# Twitter as a Data mine: Can user needs be derived from Twitter Data? - An example of Airbnb

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**ABSTRACT,**
***Over the past years, recognizing user needs and improving the overall customer experience has been an essential part of Innovation for companies to incorporate. Despite the significant amount of manual labor and cost associated with commonly used customer need analyses, many businesses continue to employ them. Current literature found that Twitter can be an alternative data source for discovering customer needs and ideas. This study examines the feasibility of identifying customer needs and ideas by analyzing tweets on the Airbnb support account. This research builds on Kuehl et al.´s (2016) research by adapting the approach to Airbnb. 10,000 twitter messages were gathered from the social media platform Twitter which were manually evaluated. The identified needs were divided into separate categories. Following the analysis of the machine learning method, BERT. These findings suggest that it is feasible to identify user needs by analyzing Tweets. Nevertheless, it is advised that more studies will be done on this topic, with further preparation of the dataset.***

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Social media analysis, customer needs analysis, data-driven development, data mining, BERT, machine learning

# 1. INTRODUCTION

## 1.1 Problem statement

In the online consumer market, users can take a very active role in improving products or developing addons. Customer needs are important considerations for organizations in a fast-changing environment to ensure customer loyalty. Customer involvement is a significant predictor of passive and active customer behavioral engagement, both of which consequently influence customer loyalty (Izogo, 2021). Customer engagement on social media can show customer needs. Customer engagement can be suggestions and ideas from users that can lead to the implementation of new software, apps, general idea generation, or valuable innovations for an organization. Therefore, user needs are invaluable for product innovation and crucial for organizations to find them.

Identifying consumer needs can be a source of inspiration for innovation management. Many research methods are being used to find sources to determine customer needs; many consist of costly interviews and surveys (Fisher et al., 2014), and such market research can be very time-consuming (Hauser and Griffin, 1993). Many customers/users post about their experiences on social media, including user needs and ideas. With the rise of the social media market and big data analysis, researchers began to focus on social media platforms like Facebook, Instagram, and Twitter to find customer needs through data mining as the approach is more efficient and accurate than the traditional methods (Kuehl et al., 2020). It is challenging to identify active users and their solutions through data mining. Even though users identify and share their needs on social media, it is exceedingly difficult to identify relevant messages out of millions of messages posted on social media daily; it is needed to overcome the quality of big data.

Twitter is a popular social media and news platform that allows people to socially network online, aiming to stay connected with friends, family, or peers. Twitter users can share their thoughts and feelings with a large audience. The communication is done in short messages called tweets that are public by default, but users can choose to protect their Tweets after signing up for Twitter. As of the second quarter of 2021, Twitter had 206 million monetizable daily active users worldwide (Statista, 2022), with around 500 million tweets posted daily (Duncombe, 2019). But Twitter is not so much a social network where the exchange of personal information is facilitated […]. Twitter has evolved into a pool of constantly updating information streams consisting of links, short status updates, and eyewitness news (Anger, 2011).

## 1.2 Research focus

This paper will focus on the approach to train machine learning algorithms to automatically identify user needs and ideas on Twitter based on the research approach from Niklas Kuehl (Kuehl et al., 2016). Niklas Kuehl's research focuses on the customer needs of e-mobility users who expressed their needs over Twitter. His research is limited to e-mobility users within Germany. This paper will focus on English-written Airbnb users' needs and their ideas. Airbnb is an online marketplace where people can offer their apartment or room as a short and midterm living solution for others, and Airbnb is a place where people are looking for a temporary stay.

## 1.3 Research question

This paper intends to answer the following research questions:

(i) Can customer needs and ideas be identified by analyzing Twitter messages on the example of Airbnb?

(ii) What percentage of Twitter messages contain relevant information and what percentage of relevant Twitter messages can be automatically detected by machine learning?

## 1.4 Academic & Practical Relevance

Through research on the example of Airbnb, the potential to improve customer needs using machine learning algorithms on Twitter will be explored. This research will look at how Twitter messages can be used as a need analysis for companies present on Twitter with an additional Twitter support account, such as Airbnbhelp. Moreover, this research will benefit and potentially improve the understanding of a specific customer group's behavior that tweets on Twitter. Additionally, it will intend to provide a new approach to simplify massive data set evaluation to find suitable user needs and ideas. In this regard, this study can potentially create a new understanding of customers' involvement and needs towards product innovation as well creating a new cheap alternative to old research methods that are time-intensive and costly. This paper aims to give new insights into big data analysis and the possibility of improving quality within big data sorting/collection.

# 2. THEORETICAL FRAMEWORK

This section will overview existing research and literature as a foundation for this research. It will provide background information on the current trends and developments of data-driven Innovation, Customer needs, and big data. Followed by introducing need mining and need analysis as an overarching topic for this research.

## 2.1 Data-driven innovation Management

Data-driven Innovation Management is essentially the management of change for big data-driven Innovation. Over the last years, we entered the "golden age" of digital Innovation (Fichman et al., 2014). Dodgson (2014) encloses that researchers have found that Innovation must be managed, considering it is an essential means by which organizations survive and thrive. Current studies highlight that leaders with the best data practices outperform competitors in every measure of Innovation (Splunk, 2021). However, digital technologies have such a broad impact that makes them a complex and hot topic that still needs further development from a research perspective (Rekonen and Björklund, 2016).

Innovation to improve a product or service is of particular importance considering the possibility for companies to increase competitiveness and productivity and gain new markets through data-driven innovation management (Dereli, 2015). Therefore, the potential of data-driven Innovation and management is immense and crucial, especially when using social media and data mining tools to generate customer requirements and ideas. As a result of data-driven Innovation, customer needs can be identified and analyzed. Additionally, utilizing data-driven Innovation is necessary because companies can no longer base their alterations only on their assumptions. A study by Casillas (2013) investigated the connection between digital Innovation and the innovation process in the way that the term digital Innovation refers to the innovation process that relies on digital technologies to offer new products, services, or processes (e.g., Martínez-López and Casillas, 2013; Nambisan et al., 2017). OECD (2015) emphasizes that data-driven Innovation aims to significantly improve existing or the development of new products, processes, organizational methods, and markets emerging rather than a complete change. Because of the significance of Innovation, it is essential to scan the external environment to find necessary alterations based on a data-driven innovation analysis of the external environment. Nevertheless,

many companies are still struggling to systematically produce bold, innovative solutions for customer challenges, making data-driven Innovation an essential topic for businesses.

## 2.2 Big data and smart data

Big data is an overall present topic when it comes to acquiring data online. Nowadays, a Decision is a matter of information, knowledge, and timing (Iafrate, 2015). Garcia-Gil (2019) has defined big data as a vast amount of information that is mostly a by-product produced by the primary service offered (Trabucchi, 2019). Big data can enable machine learning algorithms to achieve better and more accurate models than ever (Garcia-Gil, 2019). Generally, big data has three characteristics: Volume, Velocity, and Variety. The three characteristics represent data's quantity, speed, and storage (Laney, 2001). Big data has increasingly gained more attention since it is now a critical organizational asset representing a strategic basis for business competition (Morabito, 2015). Therefore, big data represents one of the most relevant emerging topics over the last years because the already existing big data can be exploited to enhance innovation processes (Trabucchi, 2019). These massive amounts of data offer excellent opportunities to obtain benefits and create values, for example, in terms of new products or making faster and better decisions (Del Vecchio, 2018).

Nonetheless, there is a lack of research on big data in the context of Twitter as a dataset. The concept of big data moved from a purely technological debate to a managerial one, seeing the chance to create value through transforming such data assets as a key challenge (De Mauro et al., 2016). To generate a value of such data assets, the dataset needs to be sorted and analyzed to become functional (Tole, 2013). The challenge here is that the huge amount of data is not always one hundred percent useful; the time spent sorting and cleaning up data is greater than analyzing the data afterward (Tole, 2013).

The concept of smart data arose after the challenges and quality of big data became more visible (Triguero, 2018). Triguero (2018) displays big data as unreliable, not scalable, and slow, whereas he sees the opportunity of smart data as more effective, robust, and scalable for knowledge extractions. Smart data aims to separate the big part of the data (volume/velocity); smart data is focused on extracting valuable knowledge from data, in the form of a subset, that contains enough quality for a successful data mining process (Garcia-Gil, 2019). Moreover, smart data can allow a broader view and understanding of customers' needs and demands.

## 2.3 Potential of Twitter as data source

In today's information-rich environment with fast-changing trends, social media plays a more vital role than ever. Social media opens new opportunities to exploit external knowledge and leverage those as a competitive advantage (Berschek, 2017). While most research focuses on social media as a marketing tool, some research focuses on utilizing social media as a data source for customer needs analysis. Fischer and Reuber (2011) analyzed the interactions on social media, specifically how interactions on Twitter affect effectual thinking and behavior. The research suggests that using Twitter can provide valuable information to customers, simplify listening to customers, and respond to customer queries or complaints (Fischer, 2011). Aral et al. (2013) argue that social media transforms firm boundaries and thereby creates a new way of interacting with customers. Social media can therefore explore the opportunity to find and analyze customers' requirements for products or services. Berschek et al. (2017) focus on user feedback on Facebook as a source of innovative ideas. The research is limited to smaller and medium enterprises in Germany.

Nonetheless, the study shows that social media can take an active role in firms' product and service innovation; the results suggest a significant positive relationship between using social media feedback and introducing a product or service innovation. In the initial stages of generating data from social media, strong skills in market research and data analysis are needed to effectively communicate to diverse types of potential customers in later stages (Roberts, 2016). Furthermore, the research of Roberts (2016) states that social media has the potential to obtain information about not only their products but also from competitors by analyzing feedback in the initial stages at a lower cost than traditional time- and money-consuming methods. Roberts (2016) elaborates on developing a well-structured strategy to ensure the suitable Customer needs and the company's needs to avoid pitfalls.

Niklas Kuehl (Kuehl et al., 2016) has done detailed research on using Twitter as a data source for customer needs analysis. He recognized the potential of Twitter in the massive amounts of tweets that are created every day. Kuehl (2019) used supervised machine learning on Tweets concerning the e-mobility domain and showed research results that using machine learning is feasible in automatically quantifying customer needs from a predefined set, this suggests that manual need identification could be replaced by supervised machine learning that identifies customer needs faster and reliably (Kuehl, 2019).

## 2.4 Customer needs

Customer needs have been essential in marketing and the innovation process. Customers' expectations are drastically rising, making it challenging to launch a new product in crowded markets (Roberts, 2016). According to Kuehl (2019), the need to recognize and understand customer requirements is one of the most critical challenges. Kuehl et al. (2016) summarize customer needs as needs, wants, and demands. However, expectations and needs toward a product from a customer perspective are unique and can differ from situational circumstances to every human being (Schwarnbacher et al., 2010). Considering these needs, researchers have become increasingly interested in deriving the needs through social media. Dunphy and Herbig (1995) theorize that if customer needs can be fulfilled successfully, the acceptance of the related product or service will increase on the market. Taking customer needs into account during the innovation process can generate new insights and ideas for product or service innovation. Nevertheless, if those needs are misinterpreted, companies can face difficulties such as losses in R&D investments and too small product sales numbers (Bayus, 2008).

## 2.5 Need analysis & need mining

A need analysis can be briefly explained as the involved process that leads to the identification and evaluation of needs, wants, and demands. As mentioned above in the Customer needs subsection, it became clear across multiple studies that customer needs are essential for a business to consider. Therefore, Customer needs analyses were introduced and are widely recognized.

Needmining is considered the next step in change for developing new services because it allows to screen huge groups automatically and continuously for needs and to include latent needs in the future (Kuehl, 2016). Furthermore, need mining is used as analytical support for automatically detecting customer needs from micro-blog data using Twitter (Kuehl, 2016). Through Kuehl's extensive research, a five-step approach to identifying customer needs through Twitter has been established. The research design will be based on these five steps and will be further explained in the Methodology section.

# 3. METHODOLOGY

This section will go over the steps in the research process for gathering, preparing, and processing Twitter data. The qualitative research requires the analysis and coding of Twitter messages, so-called Tweets. The data source, Twitter, will be used because of the rich data set created by the millions of Tweets every day. Additionally, Twitter data is available publicly without legal restrictions in place. The data will be retrieved free of charge for universities from API. However, retrieving Twitter from API costs for companies. The primary language of the Tweets is English and will be pre-processed in the statistical software program Python. After the data preparation, the machine learning algorithm will be applied to the pre-processed dataset. The scope of the research will be 10.000 Tweets consisting of 5.000 Tweets for learning and another 5.000 for validation of the study. This research will focus on identifying customer needs and ideas for the online marketplace Airbnb. The structure of the research methodology model (see Fig. 1) can be found below.

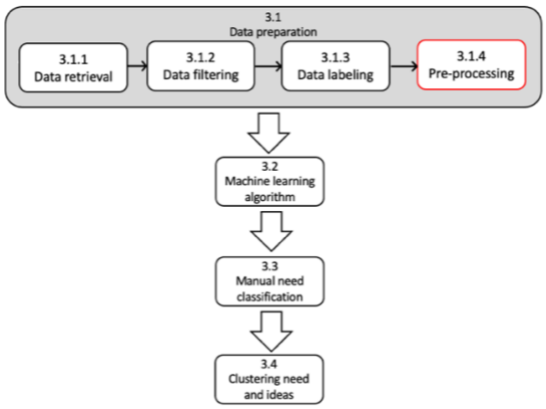


**Figure 1: Methods model based on Kuehl et al. 2016**

## 3.1 Data Preparation

Data preparation is the process of data retrieval, data filtering, data labeling, and pre-processing. The data preparation process is needed to get a smaller dataset with more relevant information to improve the result of the later applied machine learning algorithm. While Kuehl et al. (2016) use a more elaborate approach of five steps, this data preparation process will consist of four steps based on the five steps method created by Kuehl et al. (2016). The first step of the data preparation method is to get the data using a publicly accessible source, which in this research will be through an API. Furthermore, the data will be filtered to exclude irrelevant Tweets for our research. Following, manual classification of Tweets to determine whether they contain a need. Lastly, a supervised machine learning algorithm will be developed and applied. The following section will go through each step in this process.

### *3.1.1 Data retrieval*

As previously mentioned, Twitter is a promising large data set to retrieve data that includes customers' needs. This data set, however, needs to be retrieved through a streaming API that allows the researcher to access real-time Twitter data. The data downloaded will contain all the tweets from external users to the Airbnb support Twitter account. The API allows the extraction of only English-written Tweets for the research, and the data will be processed after. The time frame of the prepared tweets is from 01/02/2021 until 31/01/2022 to retrieve newer tweets to identify. Customer needs more efficiently. The dataset created will now only contain data addressed to the Airbnb help Twitter account over the last year from an English-speaking audience. The dataset can now be used in further steps.

### *3.1.2 Data filtering*

The Data filtering step is there to reduce the amount of data in the retrieved dataset and achieve a higher percentage of tweets that contain a customer need. The API as a search function already filters in a way that retweets, which are republications of an existing tweet, are eliminated. The API excludes all Tweets that are not about Airbnb and any tweets written in another language other than English. Proceeding with this research, all tweets below 50 characters will be eliminated as they are too short in an empirical observation to identify customer needs. Additionally, all tweets promoting an URL are removed from the dataset, as they overall do not offer information concerning customer needs. Furthermore, a stop word list will be used to discard all tweets likely to contain spam or promotions. The keyword filter includes the words “sale,” “deal,” “win,” “Vbro,” and “refund.” Further duplicated tweets will be eliminated as they do not offer additional information about the Customer’s needs. The data filtering guidelines might be adjusted depending on the amount and quality of data; the stricter the filtering is applied, the more the risk increases of losing information about the desired customer needs (see Fig. 2).

### *3.1.3 Data labeling*

After the data filtering, a training set of 10.000 tweets will be randomly selected from the residual 32.660 tweets. The remaining tweets must be categorized based on whether the Twitter message contains a consumer need or not to construct a supervised learning model. In this method section, a one “1” will determine that the tweet does contain a need, and a zero “0” means that the tweet does not contain a need. Therefore, each tweet will be manually scanned for a customer’s need, and the corresponding number will be assigned to the tweet. The manual labeling of tweets has limitations as some needs might not be as straightforward, and a need is only indirectly addressed. Due to the restricted number of researchers, some indirectly addressed needs cannot be identified and will be labeled with a 0 and therefore be distinct as a tweet excluding a customer need. After labeling all 10.000 tweets, 831 tweets have been identified as containing a need, whereas 9.169 tweets have been identified as not containing a tweet (see Fig. 2)

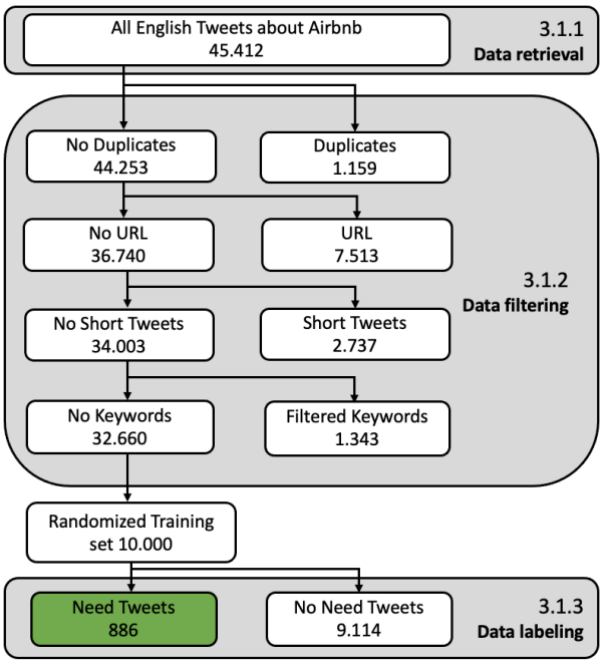


**Figure 2. The corresponding number of tweets in each individual step of the data preparation**

### 3.1.4 *Data pre-processing*

Kuehl et al. (2016) use the pre-processing step to prepare the data for the machine learning algorithm. However, this research uses the more advanced BERT machine learning method, which is a natural language encoder, and therefore no pre-processing is needed.

## 3.2 Machine learning

For the machine learning algorithm, the data set of 10.000 tweets will be split, and 5.000 Tweets will be used as the learning set, whereas the other 5.000 Tweets will be used as a validation dataset. The BERT language model will be used as the machine learning algorithm. The BERT (Bidirectional Encoder Representations from Transformers) It encodes representations from transformers bidirectionally. The model learns to detect the context of the word by looking at the words around it. The algorithm will learn from the first dataset and then apply what it has learned to the second dataset to select tweets. The model randomized the sequence of the 10,000 tweets to prevent the machine from putting disproportionately learning attention on tweets about subjects that occurred disproportioned during the first dataset compared to the second.

Based on the training dataset, the algorithm begins to assign each tweet a probability of containing a need. The BERT model precedes by labeling the tweets with a one "1", containing a need if the probability of containing a need is higher than 50%. If the probability is lower than 50%, the tweet will be labeled with a zero "0". According to the algorithm, a zero indicates that the tweet does not contain a need. The labeling is the same as the manual labeling done in section 3.1.3, Data labeling.

Ultimately, the BERT model will evaluate the data using four performance metrics: accuracy, precision, recall, and the F-score.

## 3.3 Manuel need classification

In this step of the research design, all needs and ideas will be manually classified into separate need categories according to the content of the need. Tweets that contain an innovative idea will get a particular category, which will then be further divided into subcategories.

The categories of customer needs and Innovation will be limited to better overview the needs and innovative ideas.

The categorization is intended to see if customers have similar needs or ideas for the Airbnb platform's Innovation. Following the categorization of Customer wants and ideas, the data set's most frequently expressed needs and ideas will be determined.

## 3.4 Categorizing Twitter users' needs and ideas

After classifying needs and ideas, the final step of the research design will be to make a differentiation between them. Each idea tweet is then double-checked, and categories are further based on the idea Tweets genre.

# 4. RESULTS

This section will elaborate on and summarize all the key findings from the conducted qualitative research. This chapter will focus on the 831 Tweets that were manually labeled with a "1" and have been identified as containing a need. These need tweets will be summarized, and the machine learning algorithm's outcome will be elaborated.

## 4.1 Identified User needs

Based on the 10.000 Tweets manually assessed this section will discuss the first research question:

Can customer needs and ideas be identified by analyzing Twitter messages on the example of Airbnb?

The total number of users' needs and ideas identified is 831 Tweets. Those need tweets were grouped into five categories. These categories can be found below in Figure 3, with the corresponding number of Tweets relating to that category. Furthermore, the categories will be described, and one example Tweet will be given for each category.

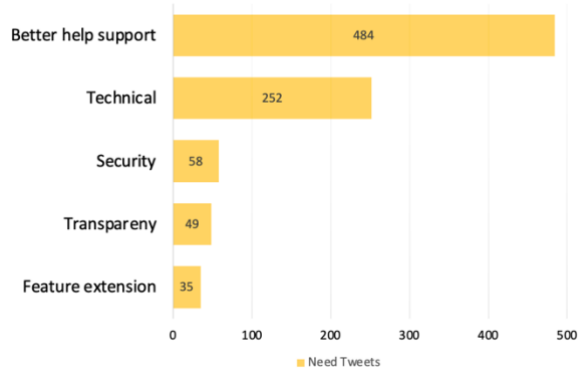


**Figure 3 Need Tweet Cluster**

### 4.1.1 *Help support – 484 Tweets*

The first category contains the most mentioned need as being better to help support. Here users expressed their difficulties with the help support; help support not speaking English; not solving their issues; not taking them seriously.

Example Tweet:

*"@Airbnb_uk @Airbnb @AirbnbHelp I have been trying to resolve an issue for weeks. For four days in a row, a manager has meant to have called me. Guess what? No calls! This is unacceptable #poorservice"*

### 4.1.2 *Technical – 252 Tweets*

The technical category summarizes all user needs concerning app features not working, e.g., the password or the password reset option. Many issues occurred with users having a change in a phone number or email; these users were unable to use the password reset option to update their contact details. Users also have the reoccurring issue of deleting their accounts or duplicated ones. Users experienced unreliable gift cards or had reoccurring issues with the Airbnb website.

Example Tweet:

*"@AirbnbHelp my password isn't working and it's asking me to contact support, but then it's saying I have to login to speak with support which obvs I cant"*

### 4.1.3 *Security & Safety – 58 Tweets*

Another need category for users is the safety and security of their stays. Safety has changed over the last years with Covid. Many users are concerned over their safety during the pandemic, e.g., Hosts want an option only to let people stay in their rental unit/s if they have negative covid tests or put in their requirements that guests have to be vaccinated. Hosts also mentioned the ID checks and criminal record disclosures. In comparison, guests request smoke detectors and camera disclosures as a requirement. Additionally, users want a better vetting process of properties and hosts as they have experienced issues before, and their security has been threatened.

Example Tweet:

*"@AirbnbHelp Hi. My guests no longer need to have ID to book? When did this change and can I add it back? The*

*following is from your site. We strongly encourage profile photos as well? some Hosts may require it, along with ID verification."*

### 4.1.4 Transparency – 49 Tweets

An additional need that user mentioned is more transparency over their accounts. They want more clarification on why their accounts have been suspended or why there were sudden host cancellations.

Example Tweet:

*"@Airbnb @AirbnbHelp You canceled our reservation with no warning and for no reason. You continue to ignore our request for answers."*

### 4.1.5 Feature extension – 35 Tweets

This category can also be seen as the category for users' innovation ideas. This category summarizes any ideas of new features that Airbnb should include in their app and website, e.g., crypto payment, preferred name option, and new filter option.

Example Tweet:

*"@Airbnb @AirbnbHelp when will you allow hosts to accept crypto as payment? Waiting patiently."*

With 484 needs, the customer support category was the most prominent, indicating some issues with customer support. Furthermore, the 272 tweets in the technical category signal that the functionality of the website and app may be compromised, and user experience is affected. The two categories concerning safety & security and account transparency pose a threat to the users' satisfaction with the usage of Airbnb as a service provider.

As a result of the research and the given data, the first research question can be affirmed. Assessing Tweets on the Airbnb support account can be used to discover users' needs and ideas since in the data set of 10.000 tweets, 831 tweets feature a user's need and idea. Roughly 8,31% of the whole randomized dataset contained a user need. It is also feasible to group these needs and ideas into clusters to better understand the needs raised by users.

## 4.2 Identified user ideas

A new cluster of categories was identified to further elaborate on user ideas, as it is a diverse and relevant category for further improvements of the Airbnb website. Many categories have one Tweet but are still worth mentioning but will not be further elaborated on. Each category will contain an example tweet of the user's ideas.

The tweets were again clustered into categories to provide a more transparent overview, as shown in Figure 4.

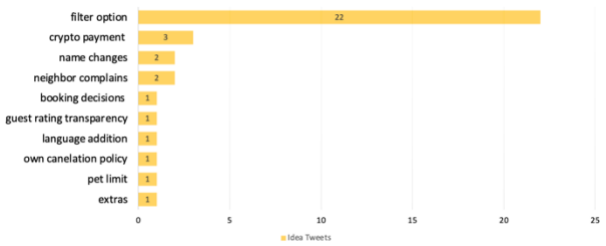


**Figure 4. Idea Tweet Cluster**

### 4.2.1 New filter option – 22 Tweets

In this category, users request to add filter options in the search bar to find an accommodation that best fits their needs. It mentioned filtering for pet-friendly accommodation and the option to search for accommodation with a bathtub or shower.

Example Tweet:

*"@SusannaLuck @Airbnb @AirbnbHelp This is actually a valid NEED. It's an accessibility thing. A tubs presence (or not) can be the difference between the ability to access a normal quality of life for many. Some can't shower and require a tub. Others need a shower and no tub. So, ur right. This should be noted. ?"*

### 4.2.2 Crypto payment – 3 Tweets

In the second category of user ideas, users request guests to be able to pay for their accommodation with different kinds of cryptocurrency, which is a relatively new payment method.

Example Tweet:

*"I am an @Airbnb host @bchesky. I would like my guests to pay in #Bitcoin ? or better yet, $DCR #DecredPlease consider this, @bchesky. Thank you!@AirbnbHelp"*

### 4.2.3 Display name – 2 Tweets

In this category, users are missing the option to display their name other than their given name. They would like Airbnb to be more inclusive and that Transgender can let go of their name before transitioning.

Example Tweet:

*"@Airbnb @AirbnbHelp Why can't we have a preferred display name on your platform on our user profile and when contacting hosts?As a trans person it sucks seeing my deadname in big bold type, and leads to hosts also deadnaming me in messages."*

### 4.2.4 Neighbor complains – 2 Tweets

Neighbors of Airbnbs´ are missing the function to report concerning and distressing behavior of the Airbnb guests.

Example Tweet:

*"@AirbnbHelp Owners of an air bnb can complain about guests and the guest can complain about the air bnb? but where can neighbors complain about an air bnb/air bnb guests??? ???"*

### 4.2.5 Booking decisions – 1 Tweet

Example Tweet:

*"@bchesky @airbnb @AirbnbHelp - HUGE Feature for us hosts would be to be able to keep the auto booking feature turned on, but allow us to make per case decisions on local bookings (you guys already warn of us potential issue local guests which we appreciate!)"*

### 4.2.6 Guest rating transparency – 1 Tweet

Example Tweet:

*"@AirbnbHelp Why no transparency for guests to see their ratings?"*

### 4.2.7 Language addition – 1 Tweet

Example Tweet:

*"@AirbnbHelp We love to use Airbnb. But when will hosts have the option to add "Catalan" at the list of languages they speak? It would help a lot for Catalan speakers (+10 millions). Thanks"*

### 4.2.8 Own cancelation policy – 1 Tweet

Example Tweet:

*"@Airbnb @AirbnbHelp Why can?t we set our own cancelation policy length? You provide lead time for booking, cancelation should be based on that. 23 days for my area, so firm at 30 is no good and mod at 7 is too little. 15 perfect, can hve 7 to decide, I still have 15 to rebook."*

### 4.2.9 Pet limit – 1 Tweet

Example Tweet:

*"@AirbnbHelp Sorry this isn?t what I asked - I say in my property description that one pet is allowed but as it stands, there seems to be no way to limit the number when people are booking?"*

### 4.2.10 Extras – 1 Tweet

Example Tweet:

*"@AirbnbHelp Thanks for replying! I was thinking of something more along the lines of a feature vs. a warning. Like, pay extra for extra baby proofing (baby gates, foam on sharp corners, chains on dangerous windows, etc.). I'd gladly sign on and I bet other parents with young kids would too!"*

The new filter option category was the most prominent category within the user idea field, with 22 Tweets. These tweets suggest that the users are missing some filter options in the search bar that would help them select their ideal stay and improve their overall user experience. Furthermore, the following categories are not addressed much, nevertheless contain useful ideas for Airbnb to incorporate, including the possibility to modify their name or display it differently. The absence of that option may seem discriminatory in the user's eye.

As a result of the given data, user ideas can be identified by labeling and categorizing Tweets.

## 4.3 AI Performance

This section will focus on the second research question:

What percentage of Twitter messages contain relevant information and what percentage of relevant Twitter messages can be automatically detected by machine learning?

After allowing the algorithm to learn from the training data containing 5.000 Tweets, the accuracy, precision, recall, and F-score were used to evaluate the outcomes after the algorithm was applied to the validation dataset.

This research focuses on evaluating user needs and ideas; therefore, the recall rate is an important factor. After running the algorithm, a higher recall rate is desired. A higher recall rate indicates that the algorithm did not miss articulated user needs in the tweets. In contrast, the precision rate indicates the overall performance of the machine learning algorithm. If the research does not evaluate the tweets after, the focus can be given more to the precision alone. However, this research will focus on the harmony between recall and precision since the number of tweets without a need outweigh the number of need tweets. An unbalanced approach between recall and precision would not be sufficient evidence since the possibility of true negatives is high.

Consequently, this metric alone cannot illustrate the algorithm's true accuracy. The f-score indicates how well the model performed overall, with a value of '1' indicating flawless performance and a value of '0' indicating a misaligned model. Thus, the F1 score will be the leading indicator.

After running the BERT method over the dataset and allowing it to learn from the learning dataset, the following outcome has been recorded (see Table 1).

**Table 1. BERT model outcome**

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 0.95 | 0.92 | 0.94 | 4576 |
| 1 | 0.37 | 0.48 | 0.42 | 424 |
| accuracy | | | 0.89 | 5000 |
| macro avg | 0.66 | 0.70 | 0.68 | 5000 |
| weighted avg | 0.90 | 0.89 | 0.89 | 5000 |

The accuracy shows how many tweets have been identified correctly. The algorithm shows in this research measurement of 0.89; therefore, 89 percent of the Tweets were correctly classified as either containing or not containing a need. The precision measures how much percent of the tweets predicted as a need Tweet by the algorithm were indeed a need Tweet. The precision for containing a need is lying at 0.37 means that around 37 percent of the need tweets were rightfully classified by the BERT method as containing a need. The recall indicates how many of the actual needs have been detected by the algorithm. The recall gives a value of 0.48, indicating that the BERT approach correctly detected 48 percent of the stated needs. Because of the uneven sample, the scores for Tweets that do not contain a need are high. For successfully recognizing no-need tweets, the precision is 95 percent, and the recall is 92 percent.

The F-score taken in this case will be the F1 score, which is the balanced F-score between the precision and recall. Therefore ß=1 (the harmonic means between precision and recall). The equation of the F-score can be found in Figure 5 below. The outcome of the F-score can be found in Table 1.

$$F_\beta = (1+\beta^2) * \frac{precision * recall}{(\beta^2 * precision) + recall}$$

**Figure 5. F-score formula**

The calculated F1 score was 0.42. As a result, the BERT method properly detected a need for 42 percent. Considering the research of Kuehl et al. (2016), who obtained a harmonic f1-score of 0.466, the BERT approach worked relatively well on the given dataset from Airbnb.

# 5. DISCUSSION

This research study was conducted to obtain an answer to the following two research questions:

(i) Can customer needs and ideas be identified by analyzing Twitter messages on the example of Airbnb?

(ii) What percentage of Twitter messages contain user needs and ideas and what percentage of Twitter messages that contain a user need or idea can be automatically detected by machine learning?

The variety of needs is notable after manually scanning and analyzing the randomized data set. The needs range - from minor additions to the user interface e.g., additional filter options - to major communication issues in case of emergencies that need improving. Customers' perspectives on which features should be incorporated in the future appear to be particularly relevant in the area of a better support system. Customer support system changes require considerable improvement and cannot be implemented quickly. However, feature extensions and user ideas can be implemented quickly and positively impact the customer experience of choosing the ideal Airbnb for their stay. Additionally, user inconveniences can be found by analyzing the needs as well. All technical tweets categories under technical and transparency are minor and major inconveniences for users lowering their experience and decreasing the likelihood of using Airbnb again.

This research shows that customers' pain points and user challenges can be found to a certain extent in the example of Airbnb. Therefore, using Twitter as a data source for a customer needs analysis can inform all internal teams about the customer's needs and ideas. The relationship and perception of the customers that tweet their needs can be identified. Therefore, companies can position their business better, while recognizing new or missed market opportunities. Besides, preferences over

the competition can be found as well. Considering that this approach is easy to set up and easy to incorporate into a business. It is also lesser time-consuming and costly than alternative approaches. Companies perchance profit from using Twitter as a data source by incorporating customer feedback. A positive experience is created for both the customer who suggested it and others who believe it is a great addition. As a result, users will appreciate the effort, and the company will create a positive experience that will ensure customer loyalty.

Focusing on the performance of the BERT method, the algorithm's accuracy of 0.95 appears promising, as the predicted approaches by Kuehl et al. (2016) achieve the highest performance of an accuracy of 0.85. Nevertheless, Kuehl et al. (2016) sampled the data set and therefore aim for more reliable results with a balanced data set compared to this outcome because only 8,31 percent of the tweets contain a need. Therefore, no balanced dataset is available, concluding that the accuracy is not a reliable indicator of the models' performance. Thus, the focus lies on precision and recall, as mentioned before. The precision of 0.37 and a recall of 0.48 are similar results that Kuehl et al. (2016) achieved. The derived f-score, on the other hand, considers both recall and precision and is a better measure of the algorithm's overall accuracy. The f-score, which is around 0.42, suggests an adequately trained classification.

With more research and more elaborate need mining methods, this customer needs analysis can achieve more efficiency and savings as it requires fewer resources. However, looking at the results, companies can profit from the research because the most time- and money-consuming aspects are the generation of the training dataset and the costs of downloading data from Twitter. Additionally, the algorithm shows promising results that can be improved with further training of the datasets. The more this method is utilized, the more reliable it will become. Furthermore, companies might use it for a variety of purposes, such as tracking patterns in user tweets.

After the creation of the training dataset, the BERT algorithm can automatically scan for new ideas every day, if the training data is advanced, the costs are minimal and needs and ideas can be found with the press of a button. Which makes it a viable method for companies.

Considering all findings from the result section, it became visible that this study can demonstrate how Twitter can be used to identify user needs and ideas for Airbnb. Moreover, it is feasible to categorize these user needs and ideas to gain an overview of existing user demands. Additionally, new innovative ideas can be acquired through the data analysis of tweets. Therefore, as a result of this research paper, the first research question, if customer needs and ideas can be identified by analyzing Twitter messages on the example of Airbnb can be affirmed. Following the second part of the research, this research shows that using the BERT machine learning algorithm has shown reliable results. Roughly 8,31percent of the dataset used contained a user need, whereas the BERT method identified 42 percent correctly. Natural language processing methods make Twitter a promising source of need and idea suggestions that can be utilized without requiring substantial technical knowledge. However, because of the data pre-processing, it still relies on human interaction and a proper training dataset.

Many companies nowadays are on Twitter and have a support account for users to share their experience with a product or service. Other online booking platforms in the same industry as Airbnb are likely to have a comparable audience and are likely to have a digital affinity. There is no evidence that this research method is not applicable to the same industry because users have very similar demands in that domain and are likely to post their experiences and needs on Twitter as well.

Secondly, there is no proof that the research is not applicable to other domains where businesses run active Twitter help accounts. A dedicated Twitter account offers customer service and support and therefore, is used by users to share their experiences and post their demands and ideas, resulting in the possibility of extending the research method to other domains.

However, it is important for companies to own a Twitter support account to identify user needs and ideas because the main Twitter account of a company is more likely to get too many unrelated tweets and therefore the quality of the dataset will be compromised.

# 6. LIMITATIONS AND FURTHER RESEARCH

The study contributes to the existing research in the areas of customer needs. Furthermore, the study adds to Niklas Kuehls' approach of using machine learning in the context of Customer needs analysis on Twitter. Moreover, some noteworthy findings have been discovered, which might be used in future studies. However, there are certain limitations to be cautious of.

## 6.1 Limitations

One is that Twitter cannot be considered a random sample group when used as a data source. Twitter is a biased data source since it only reflects the individuals that use it. According to the Twitter demographics (Aslam, 2022), 70.4 percent of users are male, and just 29.6 percent are female; this leads to another limitation. The character constraint of 280 characters per tweet on Twitter, for example, limits the capacity to formulate user demands adequately and in detail. Furthermore, customers often write reviews, mainly when they are extremely satisfied or dissatisfied with a product or service. As a result, many of these reviews are included in the tweets. Those who are typically satisfied or do not desire to express their thoughts are excluded. The requirement to manually classify user needs and ideas is another restriction. While categorizing the tweets, one researcher may miss classifying a tweet after the researcher may not see a need that should be regarded. As a result, the researcher might have a dataset that includes false positives and negatives. This may lead to inaccurate performance results of the BERT machine learning algorithm.

The research's scope is also a further limitation. After the tweets have been classified, the algorithm can be sampled to improve its performance. According to Chawla (2005), classification algorithms work best with well-balanced data sets. As the present dataset contains fewer need-tweets than tweets without a need, the data must be sampled first. The original dataset must be divided into two datasets to sample the dataset, one of which will only contain needs and the other will not, as previously specified.

Furthermore, this study only analyses data from one year's worth of tweets and only English-written tweets, presenting notable limits in terms of time and data selection. To overcome this constraint, one could code all Airbnb-related data, which would take a longer period but still be faster than traditional approaches. However, this would go beyond the scope of this study. Thus, no additional sampling has been done.

## 6.2 Further Research

Recommendations for further research, this research can be extended by sampling the tweets as previously described to obtain a well-balanced data set and improve machine learning findings. Furthermore, the period from the introduction to the present could be extended to provide a broader alternative and

assess whether demand changes over time. Moreover, the algorithm could be extended and improved to automatically cluster tweets into need categories. Lastly, further research can be done outside of Airbnb. Other sectors, services, and products can be studied to further evaluate this customer analysis method.

## 7. CONCLUSION

To summarize the study's findings, using Twitter as a data source can be a valuable data source for consumer need analyses. Based on the results of this research paper and Niklas Kuehl's research it is possible to identify user demands using a machine learning algorithm. It also illustrates that the approach can be used in other research fields. However, more human interaction is required to adequately find user needs and ideas, but when integrated with machine learning, the technique can become a valuable tool for firms to use for consumer needs analysis.

Nevertheless, there are certain limitations, including the fact that Twitter user data does not represent a random sample and human interaction is still required to identify tweets as to whether they contain a need or not. However, if more research is completed in this sector, need mining may become a valuable tool in the future for determining company user needs, as it offers many advantages over traditional techniques of determining consumer wants.

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