Characterizing Transport Perception using Social Media: Differences in Mode and Gender

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ABSTRACT

Transport planners face the growing need to understand the behavior of their users, who base their mobility decisions on several factors, including travel time, quality of service, and security. However, transportation is usually designed with an average user in mind, without considering the needs of important groups, such as women. In this context, we analyzed 300K tweets about transportation in Santiago, Chile. We classified users into modes of transportation, and then we estimated the associations between mode of transportation, gender, and the categories of a psycho-linguistic lexicon. Our results include that women express more anger and sadness than expected, and are worried about sexual harassment. Conversely, men focus more on the spatial aspects of transportation, leisure, and work. Thus, our work provides evidence on which aspects of transportation are relevant in the daily experience, enabling the measurement of the travel experience using social media.

CCS CONCEPTS

• **Information systems** → **Web mining**; • **Applied computing** → Transportation;

KEYWORDS

sentiment analysis; twitter; gender differences; transportation

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1 INTRODUCTION

Transportation plays a key role in people's development in society, greatly affecting the quality of life [7, 32] of its users, who base their mobility decisions on factors such as cost, comfort, accessibility, punctuality, quality of service, and security [10]. For this reason, transport policy-makers face the growing need to understand their needs and perceptions to better plan and manage transportation networks and public policy. However, there is a gap between the perceptions of transportation administrators and those from users, since information is collected with an "average" user in mind, usually with little consideration of the needs and opinions of other important user groups, such as women [30].

In this paper, we characterized the perception of transportation through Twitter, taking into account differences in mode of transportation and gender. We hypothesized that, if different modes of transportation have their own specific issues, or if women experience any mode of transportation in a different way than men, then this should be reflected in a difference in the linguistic components of the texts they publish. We measured these linguistic components in a two-step process. First, we classified users and their transportation-related tweets into mode(s) of transportation using semi-supervised topic modeling [9, 20]. Then, we measured perception using a psycho-linguistic lexicon and gross-community perception metrics [25].

We applied our proposed method to 300K tweets published in Santiago, Chile. We found that public transport users use Twitter to interact with service providers, while reporting a higher association with sexual and swear words. Motorized transport discussion focuses on taxis and ride-hailing apps, and the state of the driving system, where users show to be sensitive to space usage. Non-motorized transportation discussion is centered around the leisure aspect of this mode [21], where users report more optimism. In terms of gender differences, we confirmed the differences in perception and focus. Women are more associated with sociability, sexual harassment, and positive words, pointing to an ambivalence between concerns and positive experiences. Conversely, men are more associated with the spatial aspect of transportation, work discussion, and swear words.

Our work contributes a methodology to infer mode of transportation usage from social media content, and a case study of measured differences between modes of transportation, with a gender perspective, using Twitter data from a big city. Our results provide evidence on which aspects of transportation are relevant in the travel experience, as measured from social media. Our metrics could be put into operation to allow transportation planners to consider a wider range of needs and dynamics into their work, complementing traditional data sources with fine-grained data.

2 RELATED WORK

Data used to plan and manage transportation is traditionally collected through surveys [1, 8]. Women's travel patterns differ greatly from those of men due to the role they play in society, combining the tasks of workers, home-care givers and those responsible for children and the elderly [2, 19]. However, these differences often do not appear on survey data, where budget constraints of traditional

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transportation questionnaires may not allow to incorporate gender-specific questions. As result, most of the planning is targeted at average users, with a lack of a gender perspective.

The role of social media in transport analysis has rapidly grown over the last years, allowing to obtain information regarding trips and activities, while highlighting the benefits of using this type of data sources [26]. Social platforms such as Twitter, and other specialized platforms like Waze, allow users to organize in communities, contributing information about transportation, which has been used to infer patterns and dynamics of urban behavior [14, 28]. To the extent of our knowledge, there is not much literature on alternative ways to approach transport perception, except for a descriptive analysis of public transport perception from tweets in the city of Chicago [5], and the monitoring of malfunctions in public transport in Madrid [6].

Our work can be seen as a deeper analysis on the travel experience than those from previous work [5, 6], due to our focus on all modes of transportation and to our structured lexical analysis.

3 METHODOLOGY

The main goal of this study is to characterize the perception of transportation as seen on Twitter, quantifying differences per mode of transport and gender. In this section, we explain the three steps of the pipeline we used to achieve this purpose: user representation and inference of gender, inference of mode of transportation, and measurement of perception.

User Features. A Twitter user profile contains the following attributes used in our study: *id*, *name*, *description*, and *tweets*. Tweets are textual micro-posts of 280 characters at most that may contain mentions to other users, hashtags to indicate themes within the post, URLs, emoji, *etc.* To these features, we also added *gender*. We focused on a binary gender separation: {male, female}. Without losing generality, we inferred gender based on self-reported information [12, 17]. The inference was based on two heuristics. The first one matched the first name of each user with a database of known names, built from census data and from manually crafted lists. The second one matched expressions in the self-reported description (*e.g.*, "Mother, Sister, Daughter.... . .", and so on). Then, we propagated gender labels using *SGD Classifier* implemented in *scikit-learn* [23]. We did so by predicting gender based on the description content.

Mode of Transportation Inference. To measure perception per mode of transportation, we needed a way to classify users and tweets into each mode. We used the following high-level categorization of mode(s) of transportation: 1) Public Transportation (*e.g.*, bus, subway); 2) Motorized Transportation (*e.g.*, cars, ride-apps); and 3) Non-Motorized Transportation (*e.g.*, bicycles). These modes can be characterized by vocabulary usage, for instance, public transportation operators have support accounts, and use specific terms like station names. Thus, it is possible to train a model that infers the relationships between users and modes, as well as terms and modes based on the co-occurrences of words. Based on a model to infer modes(s) of transportation from mobile phone data [9], we used a semi-supervised method named Topic-Supervised Non-Negative Matrix Factorization (TS-NMF) [20], which associates users and tweets to latent features interpreted as modes of transportation.

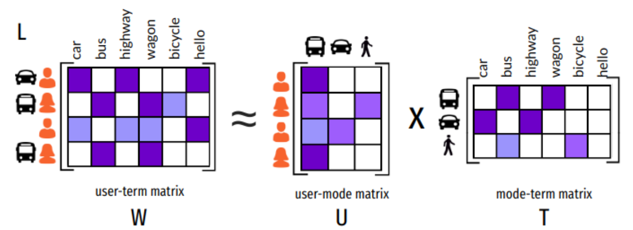

Figure 1: Topic-Supervised Non-Negative Matrix Factorization technique. The document-term matrix W holds the vocabulary used by each user in all their tweets, where each row represents an user, and columns represent the number of times a term is used. As W is positive definite, it can be decomposed in two matrices U and T of lower dimensions. These two matrices represent the latent features associations between terms and modes of transportation.

The TS-NMF method receives as input a document-term matrix W and a supervision matrix L. The matrix W was built from the concatenation of user timelines (*i.e.*, all tweets by the same user), which we treated as documents. A document d_u is defined as a vector: $d_u = [w_1, w_2, ..., w_{|V|}]$, where w_i represents the normalized frequency of term i posted by user u, and $|V|$ is the size of the vocabulary. Terms include words and n-grams (up to three), hashtags, mentions, URL hostnames, and emojis. The matrix L contains a subset of pre-labeled users with modes of transportation. For each mode, we had a list of seed words and phrases that represent it (*e.g.*, *platform* is associated with public transport, *Uber* is associated with motorized transport). Users were pre-labeled based on a calculated score defined as the sum of normalized frequencies of these seed words for each mode. Those with a score higher than a threshold were labeled with the corresponding mode (in our experiments, we defined 0.25 as a compromise between confidence and number of users labeled).

The TS-NMF method decomposes W into the product of two matrices of lower dimensions. This factorization allowed us to arrange the vocabulary into clusters (or latent components) according to the mode of transportation described by users. To do so, we decomposed the matrix into $W \approx U \times T$, where U was a $|u| \times k$ matrix that encodes k latent features of users (i.e their mode of transportation), and T is a $k \times |V|$ matrix, that encodes k latent features over the vocabulary (c.f. Fig. 1). The TS-NMF factorization takes into account the pre-labeled users in L to promote a meaningful semantic structure in the decomposition of the k latent features. For a deep review in topic-supervised factorization see [20].

In this way, the matrix U characterizes users, and the matrix T characterizes the vocabulary, allowing us to classify user tweets into modes of transportation according to their vocabulary usage.

Gross Transport Perception. We quantified transportation perception through the usage of the psycho-linguistic lexicon Linguistic Inquiry and Word Count (LIWC) [24]. This lexicon has been used to characterize perception and emotions on Twitter [11]. Particularly, it defines three high-level categories that we deemed relevant for our study: *Emotionality*, *Relativity*, and *Personal Concerns.* Emotionality includes both negative emotions such as *anger, sadness,* *fear and anxiety*, and positive emotions such as *optimism* and *positive feelings.* Relativity includes notions of *time, motion*, and *space.* Personal Concerns include themes such as *job, leisure, social, swear words*, and *sexual*-related words.

However, just counting words of each LIWC category is not enough, as social media content is subject to factors that may bias analysis. For instance, it can be expected to have more tweets about public transport than motorized modes given that transit riders may use their phones while moving. Previous work on Gross Perception [25] tackles this issue by analyzing the standardized usage of LIWC categories. We built upon these metrics by defining the Gross Transportation Perception GTP, which measured the relative use of words per each mode and LIWC category as:

$$\mathrm{GTP}_x^{p_{ij}} = \frac{x_{ij}^p - \mu_i^p}{\sigma_i^p},$$

where p is a LIWC category, i is a mode of transportation, j is a day, and x is the normalized frequency of words belonging to the category p in said day for a given group of tweets, μ_i^p and σ_i^p are the mean and sd of the fraction of words belonging to the category p of the mode of transport i. It may be a single user, a group of users, all tweets following specific criteria, *etc.* We carried out this analysis at the transport mode level, in periods of three hours, and at the gender level, at daily periods.

Having into account the previous definition, we defined the *gender gap in perception* as $GAP_i^p = GTP_{f,i}^p - GTP_{m,i}^p$, where p is a LIWC category, i is a mode of transportation, f is the set of tweets by women, and m is the set of tweets by men in a given period. As result, GAP tells us if the tendency of using a certain category is associated with females (GAP > 0) or males (GAP < 0).

4 CASE STUDY: SANTIAGO, CHILE

Santiago, Chile, is a densely populated city with almost 7 million people. We collected tweets related to transportation from March to November of 2017, leaving out the summer period in which mobility patterns change. We filtered out tweets that contain URLs of media outlets and unrelated topics, and users with a reported location different from the city of Santiago. We queried the Twitter Streaming API with words related to transportation, such as operator names, station names, and transport-application names. We collected a total of 303,800 tweets from 56,624 users living in the Santiago metropolitan area. We were able to identify 19,012 users as women, and 29,166 as men, which together represent over 85% of the sample. Note that users without inferred gender were later considered to measure differences in modes of transportation.

Figure 2 shows the aggregated hourly frequency distribution of tweets. One can see that the frequency resembles the morning and afternoon peak hours in transportation [33]. The most common terms are the institutional accounts of public transport services (@transantiago and @metrodesantiago). Such frequency hints that a big part of the discussion is held by public transport.

Mode of Transportation Inference. To associate modes of transportation to users and terms we defined seed keywords for each mode, including account names, hashtags, plain words, and emojis. With this schema, we pre-labeled 16,375 users to public transport, 2,449 users to motorized transport, and 2,447 users to non-motorized

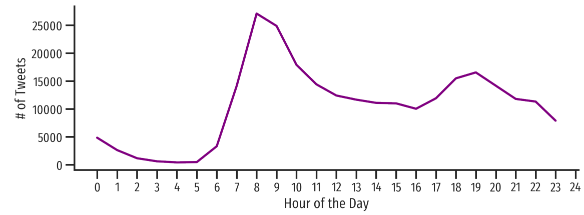

Figure 2: Tweet Frequency per hour of day. The transport-related tweeting frequency resembles the morning and the afternoon peak hours in the Santiago transportation system.

Mode	Seed Word	# Users	# Tweets
Motorized	*driving, highway, @uber_chile*	2,449	41,152
Non-Motorized	*bicycle, walking, @mobikecl*	2,447	29,051
Public	*@transantiago,* 🚌*, @metrodesantiago*	16,375	233,597

Table 1: Seed words used to characterize transportation mode. Some users were pre-labeled based according to their usage of the seed words of each mode of transportation.

transport. The TS-NMF model propagated these labels to the rest of the data set (*c.f.* Table 1).

Figure 3 shows one wordcloud per mode of transportation, with their corresponding associated words according to the TS-NMF model. The motorized transport discussion focused on terms related to taxis and ride-hailing apps (*@uber_chile, cabify, taxis, taxi drivers, #uber*), possibly due to conflicts about the legality of these services. Other related terms include the state of the driving system (*highway, driving, accident*), service providers (*@uoct_rm, @autopcentral*), and trip information via Waze, a community-driven GPS navigation software where users (who refer themselves as *wazers*) share travel times and route details. Non-motorized terms relate to riding the bicycle (*bicycle, cyclists, @mfc_stgo*) and their users show more relationship with accounts from municipalities (*@muni_stgo*) andauthorities (*@alessandrifelip*, the mayor of Santiago; or *@orrego*, the former city's intendant). This may be due to two things: people mentioning them to communicate an opinion or a retweet of information published by them. Terms related to public transportation are in respect to the Transantiago system (which integrates the buses and subway), with users mentioning station names (*e.g., Baquedano*, a downtown connection hub), and using hashtags related to the line services and service status (Lines 1 and 6, *#l1, #l6*). Also, they often interact with the Ministry of Transport and Telecommunications (*@mtt_chile*), or bus providers (*@alsaciaexpress*). They mention fewer accounts in comparison to other modes, but use more terms to describe the state and characteristics of the system (*day, minutes, wait, bus stop, wagons*).

Gross Transport Perception per Mode. Figure 4 shows the gross-perception per mode of transportation and LIWC categories. The emotionality associations show that *anger* is a less associated emotion with non-motorized transportation, which is consistent with studies that show that walking and cycling are more related to well-being and higher satisfaction [29, 31]. *Anxiety* is present in public transportation, which could indicate that there is a situation that triggers feelings of fear in users. *Optimism* signals a difference between the non-motorized and motorized transportation, where

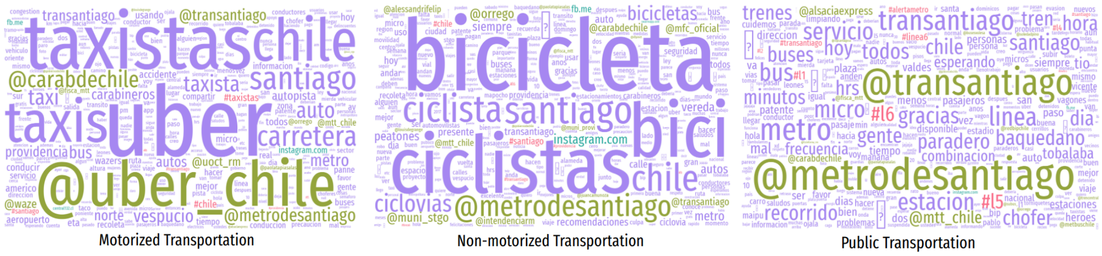

Figure 3: Wordclouds of the most associated words per mode of transportation. Motorized transportation discussion focuses on terms related to taxis, ride-hailing apps and the state of the driving system, while non-motorized transportation talk mainly about bicycles and public transportation focuses on interactions with service providers.

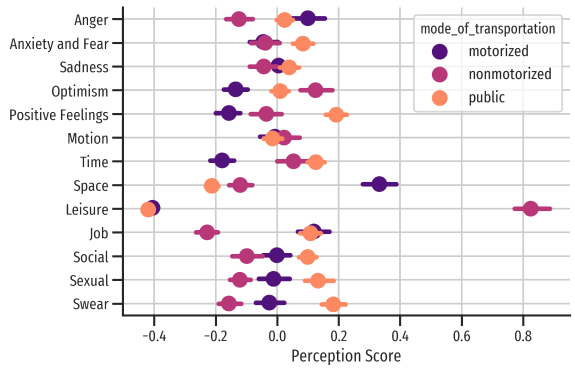

Figure 4: Gross Perception per Mode of Transportation (GTP), a measure of the relative usage of LIWC categories between modes of transportation. For instance, leisure is more associated with non-motorized transportation, in comparison to the other modes.

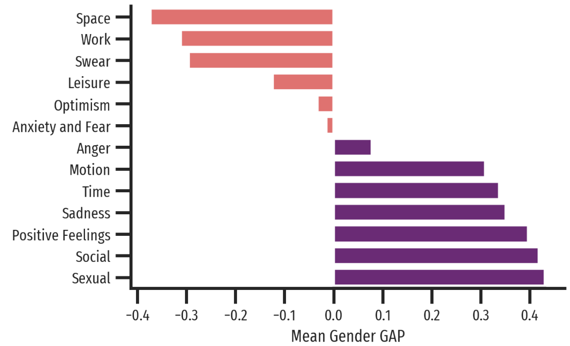

Figure 5: Mean Gender Gaps in Gross-Perception, calculated as the difference between GTPs. LIWC Categories with positive (negative) values present higher association with women (men). For instance, women report higher association to sexual words.

the latter seem to experience fewer feelings of optimism during their travels, which could be related to the stress drivers experience, as studies have shown [15]. *Positive feelings* are more associated to public transportation, contrary to the intuition that Twitter is used only for complains [13].

In terms of relativity, *time* is more associated with non-motorized and public transportation. For example, public transport users may talk about how long they have been waiting for a bus to arrive; non-motorized users may comment on their trip times. Motorized transport users pay more attention to *space*, due to issues such as the state of roads, traffic jams, and accidents. It is important to study these factors since users base their transportation decisions on them [10]. This applies even to single trips, due to the dynamic conditions of transportation, such as crowding at peak hours.

Regarding personal concerns, *leisure* is more associated with non-motorized transport. This may be related to the fact that non-motorized transportation has a strong use for entertainment purposes such as biking or taking a walk for pleasure [21]. In a similar way, public transport association to *work* emerges in the higher use of words from this feature, due to its high use for commuting. In Santiago, commuting represents more than a third of the total trips per day [33]. Public transport users seem to use more *sexual* and *swear* words. In addition to the various studies that have shown that public transport users present negative feelings during the trip [3]; factors such as crowding, delays, and accessibility increase stress, and that this perception differs according to factors such as gender [4]. It is in this mode of transport where people report high rates of sexual harassment [27].

Gender Differences. Figure 5 shows the mean gender gaps in gross-perception of LIWC categories, after estimating GTP for each gender. Men are more associated to the *space* category, which we theorize is because they tend to be the main users of motorized transport [33], where these terms are frequently used. Men are also associated with words related to *work* and *leisure*, consistent with results that show that they talk more about external events, objects, and processes, using more *swear* words [22].

On the other hand, women are more associated with words that talk about the context of transport (*motion, time*). As discussed, this may be due to factors such as time influencing their transportation decisions. It is notable that women also report a high association with *positive* words while also being highly associated with feelings such as *sadness* or *anger*, resulting in an ambivalence.We theorize that this may be caused by the use of sarcasm, or other reasons that should be explored in greater depth. Negative feelings could be related to their higher use of words from the *sexual* sphere, in accordance with studies that point to the violence they suffer in transportation [18], especially in the public type [27]. We explored the words that co-occur with those belonging to the sexual category, finding words such as *harassment, rape, street, man, sexual*, and mentions of public transport (*metro, transantiago, @transantiago, micro*), which is where women report suffering more harassment.

5 DISCUSSION AND CONCLUSIONS

Transportation is fundamental for the development in society, and the way it is perceived has a great impact on the quality of life. Hence, it is important to characterize the perception of people with respect to this activity. In this paper, we have established a method to quantify and compare the perception of modes of transportation, including gender as a factor of analysis. This method captures the subjective travel experience in an inexpensive and dynamic way. Entities such as service providers and transportation system administrators can benefit from the knowledge gained through social network data.

The creation of gender-aware subjective experience metrics could help to identify relevant issues regarding the travel experience that are ignored when transport is designed with the "average user" in mind. For instance, even though sexual harassment is a problem for women, the last travel survey in Santiago only referred to safety, potentially including harassment, but also confounding it with other unsafe situations [33]. This is of special importance in countries with high levels of gender inequality, where women are more often victims of sexual harassment in the public space [18]. Transport riding quality and satisfaction are often measured in terms of the needs of the business [5], which may be oblivious to social problems.

It could be argued that the use of social media data may be biased in terms of representativeness. Although the proportion of men and women may not be representative of the population, patterns within each group could be, particularly in commuter populations [16]. Nevertheless, future work should address this factor, not only by validating gender distribution but also including other demographic factors such as age and income. Finally, a potential line of research is the characterization of context surrounding perception, to answer questions such as: Is the *sexual* category completely related to harassment, or does vernacular language play a relevant role? What is the effect of interventions against harassment? These kinds of insights may be of value for practitioners and policymakers.

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