
6	The brick-and-mortar branch	43%	0.509	19%	0.041	-23
7	Mortgages	30%	0.008	46%	<0.00001	16
8	Pricing policy	44%	0.741	22%	0.180	-22

Table 5

Average number of topics and NPS.

Customer typology		Score	Average number of topics per comment			
Detractors	Detractors 0 to 2	0	2.392	2.352	2.314	2.197
		1	2.218			
		2	2.360			
	Detractors 3 to 6	3	2.375	2.287		
		4	2.322			
		5	2.254			
Neutral	Neutral	6	2.240	2.135	2.135	
		7	2.190			
		8	2.094			
Promoters	Promoters	9	2.070	2.067	2.067	
		10	2.064			

Table 6

Average number of topics in relation to the NPS: results of one-sided Student's t-test*.

	P-value
Comparison neutral / promoters	0.0139
Comparison detractors / neutral	<0.0001
Comparison detractors (NPS: 0–2) / detractors (NPS: 3–6)	0.0213

*For each type of population (N=1 to 3):

H0: average number of topics (population 1) ≤ average number of topic (population 2)

H1: average number of topics (population 1) > average number of topic (population 2)

Table 7

Proportion of topics in relation to the NPS: Results of one-sided Student's t-test**.

	Topic							
	1		2		3		4	
	Rate	P-value	Rate	P-value	Rate	P-value	Rate	P-value
NPS								
Promoters	7.46%	< .00001	5.49%	0.2846	36.83%	0.0069	7.62%	0.1645
Neutral	2.52%	0.6455	9.12%	0.4715	39.68%	0.3735	3.06%	0.3898
Detractors	1.73%	0.2983	8.42%	0.6312	44.45%	0.0009	4.80%	0.8181
	Topic							
	5		6		7		8	
	Rate	P-value	Rate	P-value	Rate	P-value	Rate	P-value
NPS								
Promoters	62.74%	0.0257	6.98%	0.1676	6.50%	0.1585	7.57%	0.3843
Neutral	64.50%	0.4654	13.73%	0.0316	3.32%	0.7872	11.37%	0.2543
Detractors	67.46%	0.0074	9.43%	0.6965	2.61%	0.3898	9.17%	0.9045

** For each population (N=1 to 3) and each topic (T=1 to 8):

H0: proportion of topic (topic T) (population N) ≤ proportion of topic (topic T) (population N)

H1: proportion of topic (topic T) (population N) > proportion of topic (topic T) (population N)