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## Temporal variability of emotions in social media posts

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### ABSTRACT

Employing the metadata from 627,632 Instagram posts for the Austrian capital city of Vienna over the period of October 30th, 2011 to February 7th, 2018, the present study extracts sentiment, as well as single basic emotions according to Plutchik's Wheel of Emotions, from the photo captions including hashtag terms. In doing so, an algorithm falling into the category of dictionary-based approaches to study emotions contained in written text was developed and applied. Not only are the overall polarity and the single emotions contained in Instagram posts within Vienna investigated, but also the top 54 Viennese Instagram locations. A particular novelty of this study is the measurement of longitudinal developments from emotive text and the fine-grained analysis of single emotions in addition to the overall polarity. One crucial empirical result of the study is that more experience and self-confidence in Instagram posting, as well as increasing expectations, seem to result in becoming a more critical poster over time. Companies interested in the use of influencer marketing to promote their products and services via Instagram should take this finding into consideration in order to be successful.

### 1. Introduction

Social media platforms and applications are an important part of our online experience. The information retrieved from other travelers via online platforms, websites, and mobile applications have been found to be more important and influential than official information sources (Yoo and Gretzel, 2012). Social media platforms such as Facebook, Instagram, or Twitter have become a significant segment of our daily lives. The data produced by users reviewing products, posting photos, or writing comments are examples of user generated content (UGC) data, which is one of the three typical occurrences of Big Data (Chen et al., 2012), in addition to device data (e.g., from the global positioning system, GPS) and transaction data (e.g., from web searches on Google; Li et al., 2018). This type of data can be used to track user movements, and thus measure spatial and temporal activity, as well as extracting the users' emotions from their photo captions and comments by employing sentiment analysis.

With more than one billion active monthly users in 2018, Instagram has become one of the most popular global social media platforms. Instagram has more than 120 million active users (Clement, 2020) in the United States alone and in doing so, created an estimated 9.45 billion US-\$ advertising revenue in 2019. Due to the increase in the number of

users, Instagram has also become a research area, particularly in the field of travel and tourism research as the majority of Instagram posts stems from visitors as examples from diverse locations such as Sri Lanka (Samarakoon and Mihindukulasooriya, 2018) or the Austrian capital city of Vienna (Gunter and Önder, 2020), the geographical focus of the present study, have shown.

The purpose of this research is to extract sentiment (i.e., overall polarity in terms of positive or negative), as well as single basic emotions (joy, anger, disgust, anticipation, sadness, fear, trust, and surprise; Plutchik, 1997) from the photo captions including hashtag terms of Instagram posts. Plutchik's Wheel of Emotions (Plutchik, 1980) therefore constitutes the theoretical framework underlying the present analysis.

The importance of studying emotions has been underlined by numerous researchers across disciplines. Grichnik et al. (2010), for instance, conclude that positive and negative emotions can influence otherwise unrelated entrepreneurial situations in terms of perception and decision-making. Using an experimental economic set-up, Hopfensitz and Reuben (2009) show how emotions enforce cooperation in social dilemmas. Leu et al. (2011), in turn, find that cultural differences exist towards the association of positive emotions with positive or negative feelings. Finally, Zietsma and Toubiana (2018) underline the

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importance of studying emotions for institutional actors.

In doing so, an algorithm falling into the category of dictionary-based approaches to study emotions contained in written text was developed and applied. Not only are the overall polarity and the single emotions contained in Instagram posts within a well-defined geographical location – Vienna – investigated, but also the top 54 Viennese Instagram locations (i.e., those locations with at least 500 posts containing emotional statements). A particular novelty of this study is the measurement of longitudinal developments from emotive text and the fine-grained analysis of single emotions in addition to the overall polarity.

Instagram metadata from the company Picodash (<https://www.picodash.com/>) were used as the data source. In total, the dataset consisted of 627,632 individual geotagged photos (i.e., Instagram posts) and their metadata for Vienna (such as geographical coordinates, time stamps, user IDs, photo captions, number of likes and comments, etc.) for the period of October 30th, 2011 to February 7th, 2018. The photo captions including hashtag terms from these metadata were of particular interest for this study.

Data for Vienna were chosen to apply the methodology for the following reasons. With more than 1.9 million inhabitants as of January 1st, 2020 (Statistics Austria, 2020), Vienna is one of the largest cities of the European Union. It has been a major artistic, cultural, economic, educational, and political hub for centuries. Although having lost its position of being the capital city of a European great power after World War I, today Vienna hosts a number of important international organizations such as the International Atomic Energy Agency (IAEA), the Organization for Security and Co-operation in Europe (OSCE), the Organization of the Petroleum Exporting Countries (OPEC), or the United Nations (UN) and in 2018, was declared a world city ('Alpha' category) by the Globalization and World Cities Research Network (GaWC) (Globalization and World Cities Research Network, 2020).

In 2018 and 2019, it was named the world's most liveable city by the Economist Intelligence Unit (EIU; Economist Intelligence Unit, 2020) and up until 2019, ten consecutive years by the consulting firm Mercer (Mercer, 2020). With its historic city center and the former imperial palace of Schönbrunn designated as United Nations Educational, Scientific and Cultural Organization (UNESCO) World Heritage Sites (UNESCO, 2020), Vienna features a high number of popular 'instagramable' locations for visitors and residents alike. Ranking ninth in 2018, with more than 17 million bednights, Vienna has been one of the most visited European city destinations for several years (European Cities Marketing, 2019). All of the aforementioned reasons make Vienna an appropriate location for applying the newly developed methodology.

The main contributions of this study are fourfold: first, the development and application of the methodology itself; second, the analysis of emotive text from Instagram posts using fine-grained single emotions, in addition to the overall polarity; third, the analysis of emotive text in relation to the places where the photos were taken; and fourth, the first time measurement of longitudinal developments in emotive text from social media, leading to the observation that more experience and self-confidence in Instagram posting, as well as increasing expectations, seem to result in becoming a more critical poster over time.

The remainder of the study is structured as follows: Section 2 reviews the related literature with a focus on the travel and tourism perspective. Section 3 lays out the employed material and methods. The results of the analysis are presented and discussed in Section 4. Finally, Section 5 draws some overall conclusions.

## 2. Literature review

One of the main features of social media is the ability of users to articulate themselves by writing comments, to express emotions such as joy and sadness with the help of emojis or hashtags (Mohammad and Kiritchenko, 2014), and to post photos and videos. This type of content is referred to as User Generated Content (UGC) and has proven to be an

influential source of consumer information.

For the last decade, research using textual UGC from social media platforms and their influence on consumers has been established. For instance, Gretzel and Yoo (2008) investigate online travel reviews on TripAdvisor and show that travel reviews are influential in accommodation decisions. Arsal et al. (2010), who explore the Thorn Tree online travel community, where users ask for travel advice and recommendations, indicate that residents and experienced travelers are influential in different types of travel decisions. The authors find that residents are more influential in accommodation and culinary recommendations, whereas experienced travelers are more influential in destination information, such as information related to transportation at the destination.

However, due to the increase in use of visual UGC such as posting photos and videos on Instagram and other platforms, as well as the ever-increasing number of users on these social media platforms make the analysis of this type of data interesting for research. All of this information is also important from a travel and tourism perspective in order to understand travelers' behavior by unobtrusive methods since those have been found to be more trustworthy than company website information and other official websites (Xiang et al., 2009). Furthermore, Oliveira and Casais (2019) show that in addition to restaurant reviews, photos of the restaurant and of its dishes are important for consumers when choosing a restaurant.

Hu et al. (2014) indicate that there are eight categories in terms of type of photos that are posted on Instagram: (1) friends, (2) food, (3) gadgets such as electronic devices and cars, (4) captioned photos (e.g., memes), (5) pets, (6) activity (i.e., both indoor and outdoor), (7) selfies, and (8) fashion items. Sheldon and Bryant (2016) examine the rationale behind the use of Instagram and reveal that there are four motives: (1) surveillance/knowledge about others, (2) documentation of one's life through photos to share with others, (3) coolness (i.e., self-promotion and popularity), and (4) creativity (i.e., showing one's skills and finding others with the same interests). Furthermore, perceived hedonism has been found to be one of the key aspects of consumer satisfaction, intention, and behavior on Instagram (Casaló et al., 2017).

Instagram has increased its popularity among users with the addition of stories and live streams. Thus, it has also become a favorable platform for marketing, which can be further amplified by influencers (i.e., so-called influencer marketing; Gretzel, 2018). Instagram influencers, who have a specific number of followers and who get paid to advertise products and services, are the opinion leaders on this social media platform. These influencers were traditionally celebrities, lately however, grassroots influencers or micro-celebrities that post engaging and relevant content and who reach a specific number of followers have emerged on social media (Gretzel, 2018).

Although there is no consensus on the definition of an influencer, they can be characterized by the size of their audience, the frequency of their posts, engagement metrics, and search engine optimization based metrics (Inkybee, 2016). Erz et al. (2018), for instance, define a (potential) influencer by having a high followers to following ratio in order to distinguish them from a follower (i.e., from an ordinary user not posting (much) own content). Arora et al. (2019) apply a set of regression techniques to identify (notably through engagement, growth, outreach, and sentiment) and determine influencer impact on the consumers of Facebook, Twitter, and Instagram. The authors propose a celebrities influence index and underline the importance of influencers for online marketing purposes.

Research on travel and tourism related to Instagram includes the investigation of the color composition of Instagram photos related to tourism and its marketing effects (Yu et al., 2020), examining Instagram influencers' experiences (Yilmaz et al., 2020), influencer marketing in travel and tourism (Gretzel, 2018), and understanding destination image on Instagram (Kuhzady and Ghasemi, 2019; Nixon et al., 2017).

Regarding social media in general, previous travel and tourism research has included various topics such as co-creation of real-time

tourism and hospitality services (Buhalis and Sinatra, 2019), repurchase intentions of Airbnb consumers (Liang et al., 2018), the influence of social media on hotel choice (Varkaris and Neuhofer, 2017), customer satisfaction and identifying hotel performance based on ratings on social media (Kim and Park, 2017), as well as hotel marketing effectiveness on social media (Leung et al., 2017).

In terms of understanding the influence of UGC on social media, sentiment analysis has been another important topic. Sentiment analysis refers to analyzing text and classifying emotions within the text using computational analysis. In recent years, the interest in this type of analysis has increased due to the high amount of online data that are available from social media and other internet sources. Alaei et al. (2019) investigate the different methodologies used in sentiment analysis in the travel and tourism context using Big Data. They classify the methodologies used in research as machine learning, rule or dictionary-based methods, and hybrid methods. The majority of this research has used machine learning methodologies, and the authors suggest that larger annotated data sets can be used in combination in order to understand and analyze the data.

Moreover, Kirilenko et al. (2018) suggest that sentiment analysis using humans vs. automated procedures shows similar results, however, this finding is limited to simpler data sets. With more complex data sets, humans outperform automated procedures. Schmunk et al. (2014) also propose a method for extracting sentiment from online reviews using dictionary-based and machine learning approaches. The authors conclude that dictionary-based methods are useful for recognizing the subjectivity in online reviews, whereas a support vector machine approach is useful for sentiment analysis and understanding positive and negative emotions in text.

In terms of sentiment analysis and destination image, González-Rodríguez et al. (2016) examine the pre- and post-visit destination image and perceived helpfulness of electronic word of mouth (eWOM; Hennig-Thurau et al., 2004) and propose a method for calculating the sentiment score of destinations. The sentiment score can be used by destination management organizations to improve the destination's image and to enhance their own services. Gkritzali (2017) investigates the sentiment of online conversations during the financial crisis of Athens and its impact on destination image, as well as on the recovery process. The author concludes that the sentiment regarding Athens did not show a full recovery of the destination image, although some improvement during the study period could be observed. Dickinger and Lalicic (2016) use sentiment analysis to understand destination brand personality. The authors show the connection between users' emotions and the connection between the destinations, which varies based on touristic settings.

Philander and Zhong (2016) analyze tweets to extract the sentiment regarding resorts in Las Vegas with a dictionary-based method. The authors compare the sentiment score of various resorts in the data set over an eight-week period. Overall, they conclude that the sentiment score of resorts are more effective at understanding real-time information than TripAdvisor's ranking. On the other hand, Gan et al. (2017) examine restaurant reviews and conclude that sentiments of reviews have an influence on restaurant ratings. In a different context, Geetha et al. (2017) investigate sentiment in online hotel reviews and customer ratings and show that customer ratings and feelings are consistent in online reviews.

Overall, previous research regarding UGC, irrespective of it focusing on textual or visual UGC, is still lacking in terms of the investigation of fine-grained emotions, especially on Instagram, which has become one of the most popular social media platforms. Moreover, this study connects emotive text from Instagram to places, a topic that has not been explored sufficiently to date. Finally yet importantly, the finding from the longitudinal analysis (i.e., that Instagram posters become more critical over time) is especially useful for practitioners interested in influencer marketing (i.e., for those who want work with influencers to promote their destinations).

### 3. Material and methods

#### 3.1. Data source

The dataset used hereinafter was purchased from the company Picodash, which used Instagram's application programming interface (API) to extract the data (<https://www.picodash.com/>), in early 2018. In doing so, Picodash applied the hashtag '#Vienna' to extract photos with geotags within the city limits of Vienna. For data protection reasons, only those geotagged photos that were posted by Instagram users with public profiles were downloaded, while usually about 15 to 30% of all Instagram profiles are private (<https://www.picodash.com/export-instagram-data>). The full dataset consists of the metadata of 627,632 individual geotagged photos (i.e., posts) for the period of October 30th, 2011 to February 7th, 2018.

Over 75% of all Instagram users typically fall into the age group of 18 to 24 years (Smith, 2019), and thus are likely to be over-represented in the sample. However, a preliminary comparison of the top ten locations, in terms of the total number of likes or comments, in Vienna according to Instagram has revealed that five of the top ten locations commensurate with Instagram's location IDs can also be found within the actually most visited locations of Vienna in 2017 (Statistics Austria, 2017). Notably, these are 'Schloß Schönbrunn', 'Belvedere, Vienna', 'Wiener Staatsoper', 'Kunsthistorisches Museum Vienna', and 'Albertina Museum' (all location IDs are given in the respective original language used on Instagram; official statistics are collected only for these five locations out of the Instagram top ten). Consequently, the most visited locations in Vienna coincide with the most photographed ones on Instagram, making the Instagram data viable for the subsequent analysis in the first place.

#### 3.2. Methodology

There are two mainstream approaches to study emotions contained in written text: *machine learning* and *lexicon-based* approaches (Medhat et al., 2014). *Machine learning* approaches are split into supervised and unsupervised approaches. The disadvantage of supervised approaches lies in their dependency on a large number of labeled training documents (Medhat et al., 2014), which would restrict the replicability of this research due to the associated time and cost burden. Unsupervised approaches, in turn, do not guarantee for the detection of Plutchik's basic emotions. Consequently, a lexicon-based approach was preferred against machine learning approaches.

*Lexicon-based* approaches are split into corpus-based and dictionary-based approaches. Corpus-based approaches are characterized by the same disadvantages as machine learning approaches as they require a seed list of opinion words to search for further terms with context-specific orientations (Medhat et al., 2014). Consequently, the algorithm presented here falls into the category of dictionary-based approaches and uses the freely available National Research Council Canada (NRC) Word-Emotion Association Lexicon, in short EmoLex (Mohammad and Turney, 2010, 2013) to allow for the highest degree of replicability. The following sequential steps were programmed in R, a free software environment for statistical computing and graphics (R Core Team, 2020). The process can be divided into two main tasks: 1) data preparation and 2) sentiment analysis.

The former includes all necessary data preparation steps that have to be conducted before analyzing Instagram photo captions including hashtag terms upon EmoLex terms, yet without the text contained in the followers' comments. Hashtags consist of one or several keywords preceded by a hash (#), which creates a hyperlink to track, search, group, and broadcast content (Erz et al., 2018; Page, 2012; Scott, 2015). Hashtags have also shown the ability to capture emotions on social media (Mohammad and Kiritchenko, 2014). The latter is an emotion detection technique and accompanying weighting algorithms are combined in the sentiment analysis step.

### 3.3. Data preparation

#### 3.3.1. Instagram posts: photo captions and hashtag preparation

Out of all 627,632 Instagram posts, only those relating to a specific attraction located in Vienna in terms of their location IDs were kept. General posts on Vienna were deleted. From the remaining 479,777 posts, those classified as non-English posts by Google’s Compact Language Detector 2 as implemented in the ‘cld2’ package for R (Ooms, 2018) were also deleted, resulting in 234,289 reviews. Next, uppercase letters were transformed into lowercase letters before they were handed over to the lemmatization procedure (Rinker, 2018). Afterwards, all numeric (0–9) and non-alphanumeric characters (e.g., ! or #) were deleted from the Instagram posts, resulting in 234,289 fully prepared bags-of-words (BOW) to be screened based on emotional content.

#### 3.3.2. EmoLex preparation

In the original EmoLex dictionary (Mohammad and Turney, 2010, 2013), 14,182 emotive terms were assigned to their overall polarity (positive, negative) and to basic emotions (joy, anger, disgust, anticipation, sadness, fear, trust, and surprise; Plutchik, 1997) with a value of 1 if they are related with the same. Otherwise, their value was set to 0. Those terms that were not assigned to one of the two polarities, or one of the eight emotions, and those that do not exist in the English language were deleted (Ooms, 2018).

Subsequently, the remaining 6,468 terms were lemmatized (Rinker, 2018). Lemmatization was not possible for 182 terms, resulting in 6,286 lemmatized terms. If the lemmatization step produced identical lemmas, which was true for 411 EmoLex terms, duplicates were aggregated and provided with the arithmetic mean of their original 0 and 1 allocation values. Next, the resulting 5,875 terms were normalized twice:

First, they were normalized to the sum of 1 for the overall polarity and the emotions separately. Hence, EmoLex terms that were just assigned to one polarity/emotion retained their original weight of 1, but EmoLex terms that were assigned to multiple polarities/emotions were weighted down to account for ambiguities in terms of their emotional belonging (for example, terms assigned to two different emotions received a weight of 0.5 on each emotion).

Second, they were normalized according to the term length characterizing each polarity/emotion. By dividing the cell entries by the number of terms assigned to each polarity/emotion, the dominance of polarities/emotions being described by many terms and the inferiority of polarities/emotions that come along with less emotive terms were both neutralized.

### 3.4. Sentiment analysis

After the data preparation steps, string-matching (Gagolewski, 2018) between the 234,289 Instagram posts and the 5,875 EmoLex terms was conducted. 28,318 Instagram posts did not contain emotive terms, and 1,770 EmoLex terms were not contained in any of the posts. This resulted in a  $205,971 \times 4,105$  document-term matrix,  $A$ , consisting of  $i = 1, \dots, n$  posts in rows and  $j = 1, \dots, m$  EmoLex terms in columns. Each cell,  $a_{ij}$ , contains the absolute occurrence frequency of an EmoLex term in a post:

$$A = a_{ij} = \begin{bmatrix} a_{11} & a_{12} & a_{13} & \dots & a_{1m} \\ a_{21} & a_{22} & a_{23} & \dots & a_{2m} \\ a_{31} & a_{32} & a_{33} & \dots & a_{3m} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & a_{n3} & \dots & a_{nm} \end{bmatrix}$$

Next, the absolute occurrence frequencies contained in the cells of  $A$  were weighted by the ‘term frequency – inverse document frequency (tf-idf)’ weight using the ‘lsa’ package for R (Spärck, 1972; Wild, 2020). This weight assigns more power to discriminating terms and less power to common ones. Occurrence frequencies of terms that show up in many reviews are decreased because they do not help to differentiate between

the different posts. On the other hand, occurrence frequencies of terms showing up less often are increased because they discriminate the emotional intensity in a better way.  $n$  is the absolute number of posts and  $n_j$  is the number of posts containing the respective term:

$$W = w_{ij} = a_{ij} \left[ 1 + \log \left( \frac{n}{n_j} \right) \right] = \begin{bmatrix} w_{11} & w_{12} & w_{13} & \dots & w_{1m} \\ w_{21} & w_{22} & w_{23} & \dots & w_{2m} \\ w_{31} & w_{32} & w_{33} & \dots & w_{3m} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ w_{n1} & w_{n2} & w_{n3} & \dots & w_{nm} \end{bmatrix}$$

The weighted occurrence frequency matrix was multiplied with the EmoLex matrix,  $B$ , consisting of  $j = 1, \dots, m$  EmoLex terms in rows and  $k = 1, \dots, u$  emotional dimensions in columns. The 10 emotional dimensions are composed of two overall sentiment polarities (positive, negative),  $k = 1, 2$ , and eight basic emotions (joy, anger, disgust, anticipation, sadness, fear, trust, and surprise),  $k = 3, \dots, 10$ :

$$B = b_{jk} = \begin{bmatrix} b_{11} & b_{12} & b_{13} & \dots & b_{1u} \\ b_{21} & b_{22} & b_{23} & \dots & b_{2u} \\ b_{31} & b_{32} & b_{33} & \dots & b_{3u} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ b_{m1} & b_{m2} & b_{m3} & \dots & b_{mu} \end{bmatrix}$$

The matrix multiplication step,  $W \cdot B$ , resulted in a weighted occurrence frequency matrix,  $WB$ , consisting of  $i = 1, \dots, n$  posts in rows and  $k = 1, \dots, u$  emotional dimensions in columns:

$$W \cdot B = WB = (wb)_{ik} = \begin{bmatrix} (wb)_{11} & (wb)_{12} & (wb)_{13} & \dots & (wb)_{1u} \\ (wb)_{21} & (wb)_{22} & (wb)_{23} & \dots & (wb)_{2u} \\ (wb)_{31} & (wb)_{32} & (wb)_{33} & \dots & (wb)_{3u} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ (wb)_{n1} & (wb)_{n2} & (wb)_{n3} & \dots & (wb)_{nu} \end{bmatrix}$$

The penultimate step neutralized the length of each post by dividing each cell of  $WB$  by the length of the respective post,  $T_i$ . This guarantees that the quantity of emotions contained in each post is balanced over all posts:

$$V = v_{ik} = \frac{(wb)_{ik}}{T_i} = \begin{bmatrix} v_{11} & v_{12} & v_{13} & \dots & v_{1u} \\ v_{21} & v_{22} & v_{23} & \dots & v_{2u} \\ v_{31} & v_{32} & v_{33} & \dots & v_{3u} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ v_{n1} & v_{n2} & v_{n3} & \dots & v_{nu} \end{bmatrix}$$

The very last step transformed all cells into percentages for the two overall polarities and the eight emotions separately. Transformation of the overall polarities is obtained by dividing each cell of columns  $k = 1, 2$  by the rowsum of the two polarities. Transformation of each emotion is obtained by dividing each cell of columns  $k = 3, \dots, 10$  by the rowsum of the eight emotions:

$$P = p_{ik} = \begin{cases} \frac{v_{ik}}{\sum_{k=1}^2 v_{ik}} * 100 \text{ for } k = 1, 2 \\ \frac{v_{ik}}{\sum_{k=3}^{10} v_{ik}} * 100 \text{ for } k = 3, \dots, 10 \end{cases}$$

$$= \begin{bmatrix} p_{11} & p_{12} & p_{13} & \dots & p_{1u} \\ p_{21} & p_{22} & p_{23} & \dots & p_{2u} \\ p_{31} & p_{32} & p_{33} & \dots & p_{3u} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ p_{n1} & p_{n2} & p_{n3} & \dots & p_{nu} \end{bmatrix}$$

## 4. Results and discussion

### 4.1. EmoLex terms in the Instagram posts

The average number of likes per Instagram post was 2.22. The average number of comments was 80.08. The average length after the data preparation steps was 30.35 terms with 226.79 characters. The preprocessed Instagram posts were screened upon 5,875 emotive terms contained in the preprocessed EmoLex dictionary. Column 2 in Table 1

**Table 1**  
Emotive terms in the EmoLex and the Instagram posts.

		EmoLex terms		Average number of EmoLex terms per post	
		Length	Occurrences	Total number of terms	Unique terms
Sentiment	Positive	2158	1720	3.23	2.95
	Negative	2991	1878	.77	.72
Anger		1146	707	.35	.32
Anticipation		794	668	1.46	1.35
Disgust		991	601	.20	.19
Fear		1370	926	.40	.37
Joy		636	570	1.97	1.81
Sadness		1082	743	.61	.57
Surprise		511	418	.86	.79
Trust		1183	930	1.64	1.49

Source: own calculations using R.

gives the number of EmoLex terms per emotion that were handed over to the string-matching task. The longest list of emotive terms (1,370) is associated to the emotion fear, surprise is the emotion represented by the lowest number of terms (511). It should be noted that to account for these term length differences between the eight emotions, the sentiment detection step included a normalization step so each emotion is represented in a balanced way.

Column 3 of Table 1 gives the number of unique EmoLex terms contained in any of the Instagram posts. 1,770 terms did not show up but 4,105 did. As terms could be assigned to multiple emotions in the EmoLex, the overall sum of column 3 is higher than 4,105. Ranking the number of different terms per emotion that showed up in at least one post gives a similar picture compared with the terms listed for each emotion in the EmoLex. 930 emotive terms related to trust showed up in at least one review, while fear ranks second, represented by 926 different terms. Only 418 unique terms related to surprise were used.

The fourth column of Table 1 lists the average number of emotive terms per review. The number of unique terms listed in column five of Table 1 is lower as duplicates, triplicates, and so forth are not counted

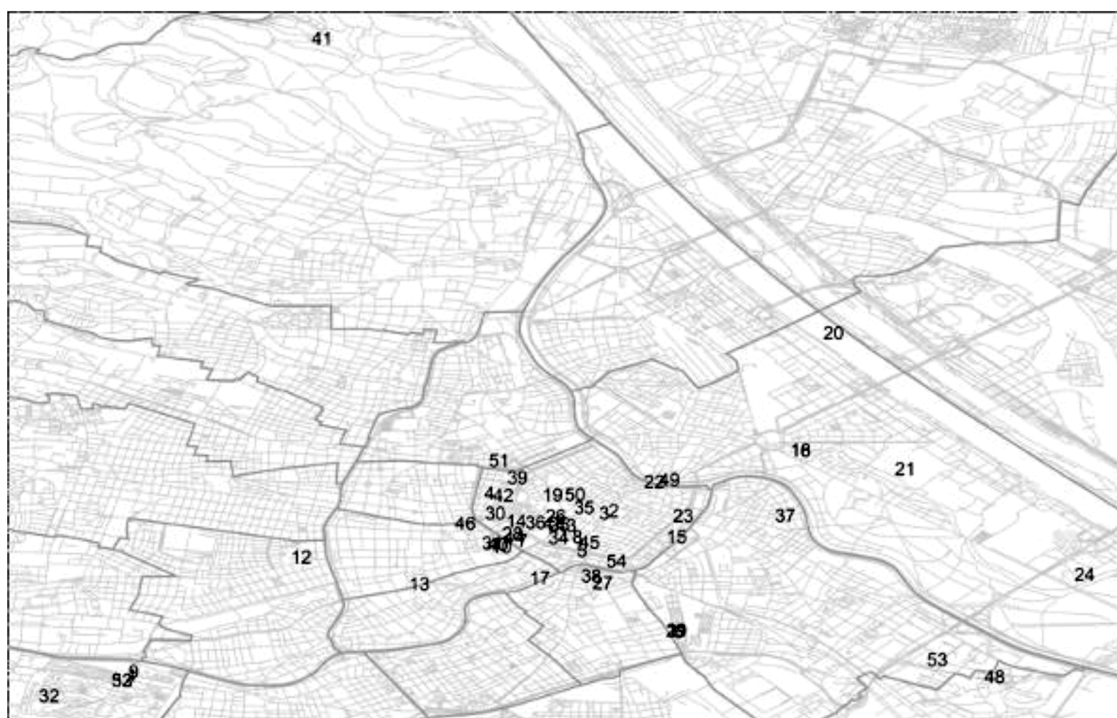
multiple times for a single Instagram post but just once. More than three positive terms (3.23) were used on average but less than one (0.77) negative term. Joy had the highest number of term occurrences, 1.97. The value of 1.81 shows that every post contains, on average, nearly two different terms listed in the EmoLex under the emotion joy. Emotive terms related to disgust are observed only in every fifth post, resulting in an average value of 0.2.

It can also be observed that the ranking of emotions by their average number of EmoLex terms per Instagram post (columns 4 and 5 of Table 1) is different from the ranking of the absolute number of emotive terms listed in the EmoLex per emotional dimension (columns 2 and 3). Hence, the varying length of terms listed for each EmoLex dimension do not seem to distort the results due to the term representedness of single emotions in the EmoLex.

#### 4.2. Sentiment and emotions towards top Viennese Instagram locations

Fig. 1 indicates the geographical dispersion of those 54 Instagram locations in Vienna for which at least 500 posts containing emotional statements were present. This street map was created in R using the ‘sp’ package (Pebesma and Bivand, 2005) and features, besides the top Instagram locations, the borders between Vienna’s 23 districts. Observed in Fig. 1, many locations are concentrated in Vienna’s First District (i.e., the historic city center). According to official statistics for the year 2017, these locations represent some of the most visited attractions of Vienna (Statistics Austria, 2017). Some Instagram locations also refer to clusters of attractions, such as the cluster containing the numbers 1, 9, 33, and 52 in the southwest of the city, which all relate to the former imperial palace of Schönbrunn and its surroundings.

Table 2 lists the percentage shares within the overall sentiment and within the eight single emotions towards the 54 locations and are ranked in descending order by the number of posts for each location contained in the dataset. Both positive and negative sentiments equate to 100%. The percentages in Table 2 are displayed as bars for better readability. Positive sentiment and joy dominate the posts. Negative sentiment and negative single emotions, in particular anger, disgust, fear, or sadness,



**Fig. 1.** Geographical dispersion of Viennese top Instagram locations.  
Source: own illustration using R.

**Table 2**  
Emotions towards Viennese top Instagram locations.

No. in Figure 1	Location	Sentiment		Single emotions							
		Positive	Negative	Anger	Anticip.	Disgust	Fear	Joy	Sadness	Surprise	Trust
1	Schloß Schönbrunn	0.83	0.17	0.03	0.18	0.02	0.03	0.41	0.07	0.13	0.13
2	St. Stephen's Cathedral, Vienna	0.88	0.12	0.03	0.18	0.02	0.03	0.41	0.05	0.10	0.19
3	Stephansplatz	0.85	0.15	0.03	0.19	0.02	0.03	0.37	0.06	0.12	0.17
4	Rathaus, Vienna	0.84	0.16	0.03	0.19	0.02	0.03	0.37	0.07	0.13	0.17
5	Wiener Staatsoper	0.88	0.12	0.06	0.18	0.02	0.05	0.31	0.09	0.17	0.12
6	Belvedere, Vienna	0.85	0.15	0.03	0.17	0.02	0.02	0.40	0.07	0.14	0.14
7	Kunsthistorisches Museum Vienna	0.84	0.16	0.03	0.18	0.02	0.04	0.32	0.08	0.16	0.15
8	Albertina Museum	0.82	0.18	0.04	0.17	0.03	0.04	0.32	0.10	0.18	0.13
9	Palace and Gardens of Schönbrunn	0.84	0.16	0.03	0.17	0.02	0.03	0.47	0.07	0.11	0.11
10	MQ – MuseumsQuartier Wien	0.81	0.19	0.04	0.19	0.02	0.04	0.32	0.08	0.15	0.15
11	Belvedere Palace, Vienna, Austria	0.86	0.14	0.03	0.17	0.02	0.02	0.41	0.07	0.14	0.14
12	Wiener Stadthalle	0.80	0.20	0.03	0.18	0.03	0.04	0.33	0.09	0.14	0.15
13	Mariahilferstraße	0.82	0.18	0.03	0.21	0.03	0.04	0.34	0.08	0.14	0.14
14	Volksgarten	0.85	0.15	0.03	0.17	0.02	0.03	0.44	0.06	0.11	0.13
15	Stadtpark, Vienna	0.82	0.18	0.04	0.19	0.03	0.03	0.38	0.08	0.13	0.12
16	Wiener Prater	0.82	0.18	0.03	0.22	0.03	0.05	0.37	0.07	0.13	0.10
17	Naschmarkt	0.84	0.16	0.04	0.18	0.04	0.04	0.39	0.06	0.12	0.14
18	Prater	0.83	0.17	0.03	0.22	0.02	0.05	0.37	0.07	0.13	0.11
19	Café Central Wien	0.88	0.12	0.03	0.19	0.03	0.03	0.39	0.05	0.12	0.15
20	Donauinsel	0.84	0.16	0.03	0.23	0.02	0.04	0.35	0.08	0.14	0.11
21	WU (Wirtschaftsuniversität Wien)	0.84	0.16	0.03	0.33	0.03	0.03	0.16	0.06	0.09	0.28
22	Donaukanal	0.81	0.19	0.03	0.21	0.03	0.04	0.34	0.09	0.14	0.11
23	MAK - Austrian Museum of Applied Arts / Contemporary Art	0.86	0.14	0.02	0.22	0.02	0.04	0.30	0.08	0.14	0.18
24	Prater, Wien, Austria	0.82	0.18	0.04	0.20	0.02	0.06	0.36	0.08	0.13	0.11
25	Hofburg	0.85	0.15	0.03	0.18	0.02	0.03	0.33	0.06	0.14	0.20
26	Hofburg Wien: Kaiserappartements   Sisi Museum   Silberkammer	0.86	0.14	0.03	0.20	0.02	0.03	0.36	0.06	0.12	0.19
27	Karlskirche	0.88	0.12	0.03	0.21	0.01	0.03	0.38	0.05	0.10	0.18
28	NhM Naturhistorisches Museum Wien	0.82	0.18	0.04	0.16	0.03	0.10	0.31	0.07	0.14	0.16
29	Belvedere Gardens - Vienna	0.86	0.14	0.03	0.16	0.02	0.03	0.48	0.06	0.11	0.11
30	Austrian Parliament Building	0.84	0.16	0.03	0.15	0.02	0.03	0.26	0.06	0.11	0.35
31	mumok - Museum moderner Kunst Wien	0.78	0.22	0.03	0.18	0.03	0.04	0.25	0.10	0.20	0.17
32	Zoo Vienna Schönbrunn	0.77	0.23	0.06	0.18	0.04	0.07	0.36	0.06	0.13	0.11
33	Schönbrunn Palace	0.83	0.17	0.03	0.17	0.02	0.04	0.41	0.07	0.14	0.12
34	Burggarten	0.85	0.15	0.03	0.18	0.03	0.02	0.41	0.07	0.14	0.13
35	Graben, Vienna	0.85	0.15	0.03	0.19	0.02	0.03	0.39	0.06	0.13	0.15
36	Heldenplatz	0.83	0.17	0.03	0.21	0.02	0.05	0.32	0.10	0.13	0.15
37	Hundertwasserhaus	0.83	0.17	0.03	0.17	0.02	0.04	0.27	0.07	0.15	0.25
38	Karlsplatz	0.82	0.18	0.04	0.19	0.03	0.04	0.35	0.07	0.13	0.17
39	Universität Wien	0.86	0.14	0.02	0.43	0.03	0.02	0.20	0.06	0.08	0.16
40	Leopold Museum	0.75	0.25	0.03	0.18	0.04	0.05	0.28	0.10	0.19	0.13
41	Kahlenberg, Vienna, Austria	0.81	0.19	0.03	0.23	0.02	0.03	0.36	0.08	0.14	0.11
42	Wiener Christkindlmarkt	0.83	0.17	0.04	0.20	0.03	0.03	0.37	0.05	0.14	0.13
43	Österreichische Nationalbibliothek	0.90	0.10	0.03	0.17	0.02	0.03	0.33	0.06	0.15	0.21
44	Maria-Theresien-Platz	0.86	0.14	0.03	0.18	0.02	0.03	0.37	0.08	0.14	0.15
45	Hotel Sacher Wien - Salzburg	0.85	0.15	0.04	0.20	0.03	0.04	0.41	0.06	0.11	0.12
46	25hours Hotel beim MuseumsQuartier	0.78	0.22	0.04	0.21	0.04	0.04	0.35	0.06	0.12	0.13
47	Hofburg Palace	0.85	0.15	0.03	0.22	0.02	0.04	0.33	0.06	0.12	0.19
48	Gasometer	0.76	0.24	0.07	0.16	0.03	0.06	0.29	0.09	0.14	0.17
49	Softel Vienna Stephansdom	0.81	0.19	0.02	0.19	0.03	0.03	0.36	0.05	0.17	0.14
50	Park Hyatt Vienna	0.85	0.15	0.02	0.19	0.03	0.03	0.40	0.05	0.12	0.17
51	Votive Church, Vienna	0.87	0.13	0.02	0.21	0.02	0.02	0.37	0.06	0.09	0.22
52	Schönbrunn Wien	0.85	0.15	0.03	0.19	0.01	0.02	0.42	0.06	0.14	0.12
53	ARENA WIEN	0.73	0.27	0.06	0.15	0.05	0.06	0.30	0.10	0.14	0.15
54	Hotel Imperial, Vienna	0.87	0.13	0.03	0.20	0.02	0.03	0.42	0.04	0.12	0.14
	<b>Range</b>	0.17	0.17	0.05	0.29	0.04	0.07	0.32	0.06	0.12	0.25

Source: own calculations and illustration using R and Microsoft Excel.

occur less frequently. Since these locations in Vienna also represent some of Vienna’s major attractions, the dominance of positive sentiment and positive single emotions for all locations is not surprising. The last row of Table 2 contains the emotional variability within the top ten ranked Viennese locations in terms of Instagram posts. Joy shows the biggest variation with 31.59%. Disgust (3.61%), anger (4.50%), and sadness (6.15%) show the smallest variations.

Some exemplary results for the single emotions are presented and discussed in the following text. The ‘mumok – Museum Moderner Kunst Wien’, i.e., Vienna’s Museum of Modern Arts (location 31), has the largest value for surprise (20.07%), the ‘Austrian Parliament Building’ (location 30) represents the greatest percentage for trust (35.17%), and the ‘Belvedere Gardens – Vienna’ (number 29) rank the highest for the

emotion joy (47.73%). These results can be considered somewhat expected and may reflect the novel, and thus the surprising nature of modern art, the trust in the democratic institutions of the country, and the appreciation of the beauty of the place, respectively.

On the other hand, the ‘WU (Wirtschaftsuniversität Wien)’, i.e., the Vienna University of Economics and Business (location 21), maintains the lowest percentage of joy (16.13%), closely followed by the ‘Universität Wien’, i.e., the University of Vienna (location 39), with 20.20%. On the other hand, these two higher education institutions score highest in anticipation (33.46% for the Vienna University of Economics and Business and 43.26% for the University of Vienna, respectively). Given the young age of typical Instagram users, most posts are therefore likely to come from university students.

Concerning negative emotions, the ‘Gasometer’ (location 48) holds the highest percentage of anger (6.50%), which may be due to it (and its surroundings) hosting a number of municipal authorities, as well as a somewhat oversized shopping center suffering from a confusing architectural design. An alternative event location for concerts, clubbings, and the like, the ‘ARENA WIEN’ (location 53) ranks highest for disgust (4.95%), which may reflect its perception of being somewhat ‘shabby’ on the part of a minority of its visitors. The ‘NhM Naturhistorisches Museum Wien’, i.e., the Museum of Natural History Vienna (location

28), is characterized by the biggest share of the emotion fear (9.55%), potentially due to it exhibiting numerous animal dermoplastics and additionally fueled by Gunther von Hagen’s ‘Body Worlds: Animals Inside Out’ exhibition in 2013 (<https://bodyworlds.com/exhibitions/animals/>), which falls within in the sampled period. Sadness is most prominent at ‘Heldenplatz’ (location 36; 10.24%), likely due to the historical fact that this was the place where dictator Adolf Hitler announced the annexation of Austria to Nazi Germany on March 15, 1938. Additionally, the ‘Wiener Staatsoper’, i.e., the Viennese State

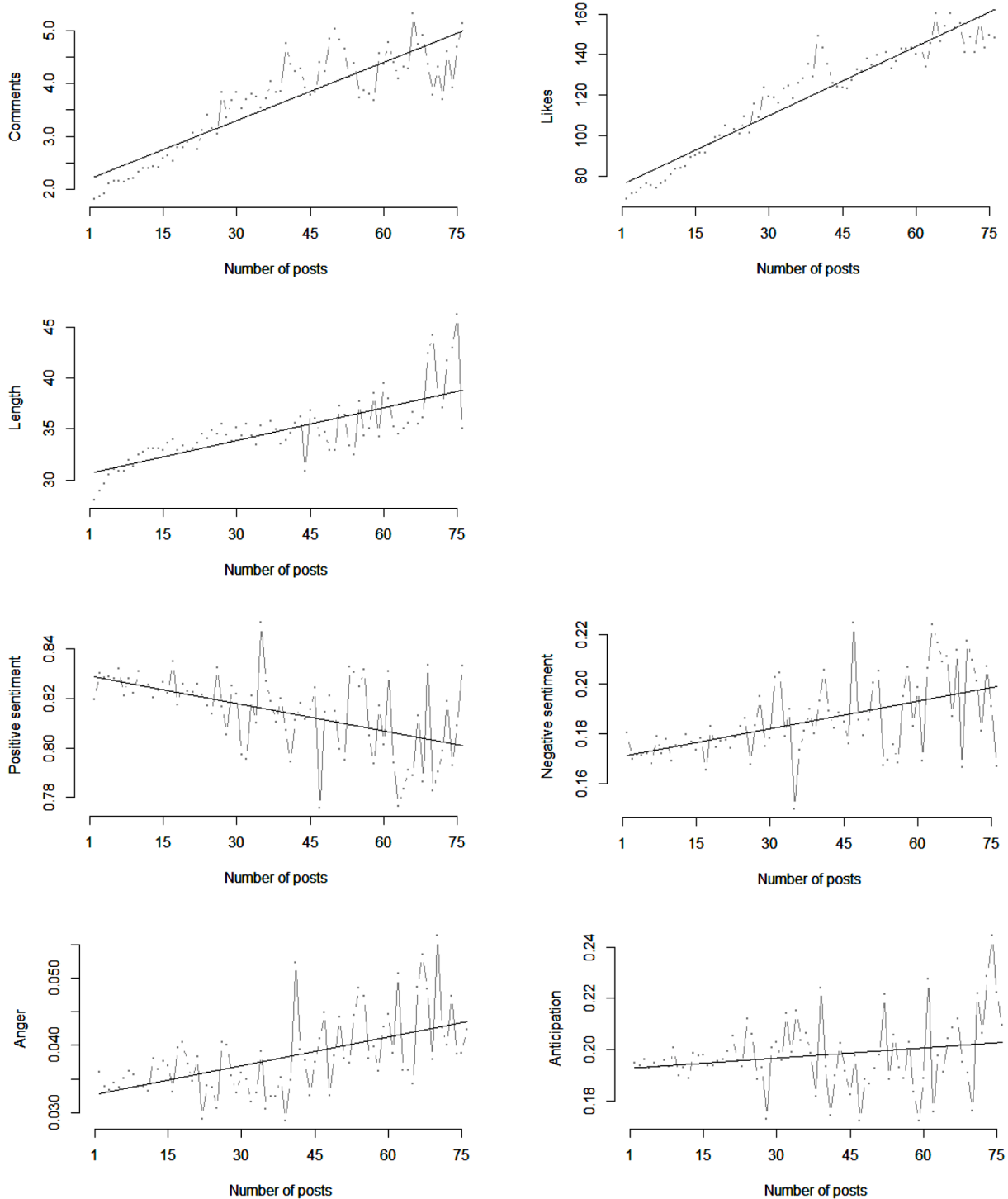


Fig. 2. Emotional changes and descriptive developments in posting behavior. Source: own calculations and illustration using R.



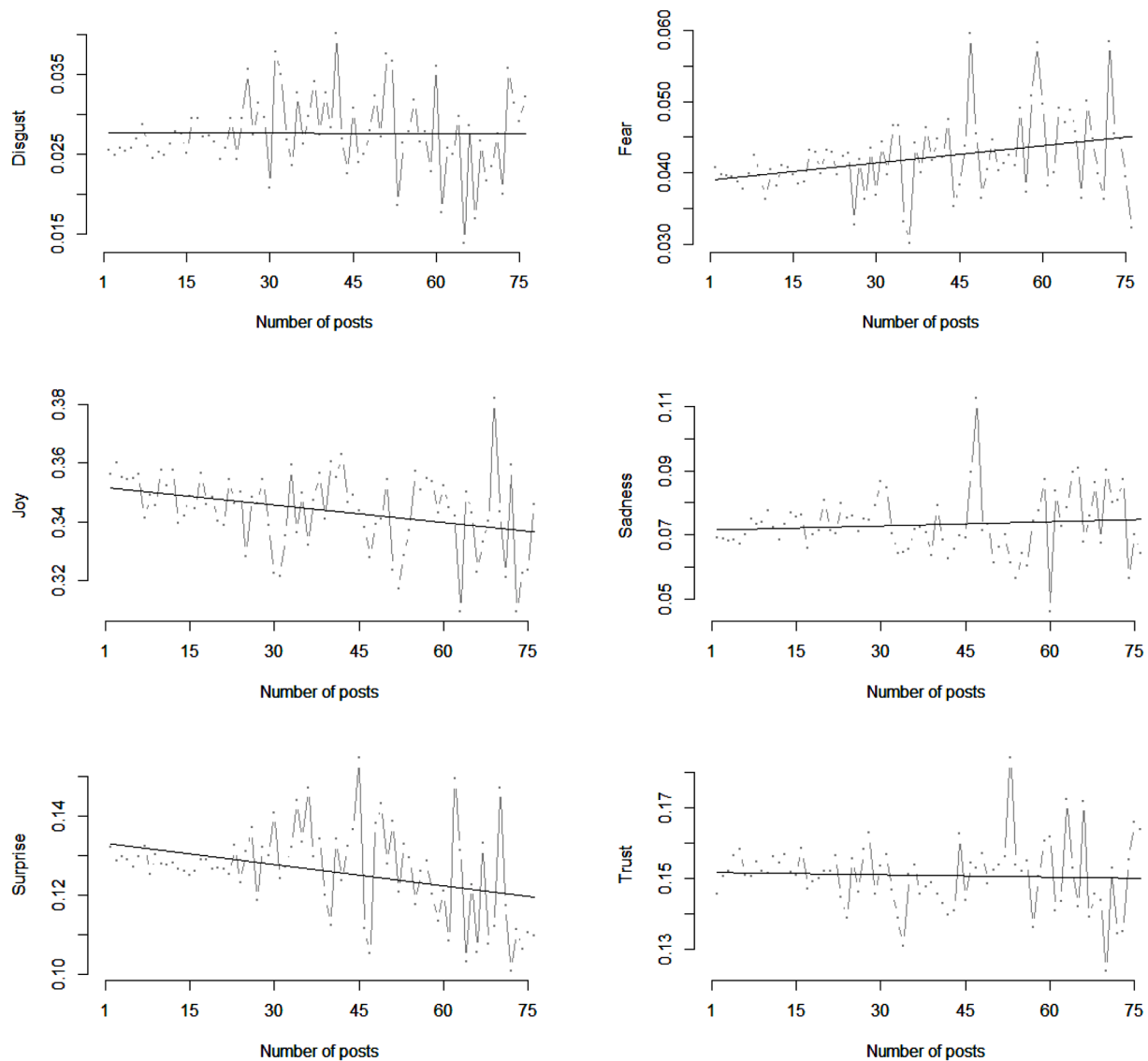


Fig. 2. (continued).

Opera (location 5), the ‘Wiener Stadthalle’, a large event center (location 12), as well as the aforementioned ‘ARENA WIEN’ and ‘Gasometer’ feature sadness values greater than 9%. Their communality is that they either are or contain locations for music performances.

A likely explanation for opera performances evoking sadness is that professionally staged operas are able to convey the positive and negative emotions contained in the work and displayed by the opera singers to the audience during the performance (Scherer and Coutinho, 2013). These are perceived as authentic in terms of being a credible expression of a character from the opera’s libretto, subject to the constraints of the music, the libretto, and the director’s interpretation of the work (Scherer et al., 2013). Concerning other types of music performances, sadness may potentially be triggered by feelings of nostalgia.

#### 4.3. Longitudinal variations of sentiment and emotions

Apart from this cross-sectional perspective on emotional variability, longitudinal variations are observable for the posting behavior itself. Fig. 2 gives the average percentage of an emotion on the y-axis and the sequential number of the post published by an individual on the x-axis. For this purpose, the data were grouped by the Instagram user ID, sorted by the publishing date and numbered consecutively. Finally, they were

grouped by their consecutive numbers and mean values for the two sentiment polarities and the eight single emotions were determined. To guarantee for reliable results, only mean values based on a minimum of 100 Instagram users were included in the visualizations on the x-axis. This was the case for a sequence of 76 posts generated by individual Instagram users.

Estimated linear regression lines based on ordinary least squares (OLS) were added to the scatterplots. An increasing number of posts goes hand in hand with an increasing number of likes and comments for the posts, as well as an increasing number of terms, considered the average length of the post.

Furthermore, it can also be observed that Instagram users become more critical with every additional post. The quantity of negative sentiment, as well as negative emotions increases over time (e.g., anger and fear). On the other hand, positive sentiment and related emotions decrease over time (e.g., joy and surprise). A tentative explanation of the positive correlation between number of posts and average post length could be the observed phenomenon of hashtag use by Instagram influencers per se driving the addition of hashtags in future posts, thus automatically increasing average post length (Erz et al., 2018). The same authors also conclude that certain personality traits of influencers (i.e., extraversion, narcissism, self-monitoring, self-presentation, and status

seeking) constitute the major motives for their hashtag use.

In combination with more experience and self-confidence in Instagram posting, these personality traits, as well as increasing expectations, could also result in becoming more critical over time (thus the positive correlation between number of posts and negative sentiment and negative single emotions, respectively), thereby again inducing an increased average post length. Over time, attracting more followers also means an increasing pool of potential likes and comments, thus leading to the positive correlation between number of posts and the number of the latter.

This finding also has an important managerial implication. Companies interested in the use of influencer marketing, a form of digital marketing relying on the electronic word of mouth (eWOM; Hennig-Thurau et al., 2004), to promote their products and services via Instagram should take the finding of influencers becoming more critical over time into consideration to be successful. For the present case, WienTourismus (i.e., the destination management organization of Vienna) would need to ensure a continuous satisfaction of the influencers' expectations when trying to promote its major attractions via Instagram using this marketing channel. In addition, a life cycle assessment of the engaged influencers may become necessary.

## 5. Conclusions

This research extracted sentiment, as well as single basic emotions according to Plutchik's Wheel of Emotions from the photo captions including hashtag terms from 627,632 Instagram posts for the Austrian capital city of Vienna over the period of October 30th, 2011 to February 7th, 2018. To achieve this, an algorithm falling into the category of dictionary-based approaches to study emotions contained in written text was developed and applied. Not only were the overall polarity and the single emotions contained in Instagram posts within Vienna investigated, but also emotions towards the top 54 Viennese Instagram locations. A particular novelty of this study was the measurement of longitudinal developments from emotive text and the fine-grained analysis of single emotions in addition to the overall polarity.

One important empirical result of the study was that more experience and self-confidence in Instagram posting, as well as increasing expectations, seem to result in becoming a more critical poster over time. Companies interested in the use of influencer marketing to promote their products and services via Instagram should take this finding into consideration to be successful. Apart from this empirical finding and managerial implication, the development and application of the methodology itself, the analysis of emotive text from Instagram posts using fine-grained single emotions in addition to the overall polarity, the analysis of emotive text in relation to the places where the photos were taken, as well as the measurement of longitudinal developments are the major contributions of this study to the existing literature.

The main limitations of this study are its geographical focus on Vienna, its temporal focus on the period of October 30th, 2011 to February 7th, 2018, and the analysis of Instagram posts. Nonetheless, the methodology can be easily applied to other cities and periods, thus making the present research fully replicable. The methodology is also not limited to Instagram posts. It can be directly applied to other social media platforms such as Facebook, TripAdvisor, or Twitter, provided that access to data from those platforms can be obtained in both legal and technical terms. One straightforward idea for future research would thus be the replication of this study using data from different social media platforms for different cities and periods.

## Author statement

Christian Weismayer: Formal analysis, Methodology, Software, Visualization, Writing - original draft, Writing - review & editing  
Ulrich Gunter: Conceptualization, Funding acquisition, Project administration, Supervision, Visualization, Writing - original draft, Writing - review &

editing  
Irem Önder: Data curation, Investigation, Resources, Validation, Writing - original draft, Writing - review & editing.

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