Paper-Based Master Thesis

submitted within the UNIGIS MSc programme
Interfaculty Department of Geoinformatics - Z_GIS
University of Salzburg

Measuring urban quality of life by analysing geotagged Tweets

by

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A thesis submitted in partial fulfilment of the requirements of the degree of
Master of Science – MSc

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Table of Content

List of figures

List of tables

1. Introduction

The extent to which our environment and our place of residence affect our well-being and our Quality of Life (QoL) has long been a significant subject of theoretical and empirical work in fields ranging from human geography, regional economics, and science to urban and regional research (Ballas, 2013). We consciously and subconsciously evaluate our environment and transform these evaluations into positive or negative emotions (Hadzhieva, 2017). The past decade has experienced a surge of interest in measuring emotions (Roza, Postolache, & Ieee, 2016; Zeile et al., 2015) as well as QoL and well-being (Ballas, 2013; Keles, 2012; Zivanovic, Martinez, & Verplanke, 2020). According to the World Health Organization (WHO) definition, "quality of life is an individual's perception of their position in life in the context of the culture and value systems in which they live and in relation to their goals, expectations, standards and concerns" (World Health Organisation, n.d.). In his work, Marans (2012) gives a related interpretation, pointing out that the objective features of society - such as poverty, crime rates, and pollution, but also families, work, current financial situation, and health - are the primary contributors to how people evaluate their lives. Furthermore, the author argues that the environment in which we live, starting from the individual dwelling, through to the district and the city, up to the state, influences our sense of well-being and, thus, our perceived QoL.

In general, QoL can be measured in subjective and objective terms (Marans, 2012; Zivanovic et al., 2020). The latter measures QoL using information about the human environment based on official statistics, while a subjective approach assesses people's perceptions in combination with a particular area or event (Zivanovic et al., 2020). There have been extensive efforts in the social sciences to define, measure, and analyse individuals' subjective awareness of their surroundings (Ballas, 2013). Nowadays, many people use social media platforms to share their opinions, ideas, desires, thoughts, and concerns with the world (Zivanovic et al., 2020).

Social media has become ubiquitous in our everyday lives. One of the most popular platforms is Twitter, with almost 400 million (Dean, 2022) active users. More than 80% of them access the service via mobile devices (Cao et al., 2018) to send brief messages, which can be tagged with the longitude and latitude of the location from which they were sent (Meyer et al., 2019). This geolocated post, which Goodchild *(2007)* refers to as Volunteered Geographic Information (also known as geotagging), allows further location analysis to be performed (Meyer et al., 2019). The resulting possibility to gain information about specific events in space and time offers new perspectives in urban analysis by helping to identify urban processes and characterise socio-cultural trends and dynamics (Resch, Summa, Zeile, & Strube, 2016).

However, the analysis of data from social media is subject to various sources of uncertainty. The accuracy of the geo-location of a Tweet can be affected by the nature of the mobile devices, densely built urban spaces, or other factors such as GPS dilution of precision. Equally, users do not distribute their posts evenly in space and time, which leads to a rather heterogeneous diffusion of Tweets. It is also essential to note that geo-referenced posts represent only a fraction (2-4 %) of the total number of Tweets that are generated (Steiger, Resch, & Zipf, 2016).

Finally, analysing subjective perceptions conventionally can be time-consuming, and expensive, which is why social media data sources could play an essential role in capturing people's perceptions in real-time, and providing significant benefits over traditional surveys (Zivanovic et al., 2020).

Because users do not always pay attention to grammatically correct sentence syntax and given the amount of emojis, slang words, URLs, and images therein, Tweets often have, as Barbosa & Feng (2010) describe "noise," which complicates their investigation (Roberts et al., 2018; Zivanovic et al., 2020).

A significant amount of unstructured, noisy data is generated incessantly on social media platforms. Methods are needed to analyse the data when it is created to understand the human psychology behind it and extract useful information (Nandwani & Verma, 2021; Resch et al., 2016; Zivanovic et al., 2020).

Examples of such methods include machine learning or natural language processing (NLP), such as sentiment analysis or emotion detection. Sentiment analysis or opinion mining identifies a word, phrase, or acronym in a sentence or document and categorises the associated sentiment according to its polarity. It evaluates whether an individual has a negative, positive or neutral attitude towards an object, event, situation, person, or geographical location. Emotion detection addresses specific emotions such as joy, sadness, anger, or disgust related to comment, feed, sentence, or document (Nandwani & Verma, 2021).

Not much research has been done on the feasibility of using social media data to understand people's perceptions of QoL and how traditional methods can be adapted to analyse social media feeds (Zivanovic et al., 2020). Accordingly, this work aims to assess public perceptions of QoL in transport, safety, free time and culture. For this purpose, Twitter datasets were collected for the metropolitan areas of Hamburg and Berlin for the period from 2013 to 2021. To extract valuable data that can be applied to emotion and QoL analysis, the first step was to cleanse and simplify the datasets. The emotion analysis was then performed using the open-source framework BERT (Bidirectional Encoder Representations from Transformers). For the QoL analysis, Twitter corpora were searched for specific words and the resulting data was categorised into the aforementioned groups. The rest of this paper is organised as follows: section two reviews the existing literature on emotion and QoL analysis using social media data; section three elaborates on the methodology used; results are presented in section four and discussed in section five, and the paper ends with a conclusion.

2. Related Works

2.1 Emotion analysis

2.1.1 Spatiotemporal emotion analysis of Twitter data

Hauthal (2019) studied people’s reactions via Twitter to different events and analysed geographic and temporal patterns to better understand the emotions behind the Tweets. To capture the emotional semantics of Tweets, emojis must be considered as they provide a simple indicator of the emotion (joy, fear, sadness, etc.) of a given reaction. Using Tweets from Massachusetts, Cao et al. (2018) suggested that emotions extracted from social media could be used to better understand the spatial and temporal patterns of urban and regional public happiness and well-being. Resch et al. (2016) present a citizen-centric urban planning approach that uses Tweets to evaluate citizens' perceptions of the city of Boston and their related emotions. Using a graph-based semi-supervised machine learning and a self-labelled dataset (Gold Standard), they extracted five separate emotions from the Tweets: happiness, sadness, fear, anger/disgust and none. They concluded that the emotions can be partially detected and that the approach can potentially improve urban planning processes significantly.

2.1.2 Issue-specific analysis with data from social media

In addition to understanding people's emotions, the spatial distribution of Twitter data can provide insights into the social dynamics in urban areas. For example, Arribas-Bel et al. (2015) attempt to use Twitter posts to understand the spatial structure, dynamics, and population distribution of the city of Amsterdam. Roberts et al. (2018) were interested in exploring what emotional responses urban public green spaces evoke in a city's residents by analysing social media feeds. A similar approach was used by Meyer et al. (2019), who examined detailed information about the structure and dynamics of the city of Madrid. Tan & Guan (2021) went further by combining sentiment analysis with housing prices to establish that areas with a higher happiness density correlate with higher housing prices. In addition, Nandwani & Verma (2021) state that social media such as Twitter, Facebook, and Instagram have become one of the most critical sources of health-related information in the health sector, as people share their thoughts, worries, fears, and feelings about the COVID-19 pandemic. Samuel et al. (2020) used Twitter data to track the progressive spread of people's fear related to the rapid expansion of Coronavirus and COVID-19 infections. They provided methods for developing much-needed motivational solutions and approaches to counter the spread of negative emotions.

2.1.3 Twitter as a determinant of QoL

Because of the lack of research on the potential for using social media data to capture people's perceptions of QoL (Zivanovic et al., 2020), there is growing interest in Twitter-based approaches to studying QoL in cities and regions (Cao et al., 2018; Zivanovic et al., 2020). Zivanovic et al. (2020) aimed to explore this question and contribute to the current debate by evaluating the use of social media data to capture and map people's perceptions of their lives in Bristol. Their methodological approach is based on a mixed-methods approach combining manual coding of messages, automatic classification, and spatial analysis. They compared their results statistically and spatially with the official QoL survey results in Bristol and concluded no correlations between the two studies. Marans (2012) made the same observation and explains it by stating that the relationship between urban characteristics and subjective judgments or perceptions is very complex. People differ in how they perceive their surroundings and what they consider essential in judging their life satisfaction. Similarly, people may perceive things differently in the same situation or environment. Guhathakurta et al. (2019) used Twitter data to explore neighbourhood QoL perceptions as an early indicator of neighbourhood transition. They illustrated the potential of crowdsourcing as a complementary solution for obtaining neighbourhood perception data, while Riga et al. (2015) highlighted the potential use of social media data as a valuable additional source of environmental information by exploring the atmospheric environment aspect of people’s QoL.

2.2 Methods

2.2.1 Emotion detection and emotion mapping

The analysis of emotions in texts can be performed using machine learning techniques to understand human language and grammar. This technique is known as Natural Language Processing (NLP) (Demszky et al., 2020).

Since the two NLP areas (sentiment analysis and emotion detection) attempt to extract emotions from texts, researchers often use them synonymously. However, they differ in certain respects (Nandwani & Verma, 2021).

Sentiment analysis categorises an emotional state into positive, negative, or neutral. In contrast, emotion detection extends the field of sentiment analysis by identifying a particular emotion related to a text (Becker, Moreira, & dos Santos, 2017).

Zivanovic et al. (2020) used three-domain lexicons - health, transportation, and environment - to conduct a sentiment analysis on the QoL in Bristol. The results were visualised on maps to reveal spatial similarities and differences in perceptions between districts in Bristol. Resch et al. (2016) used an emotion detection approach to assign a distinct emotion class to Tweets to reveal new insights into citizens' perceptions of a city by visualising the gained emotion information on a map. Hauthal et al. (2019), on the other hand, combined the two approaches to analyse reactions to Brexit on Twitter. They obtained sentiments through hashtags and emojis and classified each Tweet as either positive or negative. In addition, they used emojis to assign emotional categories to the Tweets. In their paper, Demszky et al. (2020) present a dataset called GoEmotions, which consists of 58K Reddit comments manually labelled for 27 emotion categories or neutral. They perform transfer learning experiments using a BERT-based model with existing emotion benchmarks to demonstrate that their GoEmotions dataset is well transferrable to other domains and different emotion taxonomies.

3. Methodology

This section describes the methods used to obtain the data for the analysis of QoL in Hamburg and Berlin (see Figure 1). First, the (raw) Twitter data was cleaned using regular expressions (Regex) based on cleaning criteria (see Chapter 3.3). To perform emotion categorisation for German Tweets, a dataset consisting of 58K Reddit comments was translated into German. Next, each Tweet was assigned with a specific emotion (anger, disgust, joy, sadness, surprise, fear, or neutral) using a BERT-based model (see Chapter 3.4). Regex was then applied again to filter the Tweets that could be used to assess the QoL (see Chapter 3.6). The results were assigned into three QoL groups (transportation, safety, free time & culture). Finally, GIS software was applied to analyse the data spatially.

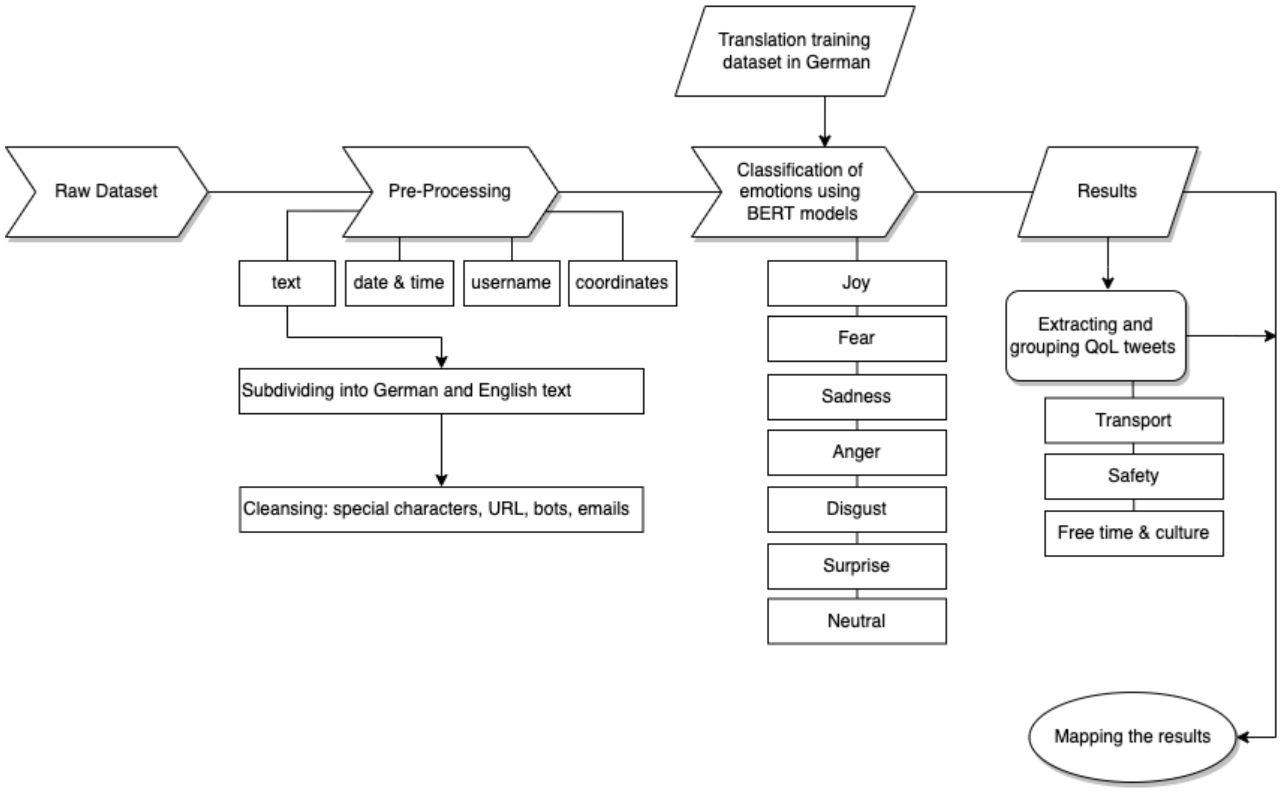


Figure 1. Used methods for labelling the Tweet-dataset

3.1 Study areas - the cities of Hamburg and Berlin

Hamburg is a city and federal state located in northern Germany. The city is the second-largest city in the country and has a population of 1,852,478 (Statista, 2021c). The direct connection to the North Sea via the river Elbe makes the city an important international trade centre. The Port of Hamburg is the second-largest port in Europe and the most important port in Northern Europe. In terms of QoL, the city has taken a major green turn in its urban development policy. This has involved the urban redevelopment of abandoned industrial sites and the most degraded parts of the city, upgrading the network of public transport, expanding the bicycle lanes, and increasing green spaces (Graniero, 2015). The town is divided into seven districts, consisting of 104 neighbourhoods (see Appendix 3).

Berlin is the largest city in Germany and has a population of 3,664,088 (Statista, 2021c). Like Hamburg, Berlin is a city and a state and has been Germany's capital since 1991. Berlin is Germany's most visited tourist destination and ranks among the top three most visited places in Europe, after Paris and London. Berlin enjoys an international reputation as a venue for conferences and trade fairs. In 2006, UNESCO honoured Berlin as a “City of Design”, making it the first European city to receive this title, joined only by Graz in 2011. Over the years, Berlin has become a centre of attraction for the younger generations, with 40% of the current population under the age of 35. Today, the city is characterised by creativity and holds the title of "European Art Center", according to which it has a large influx of international creative entrepreneurs, especially from other parts of Germany, Europe, and North America. The city is home to over 500 galleries, making it the city with the largest gallery density in Europe (Arandjelovic & Bogunovich, 2014). Berlin is divided into 12 districts, consisting of 96 neighbourhoods (see Appendix 4).

3.2 Data

In general, Tweets are transmitted via mobile devices and represent a status update of up to 280 characters that can include emojis, slang words, URLs, and images (Roberts et al., 2018; Zivanovic et al., 2020). Twitter allows the Tweets to be geotagged with the longitude and latitude of the location from where they were sent. These geolocated posts, which (Goodchild, 2007) refers to as volunteered geographic information (also known as geotagging), allow further location analysis to be performed (Meyer et al., 2019).

Two Twitter datasets (for the Berlin and Hamburg metropolitan areas) were used in this study. These were collected by the University of Salzburg for the 2013-2021 period and provided in raw form, as shown in Table 1.

501845044870270976,2014-08-19 21:35:57,@SplashyChan @_ShutThemDown_ aber...es ist Teen Wolf!!,,,Twitter for Android,,0101000020E6100000B1DF13EB54092440253E7782FDBD4A40,,,,501844549384552448,254058008,angel_of_sand,,,,,,,53.484299,10.018226,2

501845464434900992,2014-08-19 21:37:37,"@SplashyChan @_ShutThemDown_ ach,Pff xD also so viel wie eines der Goldtickets bei der Lunar Con",,,Twitter for Android,,0101000020E610000045F5D6C056092440D2E3F736FDBD4A40,,,,501845296494952449,254058008,angel_of_sand,,,,,,,53.48429,10.01824,2

501845710602375168,2014-08-19 21:38:35,#outside #nature #landscape #panorama #flight #on #plane #wing #airplane #lufthansa #white #grey,Ä¶ http://t.co/CmgQCDCj1C,,,Instagram,,0101000020E610000006F4C29D0BF32340CFBA46CB81B64A40,,,,,215399910,NicksProduction,,,,,,,53.425836,9.974698,2

501845938508673024,2014-08-19 21:39:30,@SplashyChan @_ShutThemDown_ Beta?! I'm always be the Alpha!!!,,,Twitter for Android,,0101000020E6100000BF29AC5450092440C078060DFDBD4A40,,,,501845714230845440,254058008,angel_of_sand,,,,,,,53.484285,10.018191,2

Table 1. Raw Twitter data

3.3 Data Pre-processing

Regex were applied to generate usable data from the raw Tweets, filtering out only the Tweets with text and coordinates, as illustrated in Table 1 (highlighted grey). The usernames and the timestamp (date, time) were also extracted. Only the text of German and English Tweets was considered for further processing. As mentioned before, Tweets often contain URLs, HTML, emails, spaces, mentions, and numbers. Since this, as Barbosa & Feng (2010) call "noisy data" only complicates its analysis, these elements were removed from the Tweets. In addition, text messages generated by bots were often observed in the Twitter datasets, as well as Tweets by news bots such as DE-Newsblog or ES-News. Since these are machine-generated messages that do not reflect emotions felt by real humans, they were removed using a manually generated list of syntaxes and usernames. Furthermore, as the German language consists of unique characters that do not occur in other languages (ä, ö, ü and ß), they were replaced by ae, oe, ue and ss, respectively.

3.4 Advanced supervised deep learning model BERT for labelling Tweets.

The classification approach used in this study is based on the optimised GoEmotions-Pytorch BERT-based model by Park (2021), which closely aligns with the work of (Demszky et al., 2020).

BERT stands for Bidirectional Encoder Representations from Transformers and is an open-source machine learning framework for natural language processing (NLP). It was developed to pre-train comprehensive bidirectional data from an unlabelled text by assessing left and right text jointly in all layers and is thus a very effective technique for classifying emotions (Alaparthi & Mishra, 2021; Devlin, Chang, Lee, & Toutanova, 2018).

The six basic emotions proposed by Ekman (1992) were used as the basis for emotion extraction: anger, disgust, happiness (joy), sadness, surprise and fear. In addition, based on the work of Resch et al. (2016) and Demskzy et al. (2020), a seventh class “neutral” was added, in which no emotion is represented or identified in a Tweet. A training model is required to categorise emotions based on the BERT model (Devlin et al., 2018). For this purpose, Park (2018) uses the labelled dataset GoEmotions by Demszky et al. (2020), which consists of 58K selected Reddit comments and is also the largest human-categorised dataset. Accordingly, the English Tweets were categorised into joy, fear, sadness, anger, disgust, surprise, and neutral using the GoEmotions dataset and the BERT model. To be able to categorise the German Tweets based on the same model, the entire GoEmotions dataset was first translated into German using Deepl. Finally, the translated training data were applied with the German-based BERT model (Deepset, 2019), to categorise the german Tweets into the aforementioned emotion classes.

To determine whether the emotion classes were successfully categorised, Park's optimised GoEmotions-Pytorch BERT-based model calculated the true (true positive, true negative) and false

(false positive, false negative) labelled instances per class. Subsequently, the model created a confusion matrix, on the basis of which the performance metrics “precision”, “recall” and the harmonic “f-score” were calculated. Since the models have more than two target classes, the “micro” and “macro” averages were also computed (Resch et al., 2016).

In general, precision values indicate the accuracy with which the model categorised a sample as positive. Specifically, it is determined as the result of the correct categorisation of positive samples concerning the total number of positive samples (either correctly or incorrectly). The recall value, is determined as the ratio of positive samples correctly categorised as positive to the total number of positive samples. The f-score is determined using the harmonic mean of precision and recall (Nandwani & Verma, 2021).

The micro-average calculates a confusion matrix using the results obtained across all classes and evaluates them as a single class. In contrast, the macro-average individually evaluates all classes and averages the results. Accordingly, the micro-average is strongly impacted by the results of the larger classes, as it has a higher proportion of the counts in the confusion matrix. For the macro-average, on the other hand, all classes are processed identically and are not influenced by the number of available samples (Resch et al., 2016).

3.5 Categorising Tweets into QoL groups.

As mentioned above, QoL is measured using subjective and objective approaches (Zivanovic et al., 2020). To infer QoL based on people's perceptions, the labelled Twitter datasets were searched for specific words, such as fitness, jogging, theatre, cinema, rush hour, construction sites, public transportation, police operations using Python and Regex. The filtered Tweets were assigned to predefined subgroups, which were grouped into the categories of transport, safety, free time & culture (see Table 2). In the public transportation subgroup, the Tweets were sorted according to positive (joy) and negative emotions (anger, disgust, and sadness). This allows us to determine how the emotional spatial distribution of public transport is characterised in the two cities. The other subgroups are assumed to contain a specific emotion. For example, the feelings associated with "traffic jams," "construction sites," "drug dealing," or "robberies" tend to be negative. The free time & culture group, on the other hand, could have been further broken-down using emotions, but the focus was to find out whether people have access to and use the free time & cultural activities.

Transport	**Safety**	**Free Time & Culture**
Traffic	Drugs	Restaurant
Construction site	Police	Culture
Public Transport Positive	Robbery	
Public Transport Negatvie		

Table 2. Predefined groups and subgroups for quality of life

3.6 Spatial representation of the data

Finally, QGIS was used to represent the results of the emotion analysis and QoL grouping spatially. Since the datasets consist of points (each Tweet is to be understood as a point in a GIS context), the Kernel Density Estimation (KDE) was first applied to represent the Tweets' density spatially. The KDE technique determines the probability density of spatially discontinuously distributed data (Brandão, Correia, & Paio, 2018). Thus, the computation determines the density of point features around each grid cell, resulting in a uniformly curved surface (Tan & Guan, 2021).

To better understand how emotions are distributed across cities, Tweets were filtered according to their emotions and counted for each city neighbourhood. Concerning QoL, the same step was repeated for the Tweets grouped as per Table 1. However, in this case, the districts were used. Significant clustering of Tweets was observed in the spatial analysis of the data, especially on residential buildings. Since these clusters affect the results in the later stages of the research, the emotion and QoL groups were normed. For this purpose, the following formula was used:

$$\boldsymbol{Normed\ Tweets} = \frac{\boldsymbol{relTweets}}{\boldsymbol{allTweets}}$$

Where relTweets represent the relevant Tweets from the emotion or QoL-group in a neighbourhood or district, and allTweets are all the Tweets from a neighbourhood or district. To make the data readable, the results were summed by 100 or 1000. In addition, for statistical analysis of QoL data, the percentage for each subgroup was calculated based on the sum of all values in the group.

4. Results

4.1 Spatial representation of Tweet density

The Kernel Density Estimation (KDE) was used to analyse the spatial distribution of the Tweet density (see Figure 2). Visual examination shows that Hamburg's highest concentration (hotspots) of geotagged Tweets is in the inner-city area, which does not correlate with the population density (Schleswig-Holstein, 2021). The underlying assumption is that the hotspot reflects the number of people working in or visiting the inner city for work or recreation. The clustered area also includes places such as Alstersee, the city hall, and the central train station, which is the busiest long-distance train station in Germany (Statista, 2017). Clusters are also observed in the western part of the city, which has a higher proportion of residential areas (Schleswig-Holstein, 2021). A similar result can be observed in Berlin. Based on Figure 2, it can be stated that most Tweets were sent from the inner-city area, which was to be expected given the higher concentration of residents (Sentasverwaltung für Stadtentwicklung, 2021) and the fact that most of the city's landmarks are located in this area.

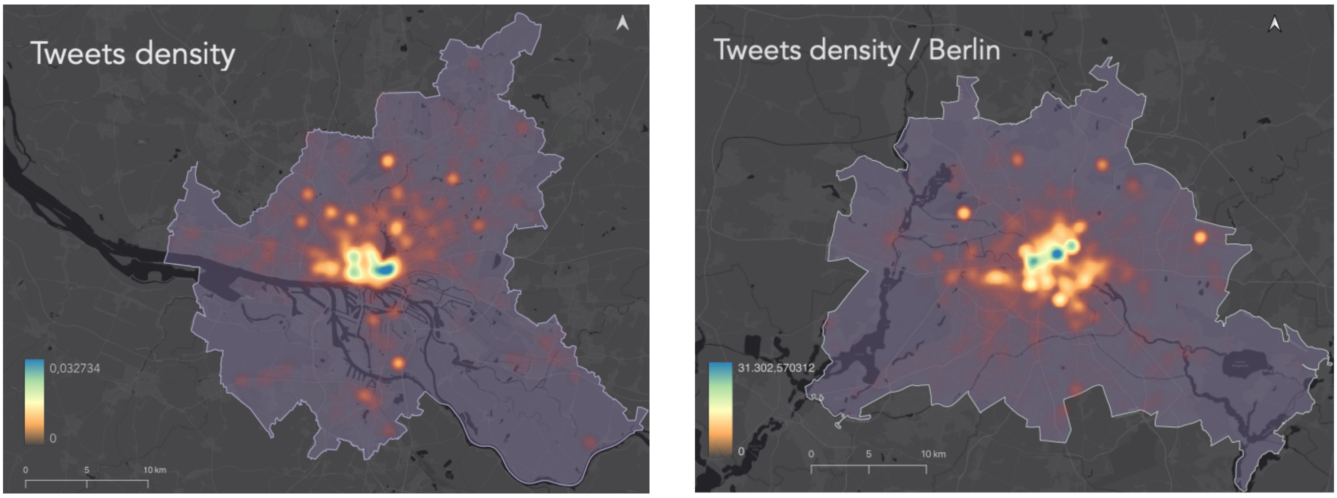


Figure 2. Spatial distribution of the Tweets for Hamburg and Berlin

4.2 Results of the emotion classification and their spatial representation

The datasets provided by the University of Salzburg consist of 1,049,262 Tweets for the Hamburg metropolitan area and 6,044,766 for Berlin. It can be assumed that this significant difference in the size of the data stems from the fact that the metropolitan region of Berlin has a higher population (see section 3.1). Furthermore, Berlin is a popular tourist destination for Germans and foreigners due to its history, culture, and nightlife (Arandjelovic & Bogunovich, 2014). After pre-processing using the criteria described in subsection 3.3, a total of 322,478 geotagged Tweets remained for Hamburg and 883,673 for Berlin (see Table 4). In the next step, the open-source framework BERT was used to classify the results into the six basic emotions proposed by Ekman (1992) - anger, disgust, joy, sadness, surprise, fear, plus an additional neutral class. Table 3 gives an example of the degree of classification.

Tweets	Emotions	Time	Date	Longitute	Latitute
Sehr sehr cool, werds ma bei bedarf ausprobiern!	neutral	11:13:30	2014-08-21	9.977023	53.46097
Warum nimmt mich hier eigentlich niemand ernst?	surprise	08:39:01	2014-09-01	10.1165	53.584437
Grosse Menschenmassen sind einfach schrecklich.	disgust	16:36:01	2014-08-02	9.981623	53.544393
Vielleicht kommen ja meine Konzertkarten heute 😍	neutral	12:53:56	2014-05-26	10.13420161	53.60346508
Maehhh, sind nicht gekommen :(	surprise	12:56:20	2014-05-26	10.13464905	53.60342007
Hilft nix. Bin zu alt fuer den Mist #abinshotel	anger	22:41:41	2014-05-15	9.95346666	53.5456871
Missing you a lot, Mary 😘😘😘	sadness	10:38:05	2014-08-18	10.020469	53.603262
We are old XD back pain, knee pain, foot pain XD #dcm #practice	sadness	14:19:16	2014-08-17	10.183383	53.496537
😳😍 holy cow you are gorgeous	joy	20:34:51	2014-08-18	10.224811	53.488908
Yes, unbelievable, or?? Doesn't feel that long ago!!	surprise	20:57:01	2014-07-31	9.907068	53.607269
I'm a god damn coward But then again So are you	anger	10:46:26	2014-09-28	10.012156	53.576676
it will grow back worse	disgust	10:56:32	2014-08-15	9.900916	53.544533
remembering my dream from last night. it was weird nd scary	fear	21:45:48	2014-07-24	10.035337	53.616388

Table 3. Samples of different emotion outcomes – German Tweets are marked in grey

The categorisation of the individual Tweets into the emotion groups revealed, as expected, a varying extent of their magnitude, as shown in Table 4. The highest emotion classes, and thus the most Tweets from the datasets, belonged to the neutral and joy classes (discussed in more detail in Chapter 5). A high level of anger, surprise, or sadness was also found, but the emotions fear and disgust were found much less frequently.

	Hamburg		**Berlin**	
	Data	Percentage	Data	Percentage
Tweets before Pre-processing	1.049.262	-	6.044.766	-
Georeferenced Tweets after Pre-processing DE/EN	322.478	-	883.673	-
Users Total	22.076	-	110.174	-
Joy	81.085	25.14	182.020	20.60
Anger	16.310	5.06	42.965	4.86
Disgust	2.420	0.75	3.644	0.41
Sadness	12.518	3.88	24.260	2.75
Fear	2.043	0.63	3.854	0.44
Surprise	31.369	9.73	68.231	7.72
Neutral	176.733	54.80	558.699	63.22

Table 4. Data summary - Results from prepossessing and emotion classification (total numbers)

Regarding the performance of the emotion classification of both models, it can be stated that based on the statistical evaluation of the results (see Table 5), the German BERT model performed with better accuracy (61 %) than the English model (52 %), which is also reflected by the high micro- and macro averages. However, the analysis of the emotion classification showed that the English model was significantly better in identifying the emotions from the Tweets than the German model.

performance metrics	**German BERT-Model**	**English BERT-Model**
accuracy	0,61	0,52
loss	0,2	0,23
macro_f1	0,63	0,59
macro_precision	0,61	0,58
macro_recall	0,65	0,62
micro_f1	0,72	0,68
micro_precision	0,69	0,63
micro_recall	0,76	0,74

Table 5. Accuracy results

The classification of the Tweets into emotion classes provided an insight into the emotional state of the population in the metropolitan areas of Berlin and Hamburg. Since the emotion "surprise" can be understood as positive, negative, or neutral, it was not included in the emotion analysis. Likewise, the emotions of anger and disgust were combined. As mentioned earlier, the data was normed to work around the inconsistencies and anomalies. Based on the normed values, differences between the emotion classes can be identified at the neighbourhood level. Figure 3 shows the distribution of the emotion classes. The neighbourhoods with the highest normed values are shown in yellow. Accordingly, it is assumed that the people living in these districts have the highest level of happiness or the lowest level of sadness.

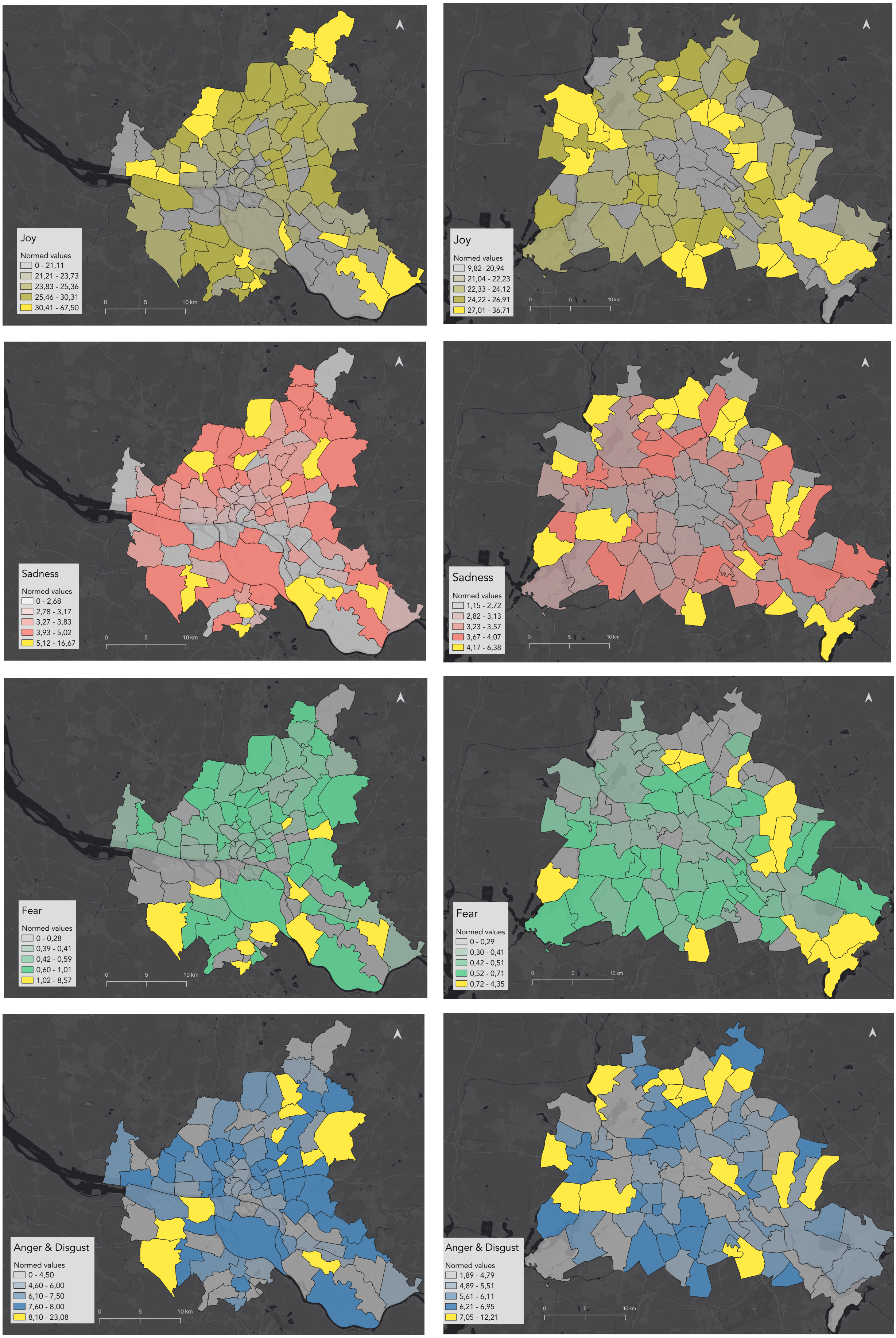


Figure 3. Spatial distribution of the emotion classes joy, anger/disgust, fear, sadness for Hamburg and Berlin (normed values)

4.2 Results related to Quality of Life

Using Python and Regex, the labelled Twitter records were searched for specific words to make a statement about the QoL based on people's subjective perceptions (see Chapter 3.6). The filtered Tweets were grouped into the categories of transport, safety, free time & culture. Tables 6 and 7 show the results (total numbers) of the grouped QoL datasets. Figure 7 reflects the normed values of the QoL results (see Appendix 1 and 2).

	Transport				Safety			Free time & Culture	
	Public Transport Positive	Public Transport Negative	Construction Site	Traffic	Drugs	Robbery	Police	Culture	Restaurants
Hamburg-Mitte	97	110	32	92	4	11	112	624	494
Altona	71	102	26	105	10	12	62	240	474
Eimsbüttel	31	46	17	93	0	31	62	108	279
Hamburg-Nord	83	60	25	103	4	17	59	392	432
Wandsbek	78	83	33	108	2	10	56	402	486
Bergedorf	62	64	26	79	7	20	51	212	193
Harburg	168	93	64	288	10	0	18	186	223
Percentage	26	25	10	39	7	18	75	46	54

Table 6. Data summary – Results from the QoL data collection for Hamburg (total numbers)

	Transport				Safety			Free time & Culture	
	Public Transport Positive	Public Transport Negative	Construction Site	Traffic	Drugs	Robbery	Police	Culture	Restaurants
Reinickendorf	20	36	3	32	6	1	3	139	55
Charlottenburg-Wilmersdorf	89	154	24	62	10	5	9	792	857
Treptow-Köpenick	33	49	10	13	3	2	1	167	113
Pankow	50	74	31	39	4	13	9	692	532
Neukölln	29	38	16	17	3	1	5	271	188
Lichtenberg	35	50	6	20	7	1	3	128	129
Marzahn-Hellersdorf	30	59	20	4	2	2	2	96	35
Spandau	15	18	1	4	2	0	1	85	50
Steglitz-Zehlendorf	23	46	4	12	4	2	1	162	116
Mitte	154	236	146	128	20	15	31	4418	1604
Friedrichshain-Kreuzberg	91	121	48	82	36	9	20	2087	1018
Tempelhof-Schöneberg	43	77	20	25	6	5	7	228	334
Percentage	26	41	14	19	41	22	37	65	35

Table 7. Data summary – Results from the QoL data collection for Berlin (total numbers)

By analysing the data, it was stated that users in both cities shared their excitement and displeasure about public transportation ("My bus was supposed to be here 4 minutes ago. I've been sitting at the bus stop for 8 minutes, I curse you!", "Buses at 7:30 in the morning always smell like an old people's home, death, decay and bad breath"), closely followed by police operations or police presence in proximity ("Police are in the occupied school. Activists are on the roof. #Münzviertel #Hamburg"; "Group is held at bay by police near Johannes-Brahms-Platz."). Furthermore, it was observed for both Hamburg and Berlin (see Figures 4 & 5) that the Tweets for public transport and traffic are highest during peak hours.

Not only negatively charged Tweets were able to be associated with the cities. Many users shared their joy about punctuality as well as generally positive experiences when using public transport ("In #Hamburg you can read #books while riding the bus"; "A work of art on the bus. Just awesome!!! I love it. 😍😍"). People also tweeted about the architectural features of certain buildings, such as Berlin's central station or the dance towers in Hamburg. Furhermore, the analysis showed that the Tweets of the class free time & culture are mostly associated with positive impressions and experiences.

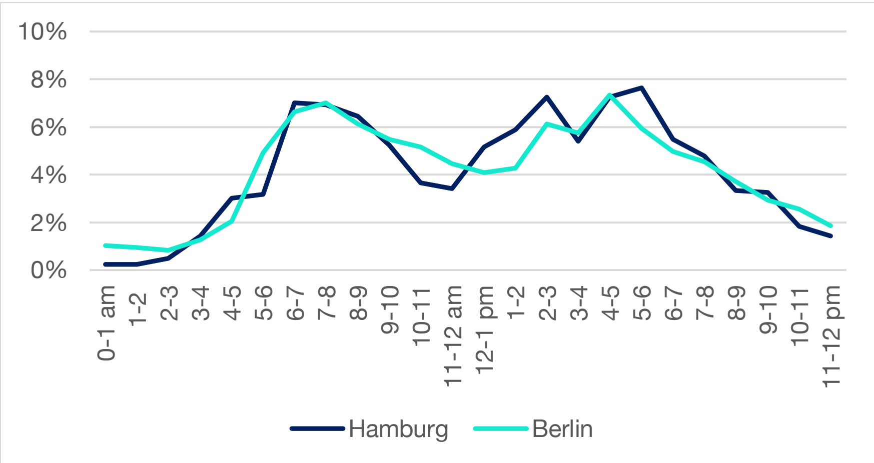


Figure 4. Share of total Tweets for public transport for Hamburg and Berlin grouped by time

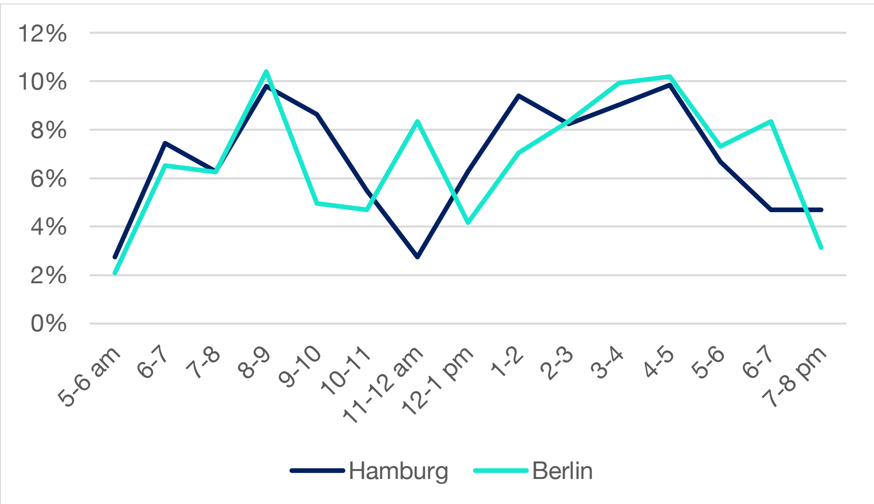


Figure 5. Share of total Tweets for traffic for Hamburg and Berlin grouped by time

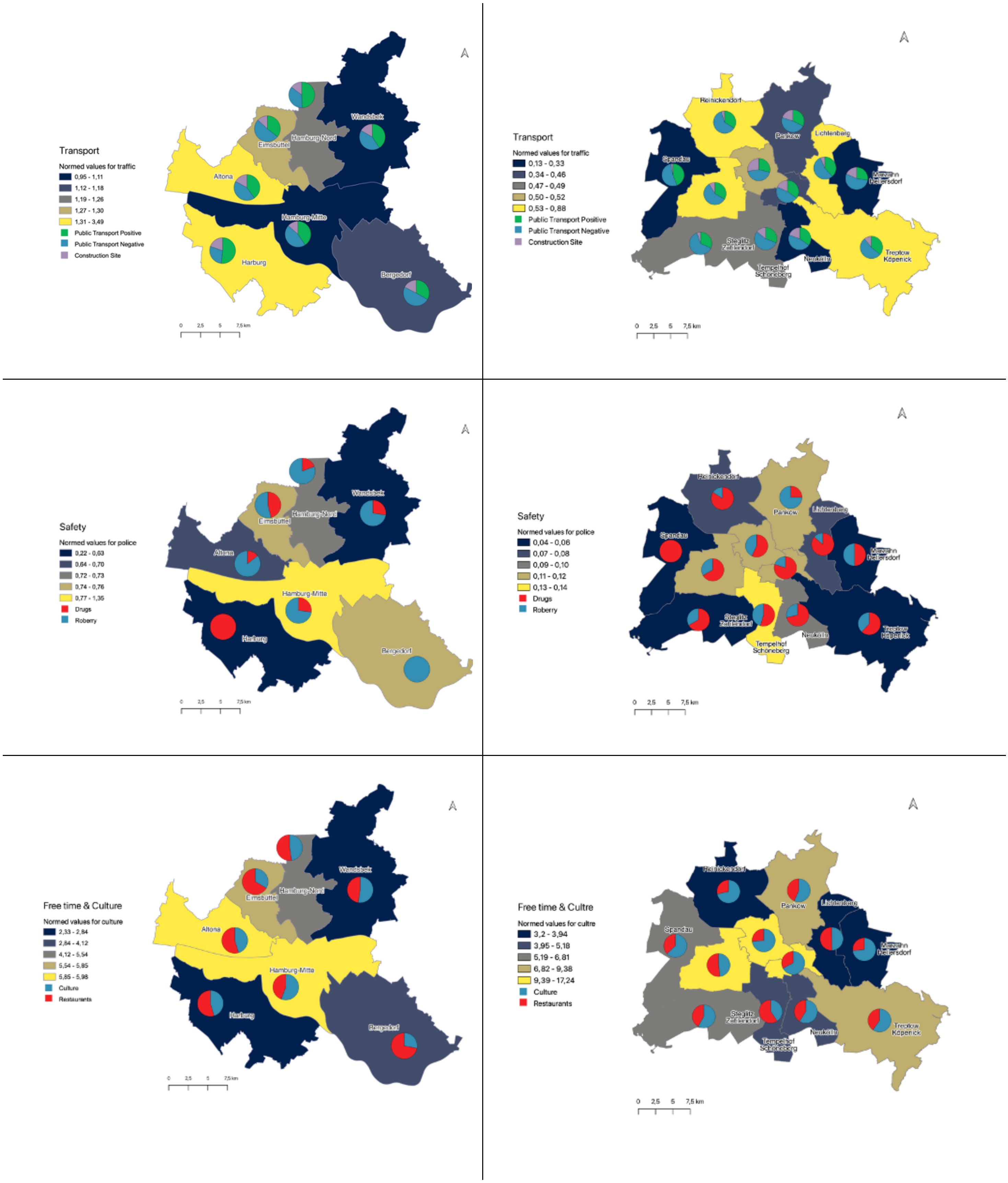


Figure 6. Spatial distribution of quality of life for transport, safety, free time and culture for Hamburg and Berlin (normed values)

5 Discussion

5.1 Results of the BERT Models

This study presented a current tool for determining the spatial distribution of emotions using social media data, which was used to assess QoL in urban areas. First, the Twitter data were cleaned to assign a specific emotion (anger, disgust, joy, sadness, surprise, fear, and neutral) to each Tweet. It was found that the German BERT model trained the German dataset more accurately but also led to more incorrect categorisations of the emotions compared to the English model. Consequently, the English model produced significantly better results after applying it to the dataset. One reason for this could be that the training model, consisting of 58K annotations, was not optimally translated into German using the Deepl API interface, as different expressions are used in the German language. Table 4 shows that more than 20% of the Tweets can be assigned to the joy class and more than 50% to the neutral. Resch et al. (2016) explain this effect to be caused by the fact that a high proportion of sad Tweets are often expressed as positive thoughts, which leads to a scattering of emotion extraction results. Another obstacle in analysing and interpreting the data is the Tweet clusters consisting of over 5000 Tweets sent by a single user (mostly about an apartment building). It is strongly assumed that these are posts that the user sends from home since they are unaffected by the time of day and day of the week.

Dividing the Tweets into emotion categories provided a spatial indication of the level of satisfaction in each neighbourhood of the assessed cities. The result for both cities shows that people are happiest in the parts of the cities, which are characterise by their single-family houses and green surroundings. Figure 3 shows an exceptionally high occurrence of the joy class in western parts of Hamburg, which are among the most popular neighbourhoods in Hamburg due to their proximity to green spaces and the Elbe River in front of the city gates. Similarly, the northeastern part of the city has high levels of positive emotions, which can be explained by the fact that these areas, with their many green spaces, are considered recreational areas. A similar development can be observed in Berlin, where positive emotions can often be seen in neighbourhoods away from the inner-city areas. It can thus be summarized that the emotion class joy occurred most frequently where the inhabitants are affluent. These findings are in line with the study of Zivanovic et al. (2020) and Tan & Guan (2021). Concerning the emotions of anger, disgust and fear, it can be observed that in Hamburg and Berlin they occur most frequently in neighbourhoods, whose inhabitants are distinguished by an average low income and high crime rates.

Attention should be paid to the fact that the emotion categorisation of BERT does not include information on why the users feel the way they do. The model categorises the Twitter data into emotions using the GoEmotions training model, but it does not determine whether the emotions inferred from a post can be related to the user's environment. After looking more closely at some of the posts from the anger & disgust class, it was observed that users were often agitated about politics, television shows, or a specific person. In this case, their mood is not generated by their environment but rather represents their opinion about a particular event or individual.

5.2 Results Quality of Life

Once the emotion classification was performed, keywords were used to categorise the Tweets into three groups - transportation, safety, free time & culture - to obtain an impression of the QoL in the assessed cities. The results show that using data from social media such as Twitter does not provide continuous quantifications of citizens' perceptions of QoL. Unlike costly surveys, however, social media data can be obtained and analysed in real-time (Zivanovic et al., 2020), which can be highly relevant to the traffic situation and transportation in cities. The study shows that Twitter data provides insights into the perception and use of public transport. Table 6, for example, shows that positive and negative Tweets are balanced in Hamburg (26% - 25% negative). Users are often impressed by the equipment of the buses ("A work of art in the bus. Simply brilliant. I love it. 😍😍"; "On the buses in Hamburg, there are bookshelves with BOOKS in them, I ❤️ it“), but also about the fact that in "Hamburg - The city where the subway runs above and the train under the ground :D.” In Berlin, on the other hand, the negative Tweets predominate (26% - 41%) as can be seen in Table 7. In general, it can be stated that users in both Berlin and Hamburg complain mainly about the unpunctuality/lateness of buses, which is directly caused by the numerous traffic jams ("Traffic jam here... Late again! Thank you HVV", " Wow, is today the day of the canceled buses? Waiting again over 20 min for a bus with 5 min interval 😩"). In the case of subways, however, users often express negative feelings about the crowded and busy trains. Likewise, it can be perceived that the negative Tweets were mainly sent when users were on their way to work or home, i.e., during rush hours as can be stated in Figure 4. These findings are consistent with the results from the study of (Ramos, Vicente, Passos, Costa, & Reis, 2019), in which the authors conducted ethnographic interviews and focus group discussions, identifying assumptions about what influences people positively or negatively concerning public transportation. In summary, based on Tables 6 and 7, it can be assumed that the people of Hamburg are more satisfied with public transportation than the people of Berlin. However, this cannot be clearly determined based on the statistics on public transport satisfaction from Statista (see Appendix 5).

Impressions about the QoL related to traffic can also be obtained using the Twitter data. The advantage of geolocated posts is that the location of the actual traffic can be determined. From this, conclusions can be drawn for a given time as to why these congestions occur more frequently. It is observed through text analysis that the Tweets related to traffic often refer to construction sites or commuting traffic. Like in the case of public transport, using Figure 5 a correlation with peak hours or rush hour traffic can be observed. Based on the analysed data, it can be stated that people in Hamburg are stuck in traffic jams more often than people in Berlin. However, the statistics for road traffic in 2020 (Statista, 2021d) show a reciprocal result. Based on Figure 6 and Table 6, the traffic jams in Hamburg occur most often in the districts of Harburg and Altona. This can be explained by the fact (and by the geolocated Tweets) that the section of the A7 freeway runs through the middle of the districts ("Stand once again in the traffic jam in front of the #Elbtunnel. Thanks for the great waste of time!"; "Two of four northbound lanes closed - traffic jam in front of the Elbtunnel"). It was also observed that the number of Tweets relating to road construction sites in the district of Harburg is exceptionally high, and, consequently, a correlation with the number of traffic jams and traffic-jam-related Tweets in the same district can be assumed. In Berlin, however, the busiest districts according to the Twitter analysis are Reinickendorf, Charlottenburg-Wilmersdrof, Treptow-Köpenick and Lichtenberg. This observation is difficult to substantiate with statistical evidence. An assumption is that the districts have a particularly high car density (Berlin-Brandenburg, 2021), however, the most car dense districts in Hamburg also had the fewest traffic jam-relevant Tweets. It was also observed that although Berlin is the busiest city in Germany (Statista, 2021d), people tweeted much less about it than in Hamburg.

In terms of safety, Tables 6 & 7 show that Hamburgers perceive the police or police operations more clearly than Berliners, which cannot be confirmed by the statistics of the Federal Criminal Police Office (Bundeskriminalamt, 2021b). The finding of Statista's statistics (2021e) even states that Berlin had the most crimes in Germany in 2020, while Hamburg was ranked 12th. However, with regard to drug dealing and robberies, the Twitter analysis shows that people in Berlin often feel annoyed or threatened (Bundeskriminalamt, 2021a), which leads to a low perception of their safety.

On the spatial distribution of tweets in the cities, it can be said that the results are not identifiable. Figure 6 shows that police operations occur most frequently in Hamburg-Mitte, followed by the districts, Eimsbüttel, Bergedorf, Hamburg-Nord, and Altona. Where as in Berlin – Tempelhof Schöneberg Mitte, Friedrichshain-Kreuzberg and Pankow. However, this finding partly coincides with the statistics of Statista (2021b) and (Statista, 2021a). Furthermore, the density of Tweets related to safety was expected to be highest in districts with high crime rates. Also, it was assumed that there would be a correlation between negative emotions (such as the class „fear" – see Figure 3), which was not found. Kounadi et al. (2015) stated in their work that the crime rate of the borough where an incident occurred does not have any influence on people's decision to post about it. In addition, a further point mentioned in their work is that the subjective fear of crime does not consistently correspond with the official crime statistics of the city districts.

Regarding the analysis of free time and culture, insights can be gained into the possibilities a city offers in terms of free time activities. It was observed using Tables 6 & 7 that the largest share of Tweets in Hamburg originates from cafés and restaurants, whereas in Berlin, it is from cinemas, theatres, museums, and concerts. This confirms the assumption that Berlin, due to its formative history and the numerous museums, some of which belong to the UNESCO World Heritage (Arandjelovic & Bogunovich, 2014), is one of the most culturally rich cities in Germany. Therefore, it is also not surprising that the districts of Berlin Mitte, Friedrichsheim-Kreuzberg, and Charlottenburg-Wilmersdorf, where most cultural institutions can be found, also have the most Tweets. A similar result can be observed for the Tweets from Hamburg. The districts of Hamburg-Mitte and Altona are also known for their cultural institutions, such as the Elbphilharmonie, Miniaturwunderland, and the Reeperbahn party mile.

It should be noted that Twitter data, especially in German-speaking countries, reflects only a small fraction of actual events. Furthermore, it should be added that not every post is geolocated, which makes the analysis of a topic particularly difficult. Accordingly, this approach should not replace traditional survey methods but rather be seen as a supporting tool. Another drawback is that many factors could influence the accuracy of the user's location determined by their mobile’s GPS, which could lead to incorrect interpretations of the spatial analysis (Meyer et al., 2019). Also, a user may express his observations, concerns, or impressions about an event at a later time and thus at a different location, which again leads to a scattering of the results (Zivanovic et al., 2020). Furthermore, this study also did not distinguish whether the Tweets were generated by tourists or residents of the city. It can be assumed that tourists view cities or places with different perspectives than the people who reside in the cities.

6. Conclusion

In summary, it can be stated that the advantage of the methods used in this study is that they are not limited to a specific language. The approaches can also be transferred to other social platforms besides Twitter, such as Facebook or Instagram. Regarding the emotion analysis, it was observed that although the BERT model has a high accuracy rate in grouping the Tweets by emotions, postings are often incorrectly categorised – for example, into the emotion classes “neutral” or „joy.” It must also be considered whether the emotion detection is the right approach for analysing the QoL. As shown in Table 4, over 7 % of Tweets were categorised into the group „surprise.” Since it cannot be determined whether these Tweets can be interpreted as positive, negative, or neutral, they were not included in the analysis. Furthermore, Table 4 shows that the Tweets were collected over eight years. In such a considerable period, cities experience many urban changes, which can be perceived positively or negatively. Accordingly, it could be problematic to make a clear statement about the QoL. Also, it is not always clear whether the geolocated Tweets refer to the location from which they were sent, leading to uncertainty in the results (Zivanovic et al., 2020). Nevertheless, the study showed that, overall, social media can be used to conduct emotion- and subsequent urban analyses on a global and district level. However, there are variations and gaps in collecting and exploring the data.

Appendixes

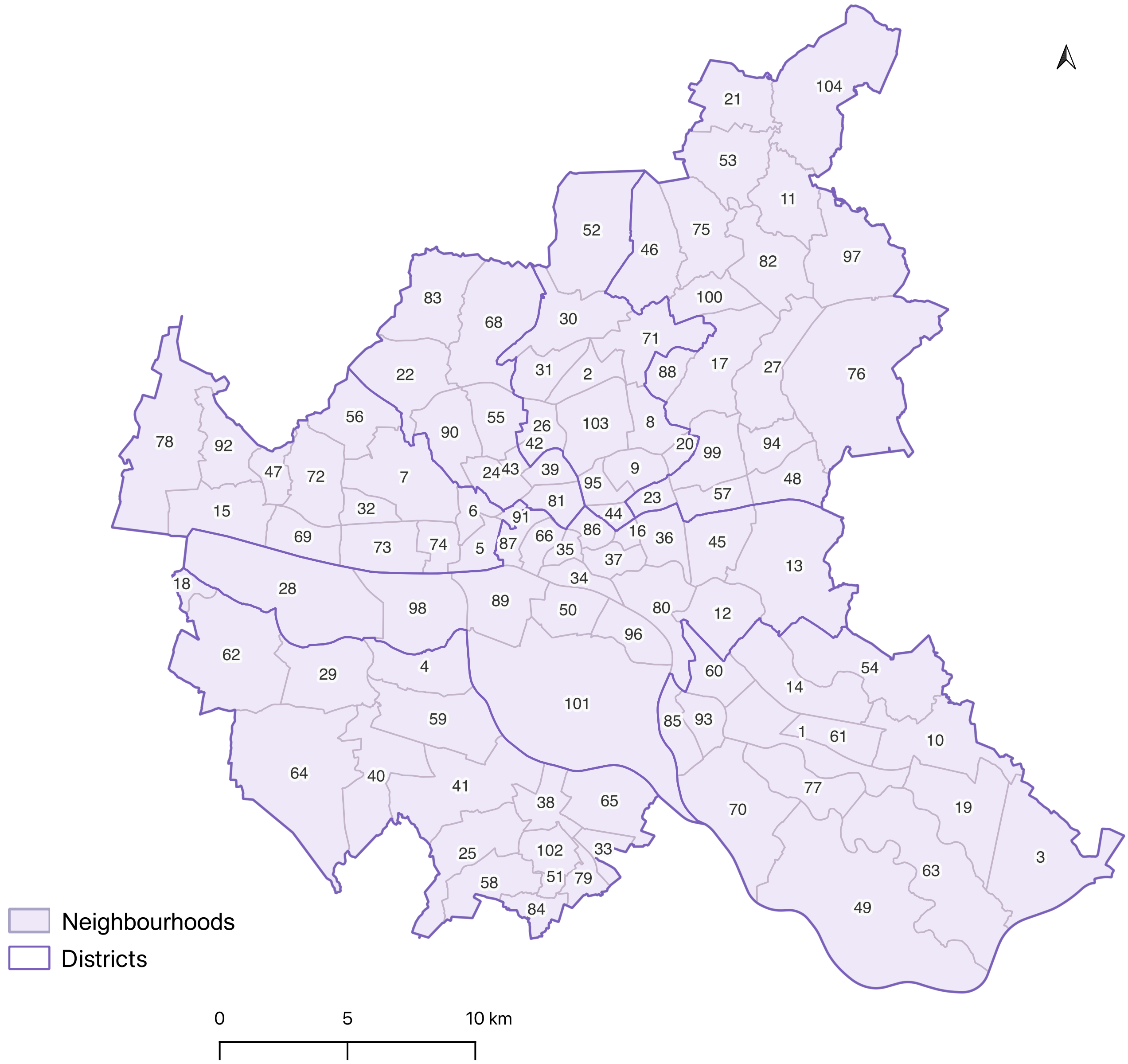
Appendix 1. Data summary – Results from the QoL data collection for Hamburg (normed values)

	Transport				Safety			Free time & Culture	
	Public Transport Positive	Public Transport Negative	Construction Site	Traffic	Drugs	Robbery	Police	Culture	Restaurants
Hamburg-Mitte	1.17	1.33	0.39	1.11	48	0.13	1.35	7.55	5.98
Altona	0.94	1	0.4	1.31	0.02	0.12	0.68	4.86	5.88
Eimsbüttel	0.86	1.23	0.32	1.27	0.12	0.14	0.75	2.91	5.74
Hamburg-Nord	1	0.73	0.3	1.25	0.05	0.21	0.71	4.74	5.23
Wandsbek	0.75	0.78	0.31	0.95	0.09	0.24	0.62	2.57	2.33
Bergedorf	0.38	0.56	0.2	1.13	0	0.37	0.75	1.31	3.38
Harburg	2.03	1.13	0.78	3.49	0.12	0	0.22	2.25	2.7

Appendix 2. Data summary – Results from the QoL data collection for Berlin (normed values)

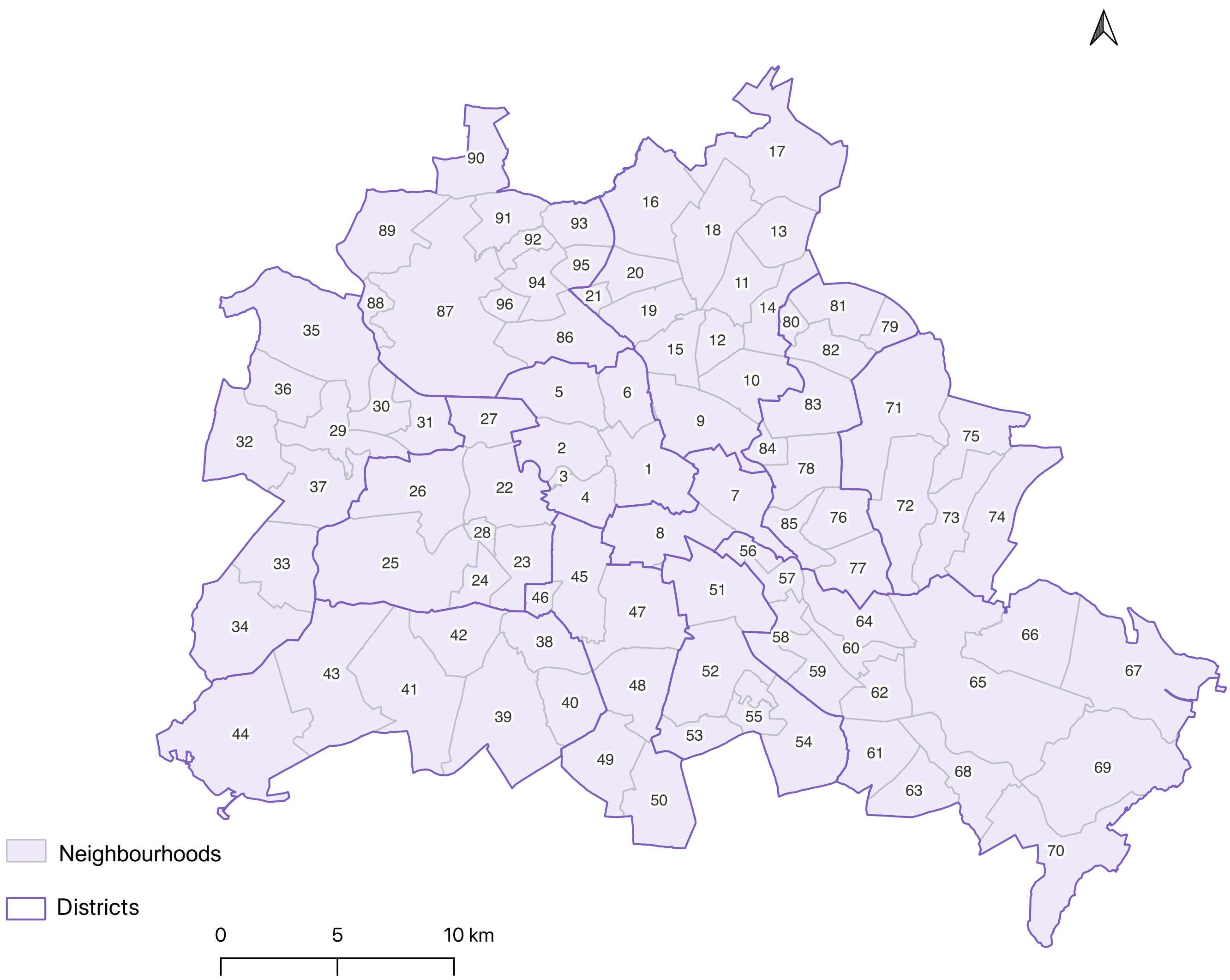
	Transport				Safety			Free time & Culture	
	Public Transport Positive	Public Transport Negative	Construction Site	Traffic	Drugs	Robbery	Police	Culture	Restaurants
Reinickendorf	0.55	0.99	0.08	0.88	0.16	0.03	0.08	3.81	1.51
Charlottenburg-Wilmersdorf	1.09	1.89	0.29	0.76	0.12	0.06	0.11	9.72	10.52
Treptow-Köpenick	1.39	2.07	0.42	0.55	0.13	0.08	0.04	7.04	4.76
Pankow	0.58	0.86	0.36	0.45	0.05	0.15	0.1	8.03	6.18
Neukölln	0.5	0.66	0.28	0.3	0.05	0.02	0.09	4.72	3.27
Lichtenberg	0.97	1.38	0.17	0.55	0.19	0.03	0.08	3.53	3.56
Marzahn-Hellersdorf	1	1.97	0.67	0.13	0.07	0.07	0.07	3.2	1.17
Spandau	1.04	1.25	0.07	0.28	0.14	0	0.07	5.88	3.46
Steglitz-Zehlendorf	0.92	1.84	0.16	0.48	0.16	0.08	0.04	6.46	4.63
Mitte	0.6	0.92	0.57	0.5	0.08	0.06	0.12	17.24	6.26
Friedrichshain-Kreuzberg	0.51	0.68	0.27	0.46	0.2	0.05	0.11	11.7	5.71
Tempelhof-Schöneberg	0.84	1.5	0.39	0.49	0.12	0.1	0.14	4.45	6.53

Appendix 3 – Hamburg districts and neighbourhoods



ID	Neighbourhoods	Districts	ID	Neighbourhoods	Districts	ID	Neighbourhoods	Districts
1	Allermöhe	Bergedorf	40	Hausbruch	Harburg	80	Rothenburgsort	Hamburg-Mitte
2	Alsterdorf	Hamburg-Nord	41	Heimfeld	Harburg	81	Rotherbaum	Eimsbüttel
3	Altengamme	Bergedorf	42	Hoheluft-Ost	Hamburg-Nord	82	Sasel	Wandsbek
4	Altenwerder	Harburg	43	Hoheluft-West	Eimsbüttel	83	Schnelsen	Eimsblttel
5	Altona-Altstadt	Altona	44	Hohenfelde	Hamburg-Nord	84	Sinstorf	Harburg
6	Altona-Nord	Altona	45	Horn	Hamburg-Mitte	85	Spadenland	Bergedorf
7	Bahrenfeld	Altona	46	Hummelsbüttel	Wandsbek	86	St.Georg	Hamburg-Mitte
8	Barmbek-Nord	Hamburg-Nord	47	Iserbrook	Altona	87	St.Pauli	Hamburg-Mitte
9	Barmbek-Sod	Hamburg-Nord	48	Jenfeld	Wandsbek	88	Steilshoop	Wandsbek
10	Bergedorf	Bergedorf	49	Kirchwerder	Bergedorf	89	Steinwerder	Hamburg-Mitte
11	Bergstedt	Wandsbek	50	Kleiner Grasbrook	Hamburg-Mitte	90	Stellingen	Eimsbüttel
12	Billbrook	Hamburg-Mitte	51	Langenbek	Harburg	91	Sternschanze	Altona
13	Billstedt	Hamburg-Mitte	52	Langenhorn	Hamburg-Nord	92	Sllldorf	Altona
14	Billwerder	Bergedorf	53	Lemsahl-Mellingstedt	Wandsbek	93	Tatenberg	Bergedorf
15	Blankenese	Altona	54	Lohbrügge	Bergedorf	94	Tonndorf	Wandsbek
16	Borgfelde	Hamburg-Mitte	55	Lokstedt	Eimsbüttel	95	Uhlenhorst	Hamburg-Nord
17	Bramfeld	Wandsbek	56	Lurup	Altona	96	Veddel	Hamburg-Mitte
18	Cranz	Harburg	57	Marienthal	Wandsbek	97	Volksdorf	Wandsbek
19	Curslack	Bergedorf	58	Marmstorf	Harburg	98	Waltershof	Hamburg-Mitte
20	Dulsberg	Hamburg-Nord	59	Moorburg	Harburg	99	Wandsbek	Wandsbek
21	Duvenstedt	Wandsbek	60	Moorfleet	Bergedorf	100	Wellingsbüttel	Wandsbek
22	Eidelstedt	Eimsbüttel	61	Neuallerm	Bergedorf	101	Wilhelmsburg	Hamburg-Mitte
23	Eilbek	Wandsbek	62	Neuenfelde	Harburg	102	Wilstorf	Harburg
24	Eimsbüttel	Eimsbüttel	63	Neuengamme	Bergedorf	103	Winterhude	Hamburg-Nord
25	Eimendorf	Harburg	64	Neugraben-Fischbek	Harburg	104	Wohldorf-Ohlstedt	Wandsbek
26	Eppendorf	Hamburg-Nord	65	Neuland	Harburg			
27	Farmsen-Berne	Wandsbek	66	Neustadt	Hamburg-Mitte			
28	Finkenwerder	Hamburg-Mitte	67	Neuwerk	Hamburg-Mitte			
29	Francop	Harburg	68	Niendorf	Eimsbüttel			
30	Fuhlsbüttel	Hamburg-Nord	69	Nienstedten	Altona			
31	Grob Borstel	Hamburg-Nord	70	Ochsenwerder	Bergedorf			
32	Grob Flottbek	Altona	71	Ohlsdorf	Hamburg-Nord			
33	Gut Moor	Harburg	72	Osdorf	Altona			
34	HafenCity	Hamburg-Mitte	73	Othmarschen	Altona			
35	Hamburg-Altstadt	Hamburg-Mitte	74	Ottensen	Altona			
36	Hamm	Hamburg-Mitte	75	Poppenbüttel	Wandsbek			
37	Hammerbrook	Hamburg-Mitte	76	Rahlstedt	Wandsbek			
38	Harburg	Harburg	77	Reitbrook	Bergedorf			
39	Harvestehude	Eimsbüttel	78	Rissen	Altona			
40	Hausbruch	Harburg	79	Rlnneburg	Harburg			

Appendix 4 - Berlin districts and neighbourhoods



ID	Neighbourhoods	Districts	ID	Neighbourhoods	Districts	ID	Neighbourhoods	Districts
1	Mitte	Mitte	41	Zehlendorf	Steglitz-Zehlendorf	81	Wartenberg	Lichtenberg
2	Moabit	Mitte	42	Dahlem	Steglitz-Zehlendorf	82	Neu-Hohenschönhausen	Lichtenberg
3	Hansaviertel	Mitte	43	Nikolassee	Steglitz-Zehlendorf	83	Alt-Hohenschönhausen	Lichtenberg
4	Tiergarten	Mitte	44	Wannsee	Steglitz-Zehlendorf	84	Fennpfuhl	Lichtenberg
5	Wedding	Mitte	45	Schöneberg	Tempelhof-Schöneberg	85	Rummelsburg	Lichtenberg
6	Gesundbrunnen	Mitte	46	Friedenau	Tempelhof-Schöneberg	86	Reinickendorf	Reinickendorf
7	Friedrichshain	Friedrichshain-Kreuzberg	47	Tempelhof	Tempelhof-Schöneberg	87	Tegel	Reinickendorf
8	Kreuzberg	Friedrichshain-Kreuzberg	48	Mariendorf	Tempelhof-Schöneberg	88	Konradshöhe	Reinickendorf
9	Prenzlauer Berg	Pankow	49	Marienfelde	Tempelhof-Schöneberg	89	Heiligensee	Reinickendorf
10	Weißensee	Pankow	50	Lichtenrade	Tempelhof-Schöneberg	90	Frohnau	Reinickendorf
11	Blankenburg	Pankow	51	Neukölln	Neukölln	91	Hermsdorf	Reinickendorf
12	Heinersdorf	Pankow	52	Britz	Neukölln	92	Waidmannslust	Reinickendorf
13	Karow	Pankow	53	Buckow	Neukölln	93	Lübars	Reinickendorf
14	Stadtrandsiedlung Malchow	Pankow	54	Rudow	Neukölln	94	Wittenau	Reinickendorf
15	Pankow	Pankow	55	Gropiusstadt	Neukölln	95	Märkisches Viertel	Reinickendorf
16	Blankenfelde	Pankow	56	Alt-Treptow	Treptow-Köpenick	96	Borsigwalde	Reinickendorf
17	Buch	Pankow	57	Plänterwald	Treptow-Köpenick			
18	Französisch Buchholz	Pankow	58	Baumschulenweg	Treptow-Köpenick			
19	Niederschönhausen	Pankow	59	Johannisthal	Treptow-Köpenick			
20	Rosenthal	Pankow	60	Niederschöneweide	Treptow-Köpenick			
21	Wilhelmsruh	Pankow	61	Altglienicke	Treptow-Köpenick			
22	Charlottenburg	Charlottenburg-Wilmersdorf	62	Adlershof	Treptow-Köpenick			
23	Wilmersdorf	Charlottenburg-Wilmersdorf	63	Bohnsdorf	Treptow-Köpenick			
24	Schmargendorf	Charlottenburg-Wilmersdorf	64	Oberschöneweide	Treptow-Köpenick			
25	Grunewald	Charlottenburg-Wilmersdorf	65	Köpenick	Treptow-Köpenick			
26	Westend	Charlottenburg-Wilmersdorf	66	Friedrichshagen	Treptow-Köpenick			
27	Charlottenburg-Nord	Charlottenburg-Wilmersdorf	67	Rahnsdorf	Treptow-Köpenick			
28	Halensee	Charlottenburg-Wilmersdorf	68	Grünau	Treptow-Köpenick			
29	Spandau	Spandau	69	Müggelheim	Treptow-Köpenick			
30	Haselhorst	Spandau	70	Schmöckwitz	Treptow-Köpenick			
31	Siemensstadt	Spandau	71	Marzahn	Marzahn-Hellersdorf			
32	Staaken	Spandau	72	Biesdorf	Marzahn-Hellersdorf			
33	Gatow	Spandau	73	Kaulsdorf	Marzahn-Hellersdorf			
34	Kladow	Spandau	74	Mahlsdorf	Marzahn-Hellersdorf			
35	Hakenfelde	Spandau	75	Hellersdorf	Marzahn-Hellersdorf			
36	Falkenhagener Feld	Spandau	76	Friedrichsfelde	Lichtenberg			
37	Wilhelmstadt	Spandau	77	Karlshorst	Lichtenberg			
38	Steglitz	Steglitz-Zehlendorf	78	Lichtenberg	Lichtenberg			
39	Lichterfelde	Steglitz-Zehlendorf	79	Falkenberg	Lichtenberg			
40	Lankwitz	Steglitz-Zehlendorf	80	Malchow	Lichtenberg			

Appendix 5 - Satisfaction of public transport for Berin and Hamburg

	Berlin und Umgebung		Hamburg und Umgebung	
Base	**193**	**in %**	**194**	**in %**

Statista Umfrage ÖPNV in Deutschland	
Methode	Online Umfrage
Quelle	Statista
Studienname	Statista Umfrage ÖPNV in Deutschland
Veröffentlicht von	Statista
Felddienstleister	CINT
Region	Deutschland
Anzahl der Befragten	n = 1872
Alter der Befragten	18 bis 69 Jahre
Stichprobenspezifikation	deutsche Online-Bevölkerung, die in einer der 10 größten Städte Deutschlands wohnt und den ÖPNV mind. 1 Mal im Monat nutzt
Erhebungszeitraum	09. bis 31. Mai 2019
Veröffentlichung	Jun 19
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