Received: 23 June 2020 | Revised: 3 November 2020 | Accepted: 29 November 2020

DOI: 10.1002/asi.24440

RESEARCH ARTICLE

JASIST WILEY

On the causal relation between real world activities and emotional expressions of social media users

Seyed Amin Mirlohi Falavarjani[1,2] | **Jelena Jovanovic**[3] | **Hossein Fani**[4] | **Ali A. Ghorbani**[1] | **Zeinab Noorian**[2] | **Ebrahim Bagheri**[2]

[1]University of New Brunswick, Fredericton, Canada

[2]Ryerson University, Toronto, Canada

[3]University of Belgrade, Belgrade, Serbia

[4]University of Windsor, Windsor, Canada

Correspondence
Ebrahim Bagheri, Ryerson University, Toronto, Canada.
Email: bagheri@ryerson.ca

Funding information
Natural Sciences and Engineering Research Council of Canada, Grant/Award Number: RGPIN-2015-06118

Abstract

Social interactions through online social media have become a daily routine of many, and the number of those whose real world (offline) and online lives have become intertwined is continuously growing. As such, the interplay of individuals' online and offline activities has been the subject of numerous research studies, the majority of which explored the impact of people's online actions on their offline activities. The opposite direction of impact—the effect of real-world activities on online actions—has also received attention but to a lesser degree. To contribute to the latter form of impact, this paper reports on a quasi-experimental design study that examined the presence of causal relations between real-world activities of online social media users and their online emotional expressions. To this end, we have collected a large dataset (over 17K users) from Twitter and Foursquare, and systematically aligned user content on the two social media platforms. Users' Foursquare check-ins provided information about their offline activities, whereas the users' expressions of emotions and moods were derived from their Twitter posts. Since our study was based on a quasi-experimental design, to minimize the impact of covariates, we applied an innovative model of computing propensity scores. Our main findings can be summarized as follows: (a) users' offline activities do impact their affective expressions, both of emotions and moods, as evidenced in their online shared textual content; (b) the impact depends on the type of offline activity and if the user embarks on or abandons the activity. Our findings can be used to devise a personalized recommendation mechanism to help people better manage their online emotional expressions.

1 | INTRODUCTION

Online social media play an increasingly significant role in various aspects of people's lives. The data collected from online social media have enabled researchers to investigate behavioral patterns and decision-making mechanisms of users (Khatua, Khatua, & Cambria, 2019; Mueller, Jay, Harper, & Todd, 2017; Paul & Dredze, 2017; Thelwall & Stuart, 2019). While actively used for descriptive analysis and predictive modeling (Althoff, Jindal, & Leskovec, 2017; Kropivnitskaya, Tiampo, Qin, & Bauer, 2017), more recently, online social media have become the focus of systematic *quasi-experimental design studies* aimed at establishing causal relations and making predictions based on the exchanged social content (De Choudhury, Kiciman, Dredze, Coppersmith, & Kumar, 2016; Saha, Weber, & Choudhury, 2018). A subset of such studies investigate the impact of users' online behavior on their offline activities (Althoff et al., 2017; Althoff, White, & Horvitz, 2016; Shameli, Althoff, Saberi, & Leskovec, 2017; Stück, Hallgrímsson, Ver Steeg, Epasto, & Foschini, 2017). Fewer studies have examined the consequences of real-world (offline) activities on users' actions on online social media (Branley & Covey, 2017; Falavarjani, Zarrinkalam, Jovanovic, Bagheri, & Ghorbani, 2019; Kiciman, Counts, & Gasser, 2018).

Overall, the reported studies indicate that cases of mutually reinforcing impact between users' online and offline activities can be found. Our work in this paper endeavors to explore this phenomenon further by specifically focusing on understanding the impact of users' offline activities on their online expression of emotions and moods. Motivation for this work is twofold and can be considered from *individual* (personal) and *scientific* (methodological) perspectives.

From an *individual* perspective, the ultimate objective is to support individuals in introspection. People can fairly easily make conclusions about the emotional impact of their activities, provided that the activity and the change in emotional state are temporally proximal (e.g., feeling more positive and optimistic after going for a walk). However, when it comes to an activity that one practices regularly over a longer period of time and that may have longer term emotional impact (i.e., impact emotions and mood over a longer period of time), establishing a connection between the cause and effect is more difficult. Many would not even realize that a regular activity they have adopted (e.g., started going to a bar often) or ceased to practice (e.g., stopped regular travels due to a global pandemic) may impact their emotions and/or mood for a longer period of time. So, having a technology that would support people in identifying such patterns of impact could facilitate introspection.

From a scientific perspective, the motive is to facilitate and advance studies of causal relationships between different life activities and different emotional states by leveraging people's digital traces on social media (e.g., status updates and posts). More precisely, the overarching idea is to propose and demonstrate a trace-based methodology that enables (a) larger scale studies (compared to traditional ones) of the causal relations connecting individual's (real-world) activities and their emotions and moods; and (b) more direct insights into people's activities, emotions, and moods, instead of or in addition to traditional self-reports (e.g., surveys).

In order to analyze both offline and online activities of users, we have extracted a large dataset that consists of both Twitter posts and Foursquare check-ins. We have collected data points such that for each user in the dataset, their Twitter posts and Foursquare check-ins are available. We view the Twitter posts of each user as a representation of their online actions and their Foursquare check-ins as a depiction of their offline activities. Based on this dataset, we systematically examine whether embarking on or abandoning an offline activity has any causal impacts on a user's online emotional expressions.

1.1 | Illustrative example

Let us illustrate the objective of our study through an example where we use the information from an actual user but for the sake of anonymity we refer to this user as @johndoe. Figure 1 visualizes the online behavior and offline activities of @johndoe, as observed, respectively, on Twitter and Foursquare. As explained later in the paper, we have used the Linguistic Inquiry and Word Count model (Tausczik & Pennebaker, 2010) to determine @johndoe's online emotional expressions, presented in the top row of Figure 1, whereas venue categories associated with the @johndoe's Foursquare checkins have been used to determine @johndoe's offline activities, depicted in the bottom row of the same figure. Figure 1 aligns the emotional expressions and offline check-ins of @johndoe for a period of 6 months in 2016. In the first 2 months of 2016 (January and February), based on his Foursquare checkins, @johndoe was consistently focused on visiting venues related to Arts, Food, and Shopping. However, at Month 3, the user changed the pattern of their offline check-ins (which we refer to as an *interruption*) and oriented towards offline activities related to Night Life, by checking in at venues including bars, lounges, night markets, and nightclubs. These offline activities began in March and constantly continued until June. Therefore, we identify this user as now actively engaged in a new kind of offline activity, while abandoning the types of offline activities practiced earlier. Based on this observation, we are interested in understanding whether the newly adopted offline activity, in this case Nightlife activities, has had any impact on the user's online emotional expressions.

As shown in Figure 1, in the first 2 months of @johndoe's activities, Positive Emotions dominated over other emotions. However, after the "*interruption*" and in the subsequent months, while the user was engaged with Nightlife activities, the expression of positive emotions decreased and the intensity of Negative Emotions (anger, sadness, anxiety) increased. This example could be considered an isolated incident that is not necessarily a part of a general phenomenon. The objective of our work is to systematically study such cases under a *quasi-experimental design*, to see if they can be generalized across a larger group of users, and for different types of offline activities,

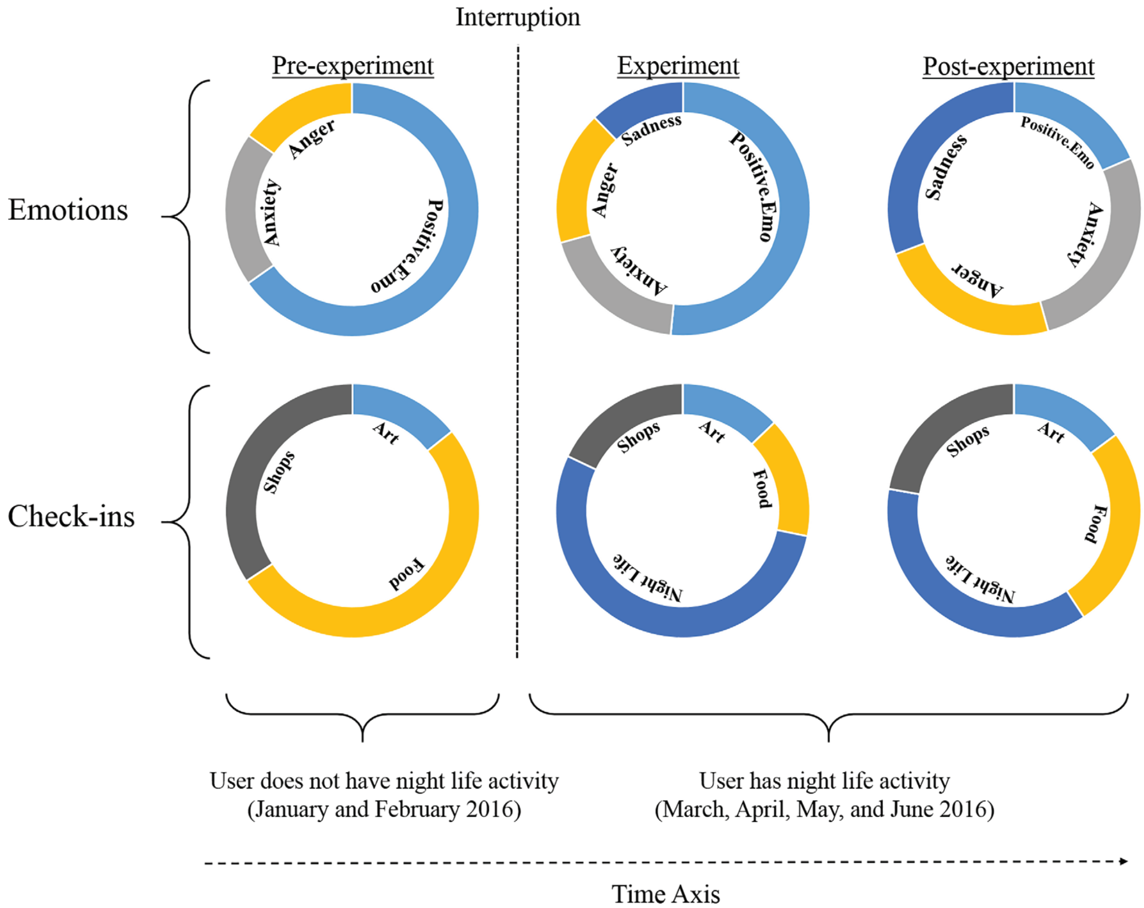


FIGURE 1 Visualization of the changes in a sample user's offline activities and emotional expressions over a period of 6 months [Color figure can be viewed at wileyonlinelibrary.com]

with the ultimate goal of identifying causal relations between offline activities and online emotional expressions.

1.2 | Contributions

We are particularly interested in addressing two complementary research questions (RQs), that is, whether embarking on (RQ 1) or abandoning (RQ 2) regular real-world (offline) activities, such as frequently shopping or going to a bar, can have any causal impact on users' online emotional expressions. To this end, we have conducted a quasi-experimental design study to examine and systematically compare online expressed emotions (Tausczik & Pennebaker, 2010) and moods (Thayer, 1990) of those users who embark on or abandon different types of real-world activities. The specific contributions of our work are as follows:

1. We have collected and aligned content from two online social media platforms, namely Twitter, representing users' online actions, and Foursquare, capturing their offline activities;
2. We have analyzed users' affective expressions within online social media aiming to infer the expressed *emotions* and *moods*. To that end, we have defined a computational model for determining users' dominant emotions and moods, based on the textual content they shared through an online social media platform over a period of time;
3. To overcome the fact that in quasi-experimental design studies, such as ours, the subjects are not randomly assigned to experimental and control groups, we rely on stratified propensity score matching. In doing so, we have applied an innovative model of computing propensity scores based on the subjects' past offline activities, with the objective of minimizing the impact of covariates.
4. We show that offline activities do in fact impact users' affective expressions, both of emotions and moods, as evidenced in their online social content. The impacts are dependent on whether a user engages in or disengages from offline activities and are associated with the type of offline activity, as well.

2 | RESEARCH FRAMEWORK

2.1 | Theoretical background

The theoretical background of our work includes (a) psychological studies and (b) computational causal studies.

2.1.1 | Psychological studies

The theoretical underpinning for our work from the perspective of psychological studies includes the existing literature on the effects of different offline activities on people's psychological health and cognitive function. For example, the literature has reported the impact of (a) *active travel* (Cerin, Nathan, van Cauwenberg, Barnett, & Barnett, 2017) on one's physical and mental health where the researchers report that active travel could decrease disorders such as depression; (b) regular exercise (Schuch et al., 2016) on addressing issues of depression and anxiety; (c) *social prescribing* where physicians prescribe social activities to improve the health of their patients, are correlated with positive impact on the patients' emotional expressions (Chatterjee, Camic, Lockyer, & Thomson, 2018), and (d) *art therapy* where people participate in art-related activities has shown to benefit people with mental health difficulties. Art therapy increases levels of empowerment and therefore has the potential to impact mental health (Macpherson, Hart, & Heaver, 2016).

The literature has also shown that social activities can help seniors reduce social isolation. A study by Todd, Camic, Lockyer, Thomson, and Chatterjee (2017) showed that when elderly adults visit museums, they experience higher levels of confidence, mental stimulation, and privilege. Such activities were also associated with increased self-confidence and less anxiety. This study is a part of a broader body of evidence that engaging in offline cultural activities can reduce the risk of social exclusion and lead to improved positive emotions. Other offline social activities such as playing or listening to music can improve mood and cognitive function (Ploukou & Panagopoulou, 2018). For instance, Hudak et al. showed that piano lessons could have a positive impact on cognitive functions and mood in adults (Hudak et al., 2019).

Not surprisingly, regular exercise has been associated with positive emotions. In a meta-analytical review, Falck and colleagues found that regular exercise led to improved mood in the participants (Falck, Davis, Best, Crockett, & Liu-Ambrose, 2019). Similarly, Mikkelsen et al. reported that exercises not only led to better mood but significantly greater mood changes were observed among individuals who had reported symptoms of depression before engaging in exercises (Mikkelsen, Stojanovska, Polenakovic, Bosevski, & Apostolopoulos, 2017). Researchers have also indicated that offline activities such as those associated with pleasurable pastime can help improve mood and mental health. For instance, Paggi et al. indicated that physical health was related to leisure activities and leisure activities were related to well-being (Paggi, Jopp, & Hertzog, 2016; Pressman et al., 2009).

2.1.2 | Computational causal studies

The other set of studies relevant to our paper pertains to work that have benefited from computational methods to capture users' emotions and moods based on their online actions. Such work are instrumental in showing that people's mental health, emotions, and moods can be effectively captured and studied based on their online actions.

In the context of mental health, Choudhury and Kiciman (2017) and De Choudhury et al. (2016) have studied the shift from mental illness to suicide ideation and its relationship to the language used in comments and posts found on Reddit mental health groups. The researchers leveraged the psychoanalysis content of anonymous support groups on Reddit as a source of information for an observational study using a corresponding statistical matching methodology. In Ernala et al. (2018), the researchers presented a quantitative methodology for understanding audiences and their engagement in stigmatized self-disclosures on Twitter. They chose Schizophrenia as the specific case of self-disclosure and obtained a list of individuals who had publicly shared their diagnosis of Schizophrenia on Twitter. The researchers characterized the temporal variation in the audience engagement with the disclosed content and studied its alignment with respect to what was disclosed. They found that the users and their followers' behavior had a significant correlation with the signs of Schizophrenia after the users revealed their mental illness. Saha et al. (2018) studied the importance of counseling for students who had experienced a deadly incident in college by evaluating students' comments from Reddit communities. By contrasting two groups of students, one consisting of students who had experienced death incidents and others who had not, Saha et al. found positive psychological effects for counseling. The common themes between these works includes the use of social content for inferring causal relations between users' online expressions and their emotional or psychological state.

Closely related to the social data used in this paper, that is, data from Twitter, other researchers have also benefited from Twitter as a low-cost, large-scale, and rich data source for quasi-experimental design studies (Paul & Dredze, 2011; Reis & Culotta, 2015). For instance, Choudhury, Gamon, Counts, and Horvitz (2013) suggested a family of measures, such as language, emotion, style, and user interaction on Twitter to describe depression, and thus predict people's depression states. Murnane and Counts (2014) relied on Twitter data to identify distinct characteristics of those who failed at the end of a smoking cessation process. Reis and Culotta (2015) combined a quasi-experimental design with statistical matching methods to examine the presence of causal relationships between exercise and mental health (anger, depression, anxiety) among Twitter users. They found that people who exercised regularly posted fewer tweets expressing depression or anxiety. Olteanu, Varol, and Kiciman (2017) conducted a quantitative analysis of Twitter data to answer some open questions related to the experiences that users had shared on Twitter and the experiences that they might have mentioned later.

Our work is motivated by the literature on (a) psychological studies, which suggests that it is possible to find causal relations between users' activities and their emotional expressions, and (b) computational causal studies, which demonstrate the use of social content for modeling user's offline activities as well as their online actions, including their affective expressions. However, it distinguishes itself from the work that explores how online activities impact offline activity (e.g., Althoff et al., 2017; Stück et al., 2017) by investigating the reverse relation, that is, how offline activities impact users' online actions. It also differentiates itself from earlier works that investigated the impact of offline activities on online actions (e.g., Falavarjani et al., 2019; Kiciman et al., 2018) by specifically focusing on changes in users' online expression of emotions and moods as a result of differing offline activity patterns.

2.2 | Research questions

Our objective in this paper is to systematically investigate whether people's offline activities impact their online affective expressions. We investigate this within a causal framework to find any potential cause-effect relations. To this end, we adopt and define computational models for two notions of affection: (a) *emotions* (Tausczik & Pennebaker, 2010), with the focus on a user's positive and negative emotions, and (b) *moods* that are considered through a user's level of arousal and valence, as proposed in Thayer (1990). We aim to understand whether changes in users' offline activities can cause changes in their expression of emotions or moods. As such, this leads to our two main research questions (RQs):

RQ1: Does, and if so, to what extent, embarking on or abandoning an offline activity impact a user's online emotions?

RQ2: Does, and if so, to what extent, embarking on or abandoning an offline activity affect a user's online moods?

We will view each research questions as two sub-research questions, namely RQ 1.1 and RQ 1.2 as well as RQ 2.1 and RQ 2.2. The first sub-research questions, that is, RQ 1.1 and RQ 2.1, investigate cases when the users embark on an offline activity, while the second sub-research questions, that is, RQ 1.2 and RQ 2.2, explore situations where the users abandon an offline activity.

3 | RESEARCH METHODOLOGY

Our research questions imply a strictly causal model for examining the relation between people's offline and online activities. Quasi-experimental design studies have been increasingly used to estimate the effect of diverse factors in the context of online social media (Austin, 2011) and are considered a reasonable and appropriate alternative to studies with complete random assignment of subjects (Rubin, 1974). As such, we conducted a quasi-experimental design study. Its main elements, described in detail below, include: (a) the dataset, (b) the experimental group (c) the control group, (d) the matching process for causal inference, and (e) the outcome variables.

3.1 | Description of the dataset

We gathered Twitter posts to represent the online behavior of the users and Foursquare check-ins to record their offline activities. These information items were collected for the period from October 2014 to April 2017. To match users across the two social media platforms, we used information from the Swarm application. This application, initiated by Foursquare in May 2014, enables users to share places they visit on Twitter and Facebook based on Foursquare venues. According to a recent comprehensive empirical analysis of the Foursquare network by Chen, Hu, Zhao, Xiao, and Hui (2018), Swarm and Foursquare had around 60 M monthly active users (51.07%

TABLE 1 An overview of Foursquare venue categories and subcategories

Venue category	Number of subcategories	Sample subcategories
Arts & Entertainment	64	Amphitheater, bowling alley, karaoke, movie theater
College & Education	38	Classroom, education, law school, medical school, sorority house, student center, university
Event	12	Conference, festival, line/queue, parade, sporting event
Food	334	BBQ, diner, food court, hot dogs, kebab
Nightlife	24	Bar, brewery, night market, nightclub
Outdoors & Recreation	107	Bridge, canal, forest, lake, playground, river
Professional	105	Business center, distributor factory, government, industrial estate, laboratory
Residence	5	Assisted living, home, housing development
Shops	172	Adult boutique, batik shop, carpet store, department store, gift shop
Travel	53	Border crossing, cruise, travel, target, hotel, light rail, moving, road

male, 41.43% female, and 7.50% undisclosed), compared to 330 M monthly active users on Twitter. Among all Swarm users 56.76% shared their locations on Twitter/Facebook.

By using Swarm, we were able to find users who were active both on Twitter and Foursquare and match their IDs across the two social media platforms by looking for users who posted their Foursquare check-ins on Twitter using the Swarm application. During the data gathering process, we retained only those users who had Swarm check-ins in at least 10% and at most 50% of their tweets, to make sure (a) for each user, we had enough check-in data and (b) there were enough other content published by users on Twitter. If a user did not meet these

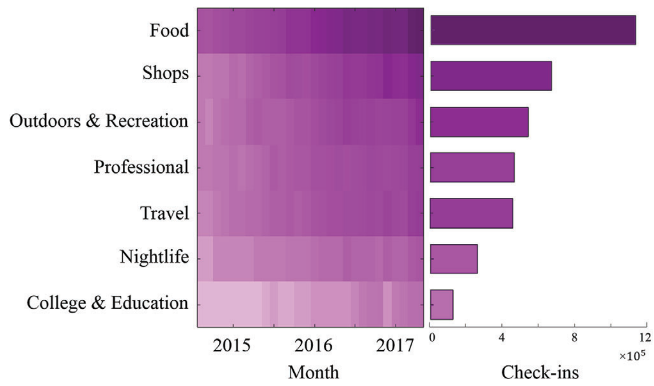


FIGURE 2 Temporal distribution of user check-ins (left) and the total number of check-ins per venue category (right) in the collected dataset [Color figure can be viewed at wileyonlinelibrary.com]

conditions we would eliminate them from the dataset to open storage space for new users who would meet the criteria. We also removed users who tweeted in languages other than English. Our final dataset comprised data for 17,220 users whose Twitter and Foursquare posting activity met the stated requirements. We would like to note that the findings in this paper are generalizeable to the extent that it reflects the activities of those users who are active on Twitter, post check-ins on Foursquare and use the Swarm application.

After downloading tweets using the Twitter API, we obtained venue IDs from tweets linked to the Swarm application. The venues, where the users checked in, were then collected using the Foursquare API. Foursquare divides venues into 10 high-level venue categories as described in Table 1.

Figure 2 depicts the monthly and overall distribution of locations in our dataset. Our observation was that over time, check-ins from Swarm and Foursquare increased. Furthermore, our examination of the distribution of check-in numbers over the examined period showed that check-ins in the Food category were the most common, whereas check-ins in the College & Education category were the least frequent.

The fact that our data are collected over a 3 year time period makes our data unbiased towards a specific topic or sporadic user behavior. Our dataset includes 17,220 users, 48,672,327 Tweets and 4,332,705 check-ins. Therefore, in terms of size, our dataset is comparable to the datasets used in similar studies in this area such as the dataset described in (Stück et al., 2017), which was collected from a commercially closed platform, and the Twitter dataset used in (Garimella, Morales, Gionis, & Mathioudakis, 2017), among others. It should be noted that all identifiable information on users were anonymized during the data collection.

3.2 | Control and experimental groups

In our research, the Experimental Condition (EC)[1] is described as engagement in (EC1) or abandonment of (EC2) an offline activity. An experimental group consists of users exposed to a particular experimental condition. Each of the two experimental conditions are studied in the context of Foursquare venue categories, as classified and provided by Foursquare and shown in Table 1.

3.2.1 | EC1 experimental condition: Embarking on an offline activity

For the EC1 experimental condition where a user embarks on a new offline activity, for example, starting with frequent Nightlife activities, in order to form the experimental group for each venue category, we recognized and chose those users who did not have any check-ins in venues of the specific venue category of interest for a period of 2 months (*Pre-Experimental* period). For example, in the case of the Nightlife venue category, we required that the user did not have any check-in in any venue of the Nightlife venue category for 2 months. In the second time period (*Experimental* period), the users would exhibit a change in their offline activities and start frequenting venues related to the venue category of interest, for example, Nightlife. We define frequent visits as at least one check-in per week in the same venue category over a 2-month period (*Experimental* period). To continue with the example of the experimental group for Nightlife, those were the users who had not visited any venue in the Nightlife venue category for 2 months (*Pre-Experimental*), based on their Foursquare check-ins, and who during the next 2 months (*Experimental* period) visited such venues at least once a week. In the final 2 months (*Post-Experimental* period), we study the effects of the experimental condition on the users' online affective expressions based on their posted tweets. Therefore, our observations of each user is done over a 6 month time period.

3.2.2 | EC2 experimental condition: Abandoning an offline activity

A similar strategy was adopted for the second experimental condition. In particular, in case of the EC2 experimental condition, we ensured that the users chosen for the experimental group had checked-in continuously at the locations of the respective venue category at least once a week over a period of 2 months (*Pre-Experimental* period). After that, the users would discontinue checking in at such venues and would have no check-ins at such venues for a period of 2 months (*Experimental* period). We gathered our data from Foursquare check-ins, and used the users' tweets to determine their online affective expression during the 2 months of the *Post-Experimental* period. Similar to EC1 experimental condition, our observations of each user were done over a 6 month time period.

3.2.3 | Control group

To form the control group for the EC1 experimental condition, we identified and selected those users who did not have any check-ins for a period of 4 months (*Pre-Experimental* and *Experimental* periods) in venues related to the venue category of interest. So, for example, the control group for Nightlife activities would consist of those users who had not been to any venue in the Nightlife venue category for 4 months (*Pre-Experimental* and *Experimental* periods) based on their Foursquare check-ins. Likewise, for each experimental group associated with the EC2 experimental condition, we ensured that the users chosen for the corresponding control group had checked-in continuously at the venues of the respective venue category at least once a week over a period of 4 months (*Pre-Experimental* and *Experimental* periods).

3.3 | Stratified propensity score matching

In a quasi-experimental design study, such as ours, the subjects are not randomly assigned to experimental and control groups. To alleviate this and assure the validity of the conclusions, our experimental methodology aims at diminishing the effect of confounding variables through the use of statistical matching. We adopt the stratification on the propensity score method (PSM) (Saha et al., 2019) conditioned on pre-experimental offline activities, in order to eliminate any confounding variable that could yield uncertain results.

To perform stratification based on propensity scores, we computed propensity score for each user based on their observable *offline* activities before the experiment. The rationale for that was multifold:

1. it is not possible to reliably access typically used confounding variables, such as sex and age, from social media platforms as users often do not report such information in their profile and in cases when they do, it is not guaranteed that such information is reliable;

2. our objective is to observe changes in users' offline activities and thus should select those users who have similar past offline activities in order to be able to observe possible changes in the future as a result of an experimental condition; and
3. we hypothesize that similarity in offline activities stems from deeper processes such as thoughts and/or personality of the user. As such by finding similar users in terms of offline activities, we are hoping to identify the users who have such similarities in their deeper processes and hence can be used to get matched against each other.

We should also highlight that the choice of *stratified* propensity score method was primarily motivated by the fact that our users were not matched based on explicit confounding variables but rather through their observed offline activities. Hence, a collective view on the behavior of users with similar offline activities placed in comparable strata would provide a more reliable basis for comparison across control and experimental groups.

3.3.1 | Computing covariates and stratification

In our study, we consider all tractable offline activities of each user before the interruption as covariates in order to match those users who had check-ins in the same venues during the *Pre-Experimental* period. We use a one-hot encoding representation in order to convert the check-in information of the users into values that could serve as the input to machine learning algorithms. We create a vector of venues for every user to represent the locations visited by the user. The elements of this vector represent each of the Foursquare venue categories. For each user, we have vector $H = h_1, \ldots, h_n$ where h_i is 1 for a given user if the venue category i appears in the user's timeline of check-ins prior to the experiment, and 0 otherwise. We consider this vector as a feature vector for every user to find the probability of being in the experimental group and calculate the propensity score. The propensity score is estimated using an average perceptron learning algorithm (Choudhury & Kiciman, 2017; Freund & Schapire, 1998).

The perceptron algorithm starts with an initial zero prediction vector $v = 0$. It predicts the label of a new instance x to be $y' = (v{\cdot}x)$. If this prediction differs from the label y, it updates the prediction vector to $v = v + yx$. If the prediction is correct then v is not changed. The *averaged* variation of the perceptron algorithm stores more information during training and then uses such elaborate information to generate better predictions on the test data. The information maintained during training is the list of all prediction vectors that were generated after each mistake. For each such vector, it counts the number of iterations before the next mistake is made, which is considered to be the "weight" of the prediction vector. To calculate a prediction, the binary prediction of each one of the prediction vectors is computed, all of which are aggregated through a weighted majority vote.

Based on the estimated propensity scores for all users in the sample, we sort the sample and split it into K subclasses (strata). The key condition for successful stratification is to keep the range of propensity scores constant within each stratum (Cochran & Chambers, 1965). As such, the number of strata plays an important role. Based on the method proposed in (Benjamin, 2003), we identified *ten* strata to effectively balance covariates in our dataset.

Furthermore, it is essential to have indistinguishable covariate distributions in experimental and control groups to ensure that any changes in the outcomes can only be attributed to the fact that one group was exposed to the experimental condition and the other group was not. Hence, we evaluate the balance of covariates to ensure that we matched statistically comparable experimental and control users. We calculate the standardized mean difference (SMD) in the experimental and control groups across covariates. According to the literature (Kiciman et al., 2018), two groups are regarded as balanced if SMD is smaller than 0.2 for all covariates. Figure 3[2] shows the cumulative count of the number of covariates with associated SMD value. Each covariate in Figure 3 represents a venue category from Foursquare and all covariates in matched dataset respect the condition of having SMD lower than 0.2. We find a significant drop in the mean SMD from 0.32 in the unmatched datasets to 0.03 in the matched datasets for EC1 experimental condition (embarking) and a significant drop in the mean SMD from 0.28 in the unmatched datasets to 0.03 in matched datasets for EC2 experimental condition (abandoning).

3.4 | Defining and measuring the outcomes

In order to quantify users' affective expressions, we used two widely adopted computational methods for detecting emotions and moods based on textual content. The purpose of using two computational methods was to rule out the possibility of influence from the computational measurement tool used for quantifying moods and emotions from online content. We describe each method in the following.

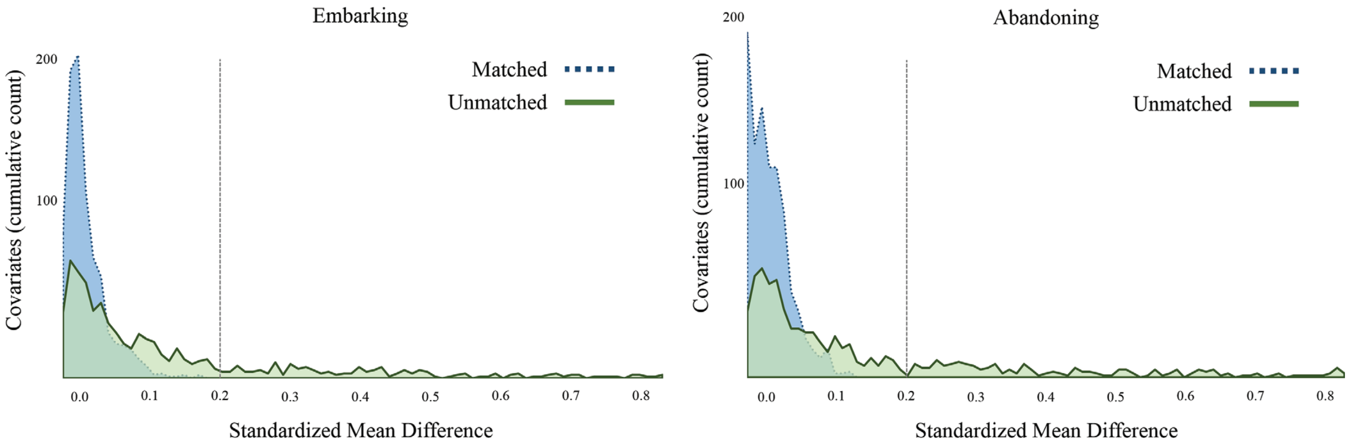


FIGURE 3 Standardized mean difference (SMD) for the covariates, as a measure of the quality of the matching process [Color figure can be viewed at wileyonlinelibrary.com]

3.4.1 | Emotionality

To identify users' emotions, as expressed in online textual content, similar to prior work (Birnbaum, Ernala, Rizvi, De Choudhury, & Kane, 2017; Saha et al., 2019; Saha et al., 2018), we rely on the psycho-linguistic aspects of affect. In particular, we use the well-validated Linguistic Inquiry and Word Count (LIWC) lexicon (Tausczik & Pennebaker, 2010). LIWC is a text analysis program that counts words in psychologically meaningful categories. Empirical studies have demonstrated LIWC's ability to detect meaning in a wide variety of experimental settings, including detection of attentional focus, emotionality, social relationships, thinking styles, and individual differences (Tausczik & Pennebaker, 2010). Validation studies done by Kahn, Tobin, Massey, and Anderson (2007) suggest that LIWC is a valid method for measuring verbal expression of positive (amusement) and negative (sadness) emotions. Golder and Macy (2011) used LIWC to identify positive and negative affect in millions of Twitter messages, aiming to identify individual-level daily and seasonal mood rhythms in cultures worldwide. Furthermore, LIWC has been extensively used in studies similar to the current one (Dutta, Ma, & De Choudhury, 2018; Tan, Friggeri, & Adamic, 2016; Wu, Tan, Kleinberg, & Macy, 2011). On the other hand, some study results indicate that dictionary-based emotion analysis may not be sufficient to infer true emotional states of social media users. For example, Beasley and Mason (2015) examined how frequencies of positive and negative emotion-related words from the LIWC dictionary relate to a ground truth measure of positive and negative emotion, by analyzing posts of several hundreds of Twitter and Facebook users. Their study revealed statistically significant though very weak correlations. Accordingly, even though LIWC has been used and validated in prior research, we have to acknowledge that, due to the intricate nature of the human language, dictionary-based tools, such as LIWC, are context sensitive and thus we cannot claim that counts of emotions-related words and true emotions are connected in the context of the current study. This is a limitation of our work that we turn to in the Limitations section.

The LIWC categories adopted in our study include Positive affect, Negative affect, and three subcategories of the latter namely Sadness, Anxiety, and Anger. Note that LIWC does not define subcategories of the Positive affect category. We process every tweet through LIWC to find the degree to which each of the LIWC subcategories used in our study is present in the given tweet. On this basis, we measure the monthly presence of different subcategories for each user as follows:

$$o_{\theta}^{i}(u) = \frac{\sum_{t \in m_u^i} \theta(t)}{|m_u^i|} \tag{1}$$

where user u is one of the members of the experimental or control groups and m_u^i is the set of the user's tweets in month i. θ stands for one of the LIWC subcategories and $\theta(t)$ is the outcome of that subcategory for tweet t. $o_{\theta}{}^{i}(u)$ is the percentage presence of category θ in the tweets of user u in month i. For instance, $o_{Anger}^{1}(u)$ is the percentage of the LIWC's *Anger* subcategory in the tweets of user u in Month 1, whereas $o_{Sadness}^{2}(u)$ shows the percentage of LIWC's Sadness subcategory for user u in the second month. To compute the outcome value for the overall *Post-experimental* period, we average monthly values of LIWC-based metrics for Emotionality (Equation (1)) for each user in the experimental and control groups. As such, it is important to note that measures of emotion as captured by $o_{\theta}{}^{i}(u)$ represent the average of the emotions

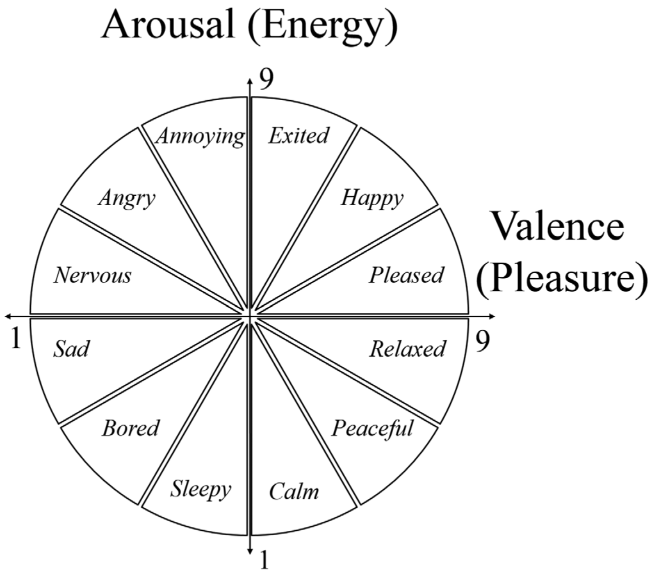


FIGURE 4 Thayer's circumplex model based on Thayer (1990)

computed by LIWC based on a user's tweets in the examined period of time. Hence, the outcome shows the dominant emotion expressed by the user in that time period.

3.4.2 | Moods

With regards to users' mood, we adopt the two-dimensional Thayer model (Thayer, 1990). The Thayer model views moods as affective states strongly related with psychophysiological and biochemical components. In this model, the essence of emotional experience consists of *valence*, which refers to the pleasurable or displeasurable aspect of feelings and *arousal*, which stands for the degree of energy (Faith & Thayer, 2001). All moods in Thayer's model are defined by a unique combination of valence and degree of arousal, and as such located in a 2 dimensional spatial structure, as shown in Figure 4. For example, *fear* is a negatively valenced, high-activation feeling, while *serenity* can be characterized as having positive valence and low-activation (Faith & Thayer, 2001).

In order to detect changes in moods of individuals based on the Thayer model, we use the Affective Norms for English Words (ANEW) lexicon (Stevenson, Mikels, & James, 2007) and its extended version (Warriner, Kuperman, & Brysbaert, 2013). We use the ANEW lexicon to find the monthly averaged expression of valence and arousal in each user's tweets. We find the valence and arousal for each tweet by calculating the average of these metrics across all words in the tweet. Therefore, the monthly average for each metric, per user is calculated as follows:

$$P_{\varphi}^{i}(u) = \frac{\sum_{t \in m_u^i} \varphi(t)}{|m_u^i|} \quad (2)$$

Similar to Equation (1), u is a member of the experimental or control groups, whereas m_u^i is the set of tweets of user u in month i. φ stands for ANEW subcategories, *arousal* and *valence*, and $\varphi(t)$ is the outcome of that category for tweet t. So, ${P_{\varphi}}^{i}(u)$ is the average of category φ for user u in month i. It is important to point out that similar to emotions, the outcome measured for moods, that is, ${P_{\varphi}}^{i}(u)$, is the average mood observed for user u in a given time period. Therefore, while the user may have expressed a range of moods in their tweets, the outcome will consider the average frequency of these moods for the user; hence, representing the predominant mood in that time period.

3.4.3 | Measuring changes in the outcomes

For measuring the effect of experimental conditions, we have adopted the *Relative Treatment Effect* (RTE), as a suitable measure in the context of our study (Lu, Zhang, & Ding, 2019). An alternative measure such as Absolute Treatment Effect (ATE) would not be applicable since the emotions and moods considered in the study tend to differ in the frequency of online expression (e.g., expressions of positive emotions tend to be more present in tweets than, for example, expressions indicative of sleepy or calm moods). We first determine the RTE in each stratum per outcome, as a ratio of an outcome measure in the experimental group to that in the control group (Khatua et al., 2019; Saha et al., 2019). After that, we acquire the mean RTE per outcome measure by using a weighted average across the strata. RTE greater than 1.0 indicates that a particular type of offline activity had a positive effect and that the outcome has effectively increased in the experimental group. While, relative treatment effects lower than 1.0 indicates the opposite.

4 | RESULTS AND FINDINGS

We report our findings organized around the two groups of measured outcomes: emotionality and mood. We note that all of our findings reported in this section are statistically significant (with a p-value $< .001$) when comparing experimental and control groups per venue category for the measured outcomes, for example, valence, arousal, anger, anxiety, among others, over the *Post-Experimental* period, using a two-tailed t test.

4.1 | First set of experiments: Emotionality

In this set of experiments, our objective is to compare the emotions expressed by individuals in the experimental group to those expressed by the control group.

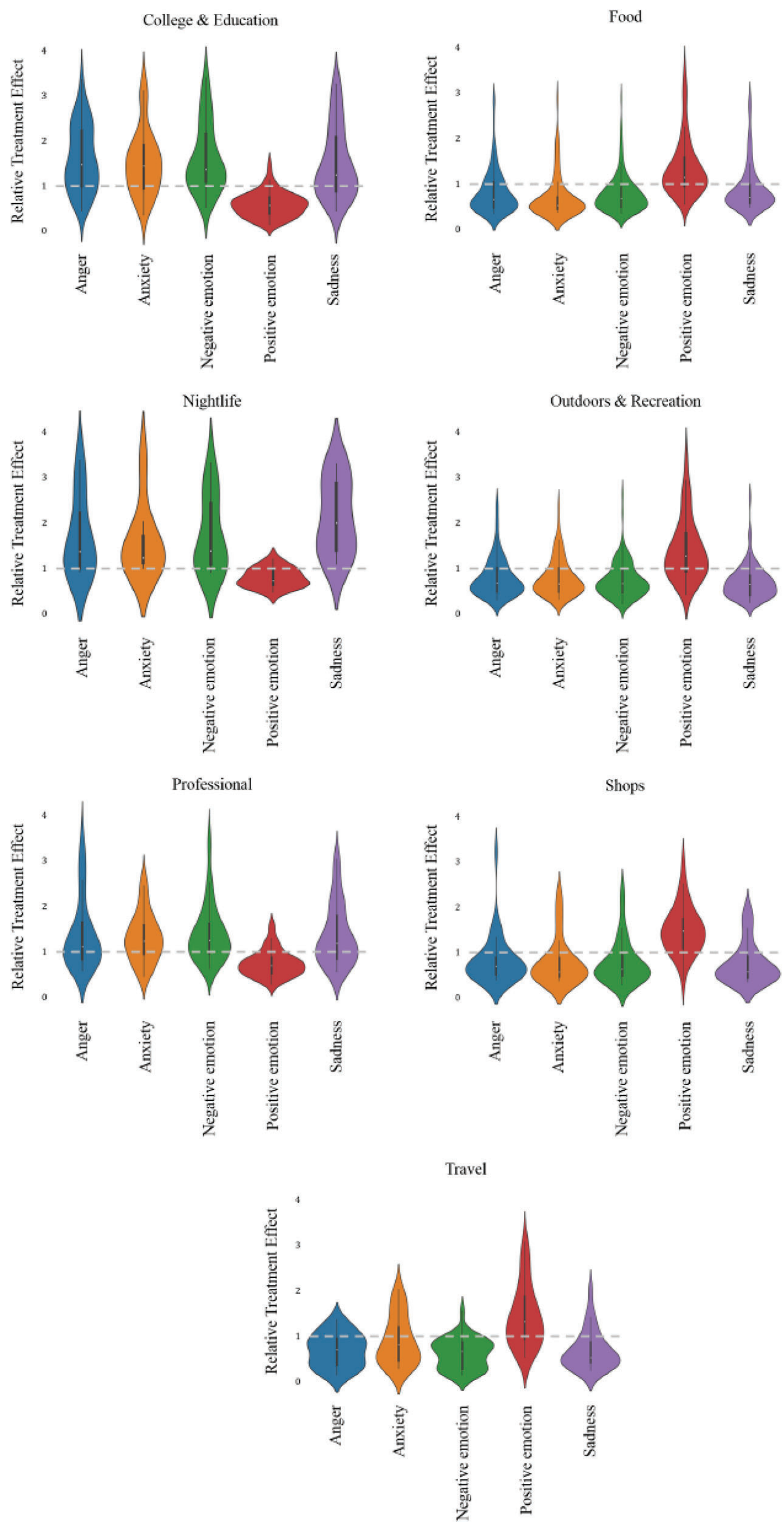


FIGURE 5 The distribution of RTE for EC1 (Embarking) and Emotions as the outcome [Color figure can be viewed at wileyonlinelibrary.com]

4.1.1 | RQ 1.1: Engaging in an offline activity (experimental condition EC1)

We first investigate to what extent engaging in various offline activities has an impact from an affective perspective. Figure 5[3] presents RTE on the emotions, as derived from online posts using LIWC. The figures show that depending on the venue category, engaging in an offline activity can lead to positive or negative impacts on the users' emotions.

Finding 1
We find that EC1 associated with Nightlife and College & Education venue categories exhibit the highest degree of impact on negative emotions. Within the College & Education venue categories, undesirable emotions such as Anger, Anxiety or Negative Emotion, in general, increase while Positive Emotions are reduced. A similar pattern can be observed for those “exposed to” Nightlife venues. In this case, negative emotions also increase. Sadness is the emotion that most prominently increases as a result of engaging with Nightlife venues.

Finding 2
Contrary to the Nightlife and College & Education categories, venues associated with Food, Shopping, Outdoor & Recreation, and Travel tend to increase positive emotions and to decrease negative emotions. Venues associated with Food proved to be especially effective in reducing Anxiety, while Outdoor activities and Shopping decrease signs of Sadness the most. Activities associated with Travel also reduce expression of negative emotions such as Anger, Anxiety, and Sadness, while leading to expressions of Positive Emotions in the experimental group.

Finding 3
Our findings show that Professional activities lead to an increase in the undesirable emotions, whereas the expression of Positive Emotion by the experimental group is reduced.

4.1.2 | RQ 1.2: Abandoning an offline activity (experimental condition EC2)

Figure 6 depicts our findings on how abandoning a frequent offline activity tends to impact users' emotions.

Finding 4
We observe that abandoning offline activities associated with Food, Outdoors & Recreation, Shopping, and Travel leads to an increase in undesirable emotions. Among the venue categories, Shopping and Travel are the two with the highest impact on the expression of Anxiety by the experimental group. Abandoning activities related to Food leads to increased expression of negative emotions in general, and particularly affects the Sadness subcategory. Disengaging from venues related to Outdoors & Recreation also increases undesirable emotions but to a lesser extent compared to the other three venue categories.

Finding 5
The findings additionally indicate that abandoning offline activities related to College & Education, Nightlife, and Professional activities leads to an increase in the expression of Positive Emotions by the experimental group. Additionally, disengaging from venues associated with College & Education leads to a reduction in Sadness whereas discontinuing Nightlife activities has the highest impact on lower expressions of Anger, which is similar to findings associated with Professional activities.

4.2 | Second set of experiments: Moods

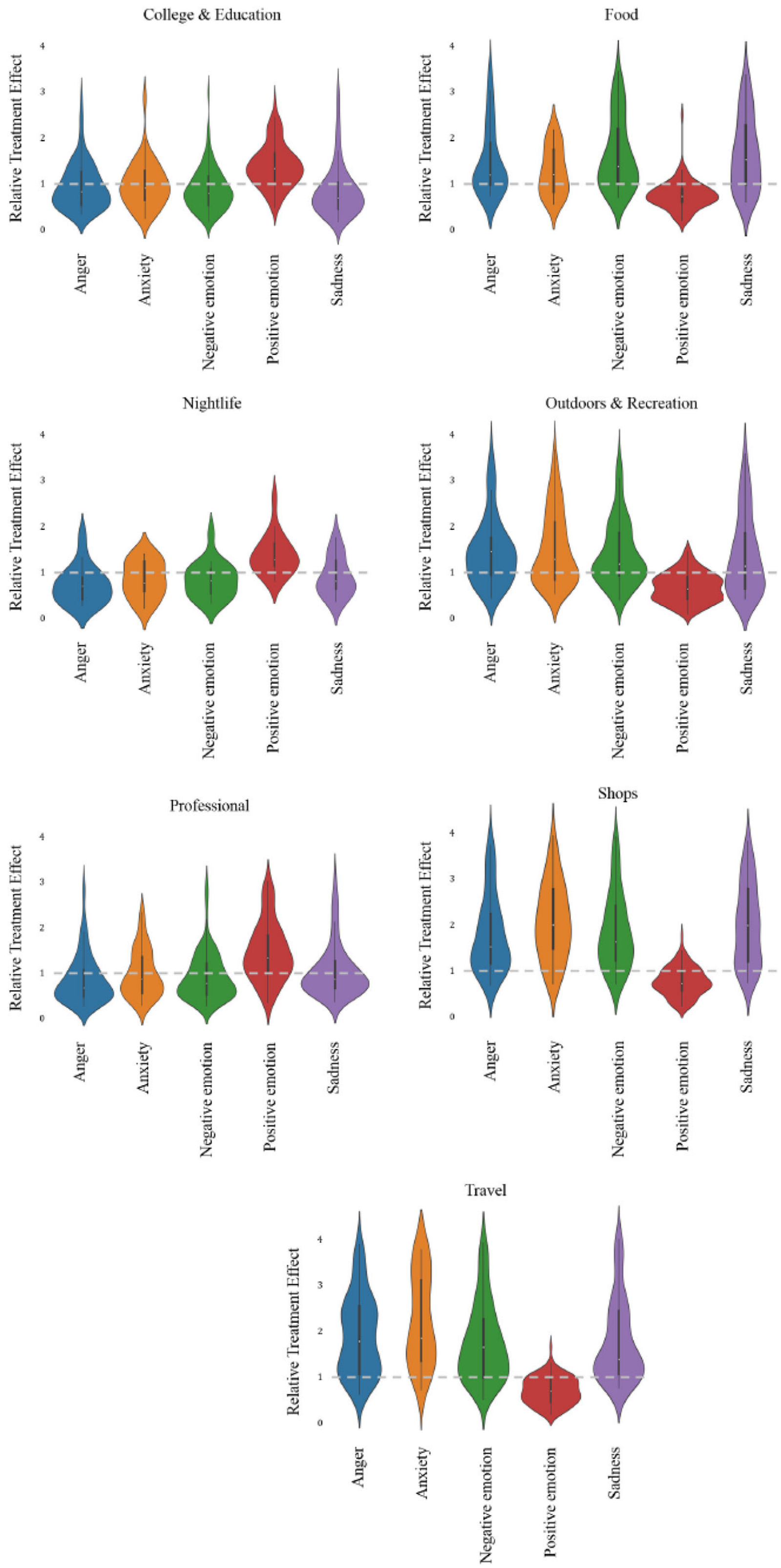
In the second set of experiments, our objective is to understand the impact of different categories of offline (real-world) activities, in the context of the two types of experimental conditions introduced earlier, on the changes in the participants' mood, as expressed in their online posts. Having adopted the Thayer model of moods (Thayer, 1990), we examine moods through two dimensions: valence and arousal, where the valence measures how pleasant a mood is, while the arousal dimension measures the intensity of a mood.

A popular representation of the Thayer model is through a circumplex, where the dimensions of arousal and valence form the axes of the circumplex, while different moods fall within specific areas of the circle (shown in Figure 4). We use this circumplex model to represent and examine the changes in moods of the participants, manifested via the textual content they shared on Twitter, for the two experimental conditions.

4.2.1 | RQ 2.1: Engaging in an offline activity (experimental condition EC1)

Using the valence-arousal circumplex model, we first investigate the relationship between embarking on a new type of offline activity and online expression of moods. We report our findings by visualizing the distribution of RTE on mood dimension in our sample in Figure 7 and by presenting the circumplex model in Figure 8.

FIGURE 6 The distribution of RTE for EC2 (Abandoning) and Emotions as the outcome [Color figure can be viewed at wileyonlinelibrary.com]



Finding 6
Consistent with our observations on emotions, we observe that offline activities associated with Food, Outdoors & Recreation, and Travel venues have highly positive impact on both arousal and valence (Figure 7). The highest positive change in arousal and valence values is associated with the engagement in activities related to Food venues. Specifically, we find that actively engaging with Food related venues has the highest positive impact on the users' mood that, according to Thayer's model,

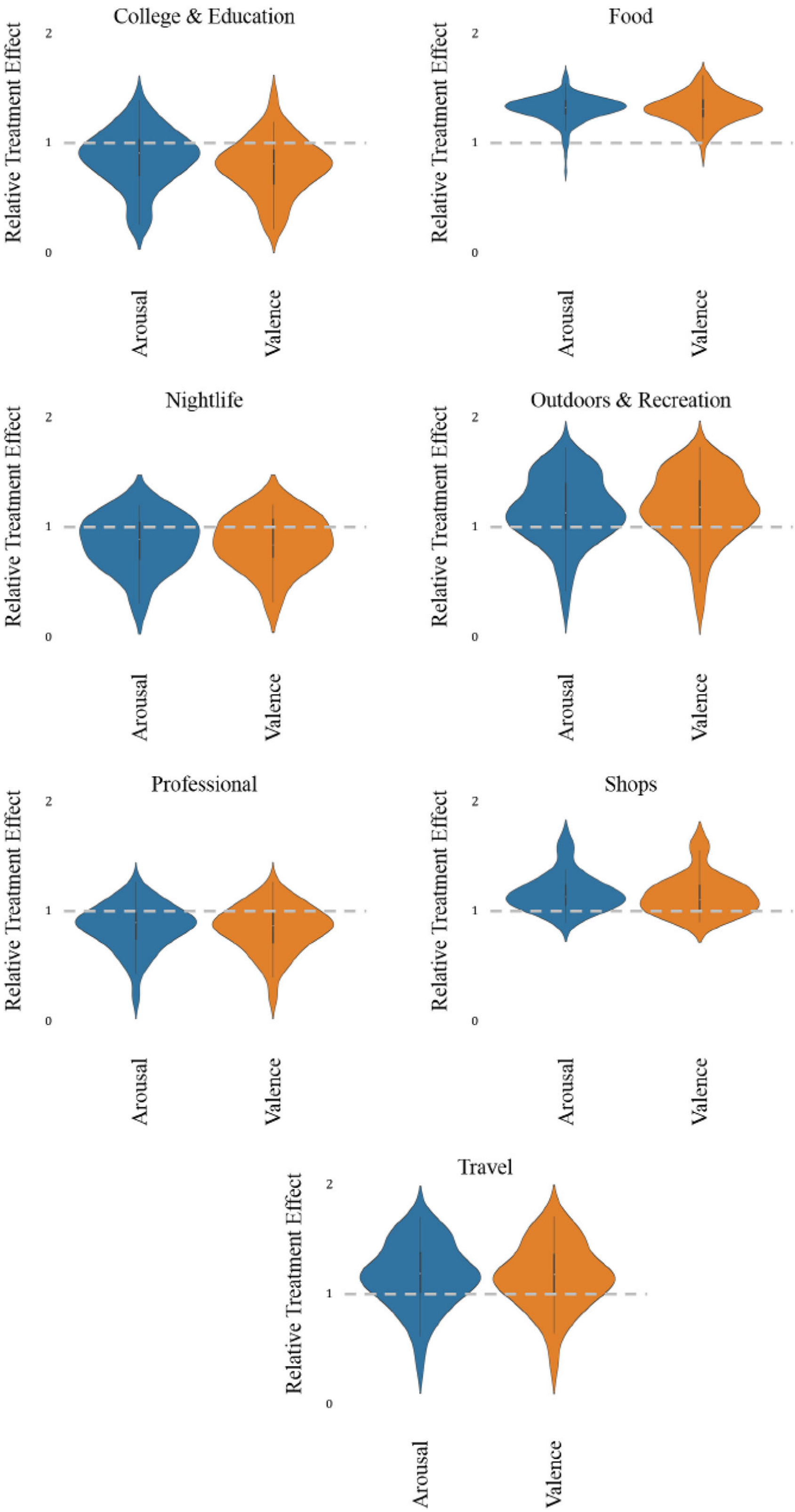


FIGURE 7 The distribution of RTE for EC1 (Embarking) and Moods as the outcome [Color figure can be viewed at wileyonlinelibrary.com]

could be characterized as being more peaceful and relaxed (Figure 8). While not that impactful, Outdoors & Recreation as well as Travel venues also move users towards moods associated with calmness.

Finding 7

Contrary to the above, our findings show a decrease in the values of arousal and valence caused by initiating activities related to Nightlife, Professional, and College &

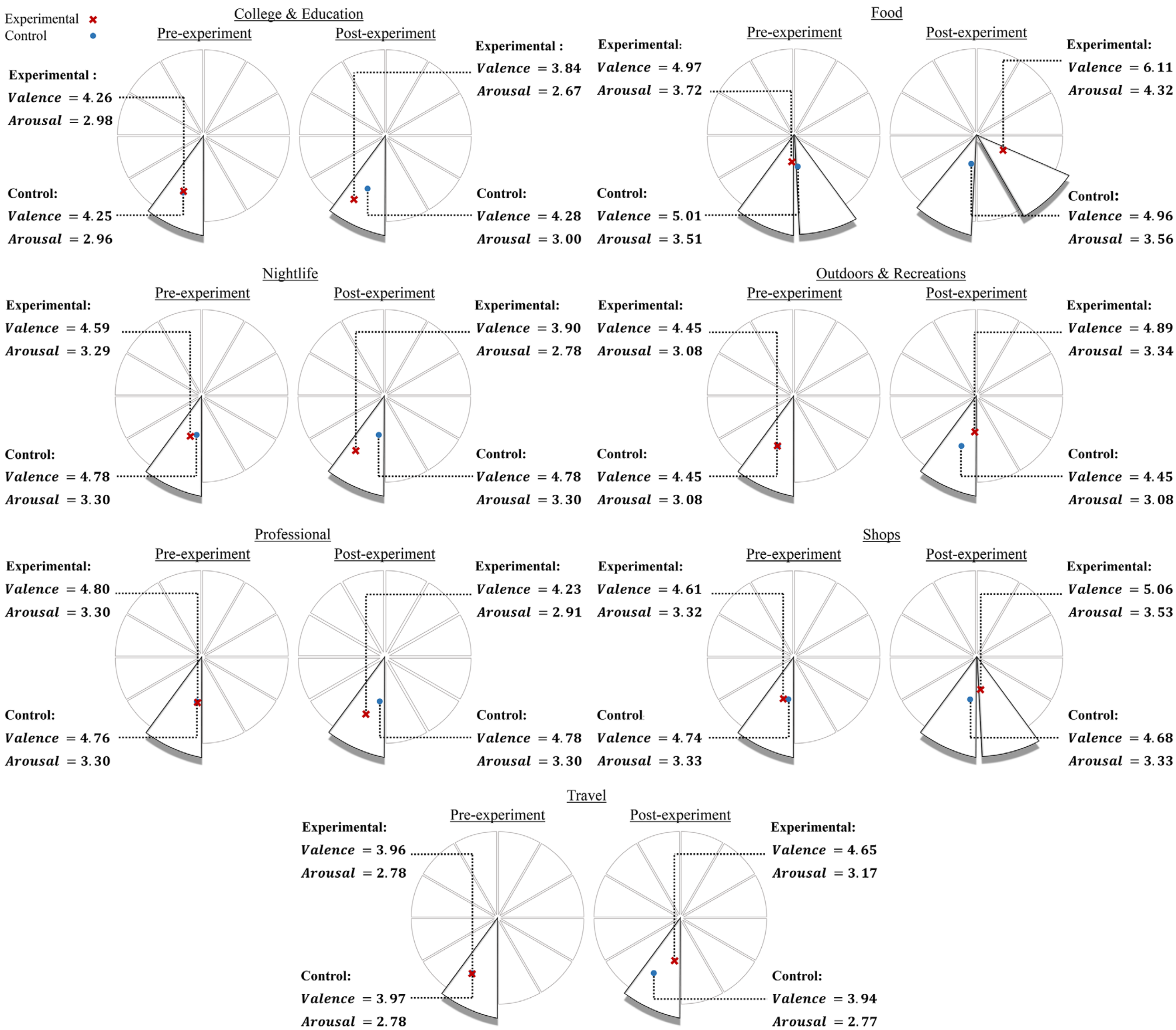


FIGURE 8 Valence and arousal measures of experimental and control groups in pre-experimental and post-experimental time periods for EC1 [Color figure can be viewed at wileyonlinelibrary.com]

Education venue categories. Among all the venue categories, embarking on Nightlife activities leads to the greatest decline in the values of valence and arousal. Thayer's circumplex model shows that when starting frequenting College & Education or Profession related venues, the participants' mood expression tend to shift towards boredom.

Finding 8

When contrasting the impact of embarking on offline activities on emotions and moods, we find that while Shopping related activities lead to an increase in positive emotions, such activities do not have the same strong impact on moods. Figure 7 shows a small positive impact on valence and arousal.

4.2.2 | RQ 2.2: Abandoning an offline activity (experimental condition EC2)

We measure the outcomes related to the values of arousal and valence when the experimental group abandons certain offline activities. As is depicted in Figures 9 and 10, our findings show the reverse pattern (to the one observed for the EC1 experimental condition) when users abandon activities related to different venue categories.

Finding 9

We find that abandoning a frequent offline activity related to College and Education, Nightlife or Profession tends to lead to an increase in the values of arousal and valence. The changes are the highest for activities related to the College & Education venue category. According to Thayer's model, we observe that after abandoning activities related to Nightlife, users' moods are more closely associated with calmness, which is similar to the effects of disengaging from venues related to Professional

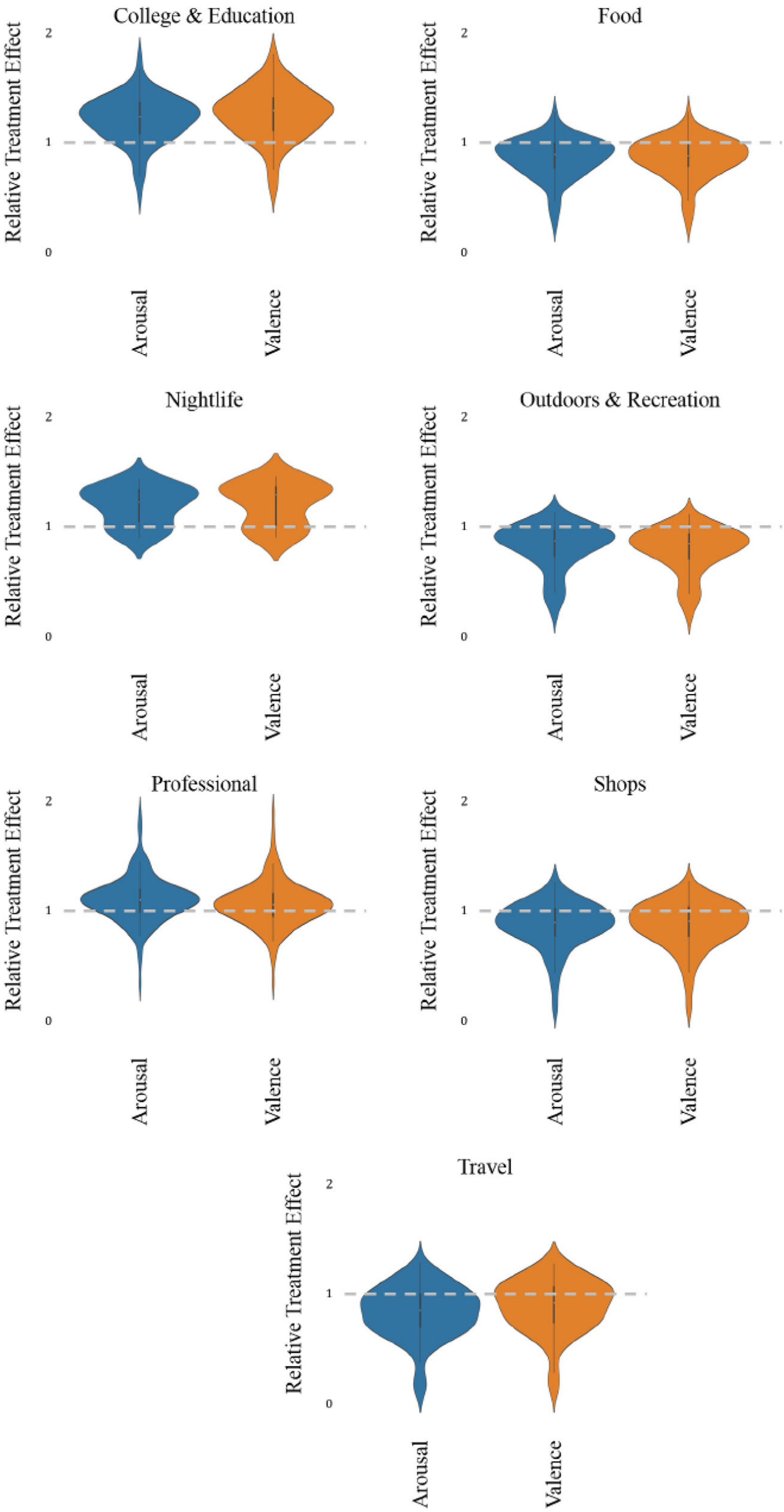


FIGURE 9 The distribution of RTE for EC2 (Abandoning) and the Moods outcome [Color figure can be viewed at wileyonlinelibrary.com]

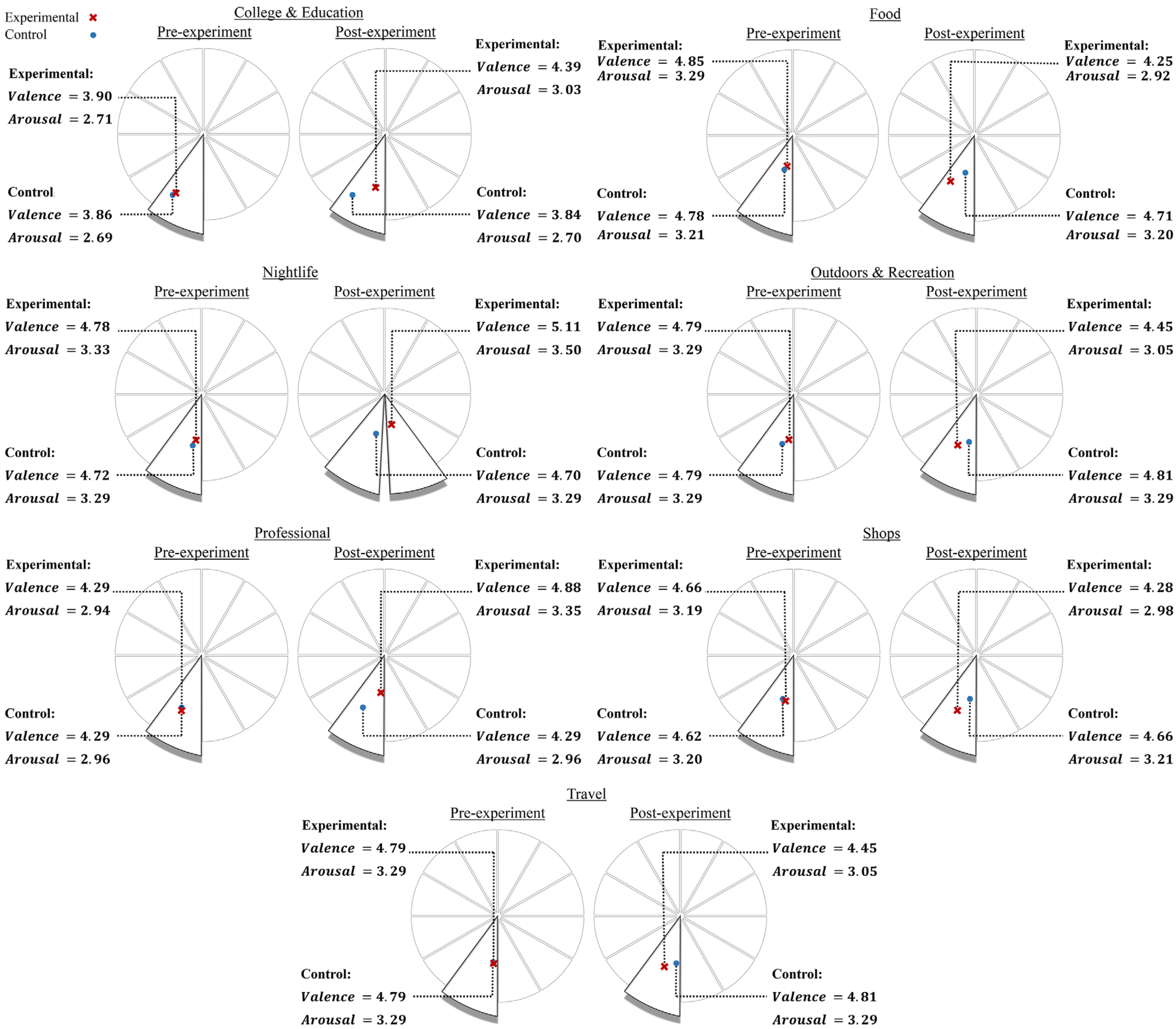


FIGURE 10 Valence and arousal measures of experimental and control groups in pre-experimental and post-experimental time periods for EC2 [Color figure can be viewed at wileyonlinelibrary.com]

activities. We also observe a similar trend associated with College & Education venues where abandoning such venues leads to moods associated with higher degrees of calmness.

Finding 10

We additionally observe that when abandoning offline activities associated with Travel, Shopping, or Food, the moods of the users in the experimental group decrease in terms of valence and arousal, though such changes are not as large as for the other venues. Furthermore, abandoning offline activities that are associated with the Outdoors & Recreation venue category showed to negatively impact both valence and arousal values, moving those in the experimental group towards the mood of boredom.

5 | DISCUSSIONS AND CONCLUSIONS

5.1 | Summary of findings

We summarize the findings of our experiments in Figures 11 and 12 by visualizing the relative treatment effect of both embarking on (EC1) and abandoning (EC2) offline activities on emotions and moods, respectively. In the figures, darker red colors indicate stronger negative

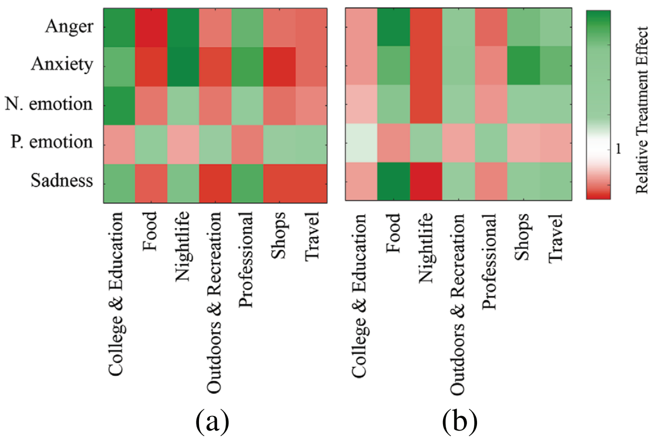


FIGURE 11 Relative treatment effect (RTE) for the Emotions outcome and the two experimental conditions: (a) embarking and (b) abandoning [Color figure can be viewed at wileyonlinelibrary.com]

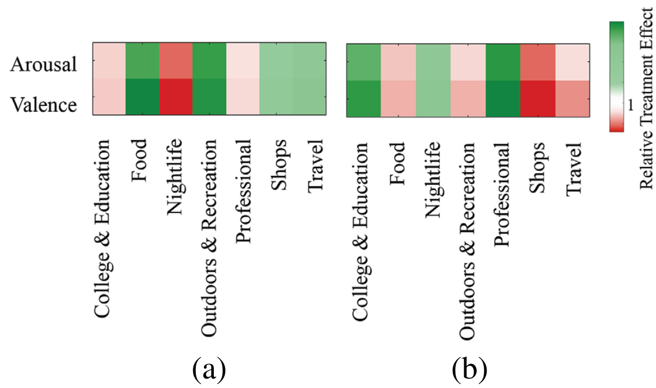


FIGURE 12 Relative treatment effect (RTE) for the Moods outcome and the two experimental conditions: (a) embarking and (b) abandoning [Color figure can be viewed at wileyonlinelibrary.com]

impact, whereas darker green colors indicate stronger positive effect. The white color, representing a relative treatment effect of 1, indicates no effect. The two figures clearly depict how users' emotions and moods are impacted depending on whether they embark on or abandon an offline activity conditioned upon the type of the offline activity.

In short, we find that actively engaging in or abandoning a frequent offline activity leads to changes in users' online affective expressions. These changes are consistently observed in our study based on both emotions and moods. As such, we conclude that users' offline activities do have causal impact on the way users express their emotions and moods on online platforms. While existing literature from the psychology domain already indicates that engaging in different forms of life activities can cause changes in a person's physical or psychological state (Chatterjee et al., 2018; Jarrett et al., 2012; Stathopoulou, Powers, Berry, Smits, & Otto, 2006), we have shown in this paper that such changes are translated and reflected in the way individuals communicate with others online and how they expresses emotions and moods on online social media.

Let us now circle back to the original motivation for this work, as laid out in the Introduction section. The findings confirm our contributions both from the individual (personal) and scientific (methodological) perspectives. From an individual perspective, the established causal connections between individuals' offline activities and their emotions and moods expressed on online social media platforms, can serve as the basis for providing users with insights about the emotional impact of their offline activities thus facilitating self-reflection and self-regulation of one's activities. This is particularly relevant in situations when such a connection is not obvious, for example, when emotions and moods are temporally distant from the activities causing them, or when an activity is causing an emotional effect different than the often expected one (e.g., our finding that activities associated with the Nightlife venues have a high impact on negative emotions). From a scientific perspective, we have demonstrated that the proposed trace-based methodology can be used for studying causal relationships between life activities and emotional states of social media users. This does not only open opportunities for large scale studies of the impact of real-world activities on emotions and moods, but also provides inspiration for scaling up similar types of studies.

5.2 | Limitations

It is important to acknowledge that this work could have been impacted by threats to validity, both internal and external. From an internal validity perspective, one could argue that the reliability of the causal relations identified in this study is dependent on the degree to which cofounding variables have been controlled. Unlike studies that adopt a strict propensity score matching process over a set of identified confounding variables, we adopt an alternative strategy as suggested by (Choudhury & Kiciman, 2017). We perform stratification based on propensity scores without reliance on typically used confounding variables such as sex, age, or occupation, but rather by computing propensity scores based on the observable user behavior before the experiment. This was done because demographic variables could not be identified from social data, nor were available on Twitter or Foursquare. Furthermore, considering the specific focus and objectives of our study, we find users' similarity based on their offline activities preceding the experiment to be relevant for matching. Another potential threat relates to the way we capture emotions and moods, which is primarily based on the counts of emotion bearing words in the text. As acknowledged in the methodology section, even though LIWC has been widely used for the detection of different kinds of psychological states, emotions included, it is a dictionary-based tool and thus has the limitation of being context agnostic. In particular, given that emotion-bearing words are sometimes systematically used for purposes other than emotion expression (e.g., "happy birthday", "I would be happy to help"), it is realistic to expect that emotions-related words would not reflect a person's true emotions in all contexts of their use.

From an external validity perspective, it is possible to argue that population validity is a consideration in our study. We have selected a range of venue categories from Foursquare; however, there is no guarantee that the venue categories are not mutually exclusive or correlated. For instance, it might be possible for those users who are traveling to start dining at restaurants because they do not have access to a home kitchen. We note that our stratified matching process controls for this to some extent since users are matched based on their check-in sequences in the past; so, if a user starts to dine at restaurants because they were traveling, then such a user would be matched against another user with a similar check-in pattern. Therefore, even though the correlation between venue categories is not explicitly captured, it is accounted for in the matching process.

The other aspect of the external validity of our experiments relates to the way users were selected for the study. We have ensured that only those users who made frequent check-ins, were considered in our experiments. While we had practical considerations for this decision, we recognize that our findings are generalizable to the extent to which this inclusion criteria is valid. The practical reason for this limitation was the bursty check-in activities of some users who would check-in at many venues for a few days and then would not check-in at all for a long period of time. Such users would negatively impact our analysis. However, our specific condition of having frequent and distributed check-ins could have excluded those users who had regular check-ins but not in the form expected by our inclusion criteria. Another potential limitation relates to how users, especially those in the experimental groups, were selected. It is possible that a user included in the experimental group, who has started regular check-ins at a certain venue did not do so necessarily because he/she has taken up that activity, but it may be due to this person accepting a new job in that venue, for example, a new employee at the gym. While this may be possible, we believe that the likelihood of this type of incident happening is quite low especially considering the fact that users are less likely to consistently check-in on Foursquare from the places of employment.

5.3 | Concluding remarks

This paper has reported on an extensive quasi-experimental design study that examined the causal relation between real-world activities of social media users and their affect-related online expressions, that is, emotions and moods the users expressed in online shared textual content. To this end, we have applied a unique methodology that combined (a) the creation of a curated dataset that aligned users' real-world activities, obtained from Foursquare check-ins, to their online affective expressions, originating from the users' Twitter posts; (b) theoretically-grounded computational methods for extracting indicators of the expressed emotions and moods from the users' online social posts; (c) the use of stratification on propensity scores coupled with an innovative model of propensity scores computation, which assures validity of findings of a study, such as ours, when traditionally used confounding factors (e.g., sex, age, occupation) are not available. Our findings indicate that real-world activities do have impact on the online expressed emotions and moods. Furthermore, the type of impact differs depending on the type of offline activity and whether the user is engaging in or abandoning it.

ENDNOTES

[1] Experimental condition is by some referred to as *treatment*, and experimental group as *treatment group*.

[2] Data related to Figures 3, 5–10 are included in the online supplemental material.

[3] The violin plots in this paper show the RTE amount on the Y axis and relevant categories on the *X* axis. The shape of the plot indicates the distribution of RTE around a particular point. RTE higher than 1 means positive effect (an increase in the outcome value) and RTE lower than 1 means negative effect (a decrease in the outcome value).

REFERENCES

Althoff, T., Jindal, P., & Leskovec, J. (2017). Online actions with offline impact: How online social networks influence online and offline user behavior. In *Proceedings of the tenth ACM international conference on web search and data mining – WSDM '17* (pp. 537–546). Cambridge, UK: ACM Press. https://doi.org/10.1145/3018661.3018672

Althoff, T., White, R. W., & Horvitz, E. (2016). Influence of Pokémon go on physical activity: Study and implications.

Journal of Medical Internet Research, *18*(12), e315. https://doi.org/10.2196/jmir.6759

Austin, P. C. (2011). An introduction to propensity score methods for reducing the effects of confounding in observational studies. *Multivariate Behavioral Research*, *46*(3), 399–424.

Beasley, A. & Mason, W. (2015). Emotional states vs. emotional words in social media. In *Proceedings of the ACM web science conference*, pp. 1–10.

Benjamin, D. J. (2003). Does 401(k) eligibility increase saving? *Journal of Public Economics*, *87*(5–6), 1259–1290.

Birnbaum, M. L., Ernala, S. K., Rizvi, A. F., De Choudhury, M., & Kane, J. M. (2017). A collaborative approach to identifying social media markers of schizophrenia by employing machine learning and clinical appraisals. *Journal of Medical Internet Research*, *19*(8), e289.

Branley, D. B., & Covey, J. (2017). Is exposure to online content depicting risky behavior related to viewers' own risky behavior offline? *Computers in Human Behavior*, *75*, 283–287. https://doi.org/10.1016/j.chb.2017.05.023

Cerin, E., Nathan, A., van Cauwenberg, J., Barnett, D. W., & Barnett, A. (2017). The neighbourhood physical environment and active travel in older adults: A systematic review and meta-analysis. *International Journal of Behavioral Nutrition and Physical Activity*, *14*(1), 15. https://doi.org/10.1186/s12966-017-0471-5

Chatterjee, H. J., Camic, P. M., Lockyer, B., & Thomson, L. J. M. (2018). Non-clinical community interventions: A systematised review of social prescribing schemes. *Arts and Health*, *10*(2), 97–123.

Chen, Y., Hu, J., Zhao, H., Xiao, Y., & Hui, P. (2018). Measurement and analysis of the swarm social network with tens of millions of nodes. *IEEE Access*, *6*, 4547–4559.

Choudhury, M. D., Gamon, M., Counts, S., & Horvitz, E. (2013). Predicting depression via social media. In E. Kiciman, N. B. Ellison, B. Hogan, P. Resnick, & I. Soboroff (Eds.), *Proceedings of the seventh international conference on weblogs and social media, ICWSM 2013, July 8–11, 2013*. Cambridge, MA: The AAAI Press.

Choudhury, M. D., & Kiciman, E. (2017). The language of social support in social media and its effect on suicidal ideation risk. In *Proceedings of the eleventh international conference on web and social media, ICWSM 2017, May 15–18, 2017* (pp. 32–41). Montréal, Québec, Canada: AAAI Press.

Cochran, W. G., & Chambers, S. P. (1965). The planning of observational studies of human populations. *Journal of the Royal Statistical Society. Series A (General)*, *128*(2), 234–266.

De Choudhury, M., Kiciman, E., Dredze, M., Coppersmith, G., & Kumar, M. (2016). Discovering shifts to suicidal ideation from mental health content in social media. In *Proceedings of the 2016 CHI conference on human factors in computing systems* (pp. 2098–2110). San Jose, CA: ACM. https://doi.org/10.1145/2858036.2858207

Dutta, S., Ma, J., & De Choudhury, M. (2018). Measuring the impact of anxiety on online social interactions. In *International AAAI conference on web and social media (ICWSM)*, pp. 584–587.

Ernala, S. K., Labetoulle, T., Bane, F., Birnbaum, M. L., Rizvi, A. F., Kane, J. M., & Choudhury, M. D. (2018). Characterizing audience engagement and assessing its impact on social media disclosures of mental illnesses. In *Proceedings of the twelfth international conference on web and social media, ICWSM 2018, June 25–28, 2018* (pp. 62–71). Stanford, CA: AAAI Press.

Faith, M., & Thayer, J. F. (2001). A dynamical systems interpretation of a dimensional model of emotion. *Scandinavian Journal of Psychology*, *42*(2), 121–133.

Falavarjani, S. A. M., Zarrinkalam, F., Jovanovic, J., Bagheri, E., & Ghorbani, A. A. (2019). The reflection of offline activities on users' online social behavior: An observational study. *Information Processing and Management*, *56*(6), 102070.

Falck, R. S., Davis, J. C., Best, J. R., Crockett, R. A., & Liu-Ambrose, T. (2019). Impact of exercise training on physical and cognitive function among older adults: A systematic review and meta-analysis. *Neurobiology of Aging*, *79*, 119–130. https://doi.org/10.1016/j.neurobiolaging.2019.03.007

Freund, Y., & Schapire, R. E. (1998). Large margin classification using the perceptron algorithm. In *Proceedings of the eleventh annual conference on computational learning theory – COLT' 98* (pp. 209–217). Madison, WI: ACM Press. https://doi.org/10.1145/279943.279985

Garimella, K., Morales, G. D. F., Gionis, A., & Mathioudakis, M. (2017). The effect of collective attention on controversial debates on social media. In *Proceedings of the 2017 ACM on web science conference, WebSci 2017, June 25, 2017* (Vol. 28, pp. 43–52). Troy, NY: Association for Computing Machinery.

Golder, S. A., & Macy, M. W. (2011). Diurnal and seasonal mood vary with work, sleep, and daylength across diverse cultures. *Science*, *333*(6051), 1878–1881.

Hudak, E. M., Bugos, J., Andel, R., Lister, J. J., Ji, M., & Edwards, J. D. (2019). Keys to staying sharp: A randomized clinical trial of piano training among older adults with and without mild cognitive impairment. *Contemporary Clinical Trials*, *84*, 105789. https://doi.org/10.1016/j.cct.2019.06.003

Jarrett, J., Woodcock, J., Griffiths, U. K., Chalabi, Z., Edwards, P., Roberts, I., & Haines, A. (2012). Effect of increasing active travel in urban England and Wales on costs to the National Health Service. *The Lancet*, *379*(9832), 2198–2205.

Kahn, J. H., Tobin, R. M., Massey, A. E., & Anderson, J. A. (2007). Measuring emotional expression with the linguistic inquiry and word count. *The American Journal of Psychology*, *120*, 263–286.

Khatua, A., Khatua, A., & Cambria, E. (2019). A tale of two epidemics: Contextual Word2vec for classifying twitter streams during outbreaks. *Information Processing and Management*, *56*(1), 247–257. https://doi.org/10.1016/j.ipm.2018.10.010

Kiciman, E., Counts, S., & Gasser, M. (2018). Using longitudinal social media analysis to understand the effects of early college alcohol use. In *Proceedings of the Twelfth International Conference on Web and Social Media, ICWSM 2018, June 25–28, 2018* (pp. 171–180). Stanford, CA: Association for the Advancement of Artificial Intelligence.

Kropivnitskaya, Y., Tiampo, K. F., Qin, J., & Bauer, M. A. (2017). The predictive relationship between earthquake intensity and tweets rate for real-time ground-motion estimation. *Seismological Research Letters*, *88*(3), 840–850. https://doi.org/10.1785/0220160215

Lu, J., Zhang, Y., & Ding, P. (2019). Sharp bounds on the relative treatment effect for ordinal outcomes. *Biometrics*, *76*(2), 664–669. https://doi.org/10.1111/biom.13148

Macpherson, H., Hart, A., & Heaver, B. (2016). Building resilience through group visual arts activities: Findings from a scoping study with young people who experience mental health complexities and/or learning difficulties. *Journal of Social Work*, *16*(5), 541–560. https://doi.org/10.1177/1468017315581772

Mikkelsen, K., Stojanovska, L., Polenakovic, M., Bosevski, M., & Apostolopoulos, V. (2017). Exercise and mental health. *Maturitas*, *106*, 48–56.

Mueller, J., Jay, C., Harper, S., & Todd, C. (2017). The role of web-based health information in help-seeking behavior prior to a diagnosis of lung cancer: A mixed-methods study. *Journal of Medical Internet Research*, *19*(6), e189.

Murnane, E. L., & Counts, S. (2014). Unraveling abstinence and relapse: Smoking cessation reflected in social media. In M. Jones, P. A. Palanque, A. Schmidt, & T. Grossman (Eds.), *CHI conference on human factors in computing systems, CHI'14 – April 26 – May 1, 2014, pages 1345–1354*. Toronto, ON, Canada: ACM.

Olteanu, A., Varol, O., & Kiciman, E. (2017). Distilling the outcomes of personal experiences: A propensity-scored analysis of social media. In *Proceedings of the 2017 ACM conference on computer supported cooperative work and social computing – CSCW '17* (pp. 370–386). Portland, OR: ACM Press.

Paggi, M. E., Jopp, D., & Hertzog, C. (2016). The importance of leisure activities in the relationship between physical health and well-being in a life span sample. *Gerontology*, *62*(4), 450–458. https://doi.org/10.1159/000444415

Paul, M. J., & Dredze, M. (2011). You are what you tweet: Analyzing twitter for public health. In L. A. Adamic, R. Baeza-Yates, & S. Counts (Eds.), *Proceedings of the fifth international conference on weblogs and social media, July 17–21, 2011*. Barcelona, Catalonia, Spain: The AAAI Press.

Paul, M. J., & Dredze, M. (2017). Social monitoring for public health. In *Synthesis lectures on information concepts, retrieval, and services* (Vol. 9, pp. 1–183). San Rafael, California: Morgan & Claypool Publishers. https://doi.org/10.2200/S00791ED1V01Y201707ICR060

Ploukou, S., & Panagopoulou, E. (2018). Playing music improves well-being of oncology nurses. *Applied Nursing Research*, *39*, 77–80. https://doi.org/10.1016/j.apnr.2017.11.007

Pressman, S. D., Matthews, K. A., Cohen, S., Martire, L. M., Scheier, M., Baum, A., & Schulz, R. (2009). Association of enjoyable leisure activities with psychological and physical well-being. *Psychosomatic Medicine*, *71*(7), 725–732.

Reis, V. L. D., & Culotta, A. (2015). Using matched samples to estimate the effects of exercise on mental health via twitter. In B. Bonet & S. Koenig (Eds.), *Proceedings of the twenty-ninth AAAI conference on artificial intelligence, January 25–30, 2015* (pp. 182–188). Austin, TX: AAAI Press.

Rubin, D. B. (1974). Estimating causal effects of treatments in randomized and nonrandomized studies. *Journal of Educational Psychology*, *66*(5), 688–701.

Saha, K., Sugar, B., Torous, J., Abrahao, B. D., Kiciman, E., & Choudhury, M. D. (2019). A social media study on the effects of psychiatric medication use. In *Proceedings of the thirteenth international conference on web and social media, ICWSM 2019, June 11–14, 2019* (pp. 440–451). Munich, Germany: Association for the Advancement of Artificial Intelligence.

Saha, K., Weber, I., & Choudhury, M. D. (2018). A social media based examination of the effects of counseling recommendations after student deaths on college campuses. In *Proceedings of the twelfth international conference on web and social media, ICWSM 2018, June 25–28, 2018* (pp. 320–329). Stanford, CA: AAAI Press.

Schuch, F. B., Vancampfort, D., Richards, J., Rosenbaum, S., Ward, P. B., & Stubbs, B. (2016). Exercise as a treatment for depression: A meta-analysis adjusting for publication bias. *Journal of Psychiatric Research*, *77*, 42–51. https://doi.org/10.1016/j.jpsychires.2016.02.023

Shameli, A., Althoff, T., Saberi, A., & Leskovec, J. (2017). How gamification affects physical activity: Large-scale analysis of walking challenges in a mobile application. In *Proceedings of the 26th international conference on world wide web companion, April 3–7, 2017* (Vol. 2017, pp. 455–463). Perth, Australia: Association for Computing Machinery. https://doi.org/10.1145/3041021.3054172

Stathopoulou, G., Powers, M. B., Berry, A. C., Smits, J. A. J., & Otto, M. W. (2006). Exercise interventions for mental health: A quantitative and qualitative review. *Clinical Psychology: Science and Practice*, *13*(2), 179–193.

Stevenson, R. A., Mikels, J. A., & James, T. W. (2007). Characterization of the affective norms for English words by discrete emotional categories. *Behavior Research Methods*, *39*(4), 1020–1024.

Stück, D., Hallgrímsson, H. T., Ver Steeg, G., Epasto, A., & Foschini, L. (2017). The spread of physical activity through social networks. In *Proceedings of the 26th international conference on world wide web – WWW '17* (pp. 519–528). Perth, Australia: ACM Press.

Tan, C., Friggeri, A., & Adamic, L. A. (2016). Lost in propagation? Unfolding news cycles from the source. In *ICWSM*, pp. 378–387.

Tausczik, Y. R., & Pennebaker, J. W. (2010). The psychological meaning of words: LIWC and computerized text analysis methods. *Journal of Language and Social Psychology*, *29*(1), 24–54.

Thayer, R. E. (1990). *The biopsychology of mood and arousal*. Oxford: Oxford University Press (OCLC: 960166004).

Thelwall, M., & Stuart, E. (2019). She's Reddit: A source of statistically significant gendered interest information? *Information Processing and Management*, *56*(4), 1543–1558. https://doi.org/10.1016/j.ipm.2018.10.007

Todd, C., Camic, P. M., Lockyer, B., Thomson, L. J., & Chatterjee, H. J. (2017). Museum-based programs for socially isolated older adults: Understanding what works. *Health and Place*, *48*, 47–55.

Warriner, A. B., Kuperman, V., & Brysbaert, M. (2013). Norms of valence, arousal, and dominance for 13,915 English lemmas. *Behavior Research Methods*, *45*(4), 1191–1207. https://doi.org/10.3758/s13428-012-0314-x

Wu, S., Tan, C., Kleinberg, J. M., & Macy, M. W. (2011). Does bad news go away faster? In *International AAAI conference on web and social media (ICWSM)*. Citeseer.

SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of this article.

How to cite this article: Mirlohi Falavarjani SA, Jovanovic J, Fani H, Ghorbani AA, Noorian Z, Bagheri E. On the causal relation between real world activities and emotional expressions of social media users. *J Assoc Inf Sci Technol*. 2020;1–21. https://doi.org/10.1002/asi.24440