Smartphone Interaction and Survey Data as Predictors of Snapchat Usage

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ABSTRACT

Snapchat is a highly popular smartphone app that allows personalised multimedia communication for spontaneous experiences, where the shared content disappears after a short period of time. In this paper, we examine the predictors of Snapchat usage based on a range of data collected through surveys and from interaction with the handset, using a cohort of 64 recruited participants. The results show that age, Smartphone Addiction, happiness and the use of the popular chatting apps WhatsApp and Facebook Messenger are significant predictors for Snapchat usage. We discuss the implications of these findings against the related literature, and also against the design of the app itself.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in HCI**; *Empirical studies in ubiquitous and mobile computing*;

KEYWORDS

Snapchat; smartphone interaction data; survey data; regression; prediction

ACM Reference Format:
Beryl Noë, Liam D. Turner, and Roger M. Whitaker. 2019. Smartphone Interaction and Survey Data as Predictors of Snapchat Usage. In *Adjunct Proceedings of the 2019 ACM International Joint Conference on Pervasive and Ubiquitous Computing and the 2019 International Symposium on Wearable Computers (UbiComp/ISWC '19 Adjunct), September 9–13, 2019, London, United Kingdom.* ACM, New York, NY, USA, 8 pages. https://doi.org/10.1145/3341162.3349298

UbiComp/ISWC '19 Adjunct, September 9–13, 2019, London, United Kingdom

ACM ISBN 978-1-4503-6869-8/19/09…$15.00
https://doi.org/10.1145/3341162.3349298

1 INTRODUCTION

Since its inception in 2011, Snapchat has allowed users to communicate through self-deleting pictures and videos and has quickly grown to be one of the most popular social media platforms. In 2016, users watched collectively some 10 billion videos per day [28] and in 2019 it has 190 million daily active users, ranking 4th in the list of most downloaded social media apps in the US [27]. Snapchat is particularly popular amongst young adults and teenagers [9, 29]. To a lesser extent, this is also the case for Instagram and Twitter, while Facebook attracts users from a much wider range of ages [20].

As with other popular social media sites such as Facebook, Instagram, and Pinterest, Snapchat has a female-skewed userbase. Pew Research Center [20] reports for 2018, that in the US, 23% of men and 31% of women declared using Snapchat. Differences in usage have been also observed, with Thelwall and Vis [30] findings that men were more likely to share images on Twitter while women used Snapchat more with the same intent. This trend was the same for posting frequency. Women were also more likely to add filters and text to their picture and video messages (*Snaps*) than men. The authors also noted that females took more screenshots and were more likely to upload Snaps to other social media platforms. In general, female users have been reported to have more concerns about online privacy and taking more measures to protect it [3].

With its short-lived, automatic deletion of Snaps, Snapchat uses not only spontaneity, but also privacy as a key selling point to attract users. This is apparent in a number of aspects. For instance, Snapchat user profiles reveal very little information, being limited to a username and profile picture. Snaps are also private and self-deleting, and Snapchat will notify the user if their interaction partner takes a screenshot of a Snap they sent, making them aware of it living on beyond its planned expiry. While Snaps are private and can only be seen by people the user directly sends them to, pictures and videos they upload on their *Story* are linked to their profile and can be seen by a wider audience. However, the app gives the user complete control over who can view this content.

Snapchat's perceived privateness allow users to feel in control of the sensitive information they choose to disclose to friends. This has consequences for how the app is used by its user base. For instance, Utz et al. [32] have reported that about half of their participants had shared drunk photos and between an eighth and a fifth had engaged in sexting.

Snapchat's private atmosphere is also shown through an emphasis on maintaining contact with friends through the incentive of collecting and upgrading friend emojis that act similarly to reward badges for achievements in games. Piwek and Joinson [21] note that while Facebook is used more for *bridging* social capital (i.e., keeping weak links by communicating with a large network), Snapchat is used more for *bonding* (i.e., keeping strong links by communicating with a small network). Perceived closeness between interaction partners was found to be significantly higher for Snapchat than for other popular social media (Facebook, Twitter, Instagram), and even face-to-face conversation in research by Bayer et al [4]. Finally, differing audiences also shape the way users communicate. Choi and Sung [6] report that Snapchat users use Snapchat for the expression of their true and actual self, while Instagram is employed for the expression of their ideal self.

Motivation and Contribution

Due to the distinctive functionality and design of Snapchat, it offers features that may appeal to particular types of user who can benefit from the interpersonal "bonding" that Snapchat may provide [21]. However, understanding what may characterise such users is not yet understood - and potentially complex to assert. There are many factors that mediate app usage [31], such as individual differences, context, other app usage and social influence, however the extent of these in predicting Snapchat usage, is not well-understood.

In this paper we seek to contribute new knowledge to understand predictors of Snapchat usage. We use a novel methodology that includes assessing the users' disposition in a number of dimensions, as determined through questionnaires and fine-grained user behaviour from interactions with the smartphone. This combination of techniques offers a broad range of potential indicators relative to both stable characteristics (e.g., a user's disposition) as well as behaviours detected through the smartphone in real time (e.g., interactions with the interface). The result is a comprehensive and multi-dimensional approach to identifying predictors of Snapchat usage. To the best of our knowledge, this has not been previously undertaken.

2 METHODS

A total of 76 participants were recruited through poster and online advertisement at Cardiff University, UK. Participants were selected on having no history of mental illness and owning a smartphone running Android 4.4 (KitKat) or higher. Since participation was voluntary and technical problems could not be avoided, 12 participants were excluded as too little or no usage data was collected from their phones, resulting in 64 participants (34 male, 30 female) aged 19 to

Table 1: Sociodemographic characteristics, Smartphone Addiction score and Snapchat usage (N = 64)

Variables	Statistics	
Age	**M**	**SD**
Years	25.4	5.87
Gender	**N**	**%**
Male	34	53.13
Female	30	46.88
Employment	**N**	**%**
Student	38	59.38
Student & employed	13	20.31
Employed	12	18.75
Unemployed	1	1.56
Education	**N**	**%**
High school, no diploma	1	1.56
High school diploma or equivalent	5	7.81
Trade / vocational training	1	1.56
Some undergraduate, no degree	14	21.88
Bachelor's degree	19	29.69
Master's degree	21	32.81
Doctorate	2	3.13
No answer	1	1.56
Smartphone Addiction Scale	**M**	**SD**
Score	87.8	20.26
Snapchat usage	**M**	**SD**
Number of daily interaction events	683.04	1501.62

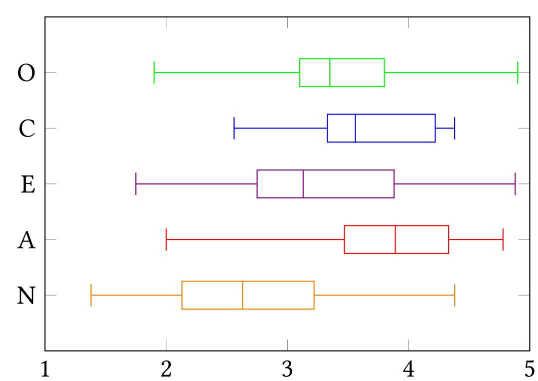

Figure 1: Scores for Big Five personality facets: Openness to Experience (O), Conscientiousness (C), Extraversion (E), Agreeableness (A), and Neuroticism (N), N = 64

46. A detailed overview of the composition of our sample is given in Table 1.

All participants took part in a briefing and a debriefing session where they completed 5 surveys: the Smartphone Addiction Scale (SAS) [14] (see Table 1), the Positive And Negative Affect Schedule (PANAS) [34], the Big Five Inventory (BFI) [11] (see Figure 1), the Monetary Choice Questionnaire (MCQ) [13], and a demographics and smartphone use questionnaire. This latter survey captured information such as gender, age, and education (see Table 1) but also where participants habitually kept their phone while sleeping and at which frequency it woke them up at night.

In this study, only survey results from the briefing session were used. In the briefing session, participants additionally gave their informed consent and installed our bespoke app *Tymer* [17]. They were further introduced to its functionalities: what micro-surveys it would ask them to answer on a daily basis and what type of data it was going to collect from their phone. They were also asked to keep Tymer installed on their phone and use it over a period of 8 weeks. In the debriefing session, participants received monetary compensation for their participation.

Smartphone collected data was comprised of two types of data:

(1) Smartphone usage data (collected automatically in the background), including interaction events between the user and apps on their device.
(2) Micro-surveys (answered by participants), including the participant's daily mood, sleep quality and sleep quantity.

Interaction events were recorded by logging the type of event (e.g., a tap), the timestamp (i.e., time and date), and the source of the event (i.e., the app with which the user interacts with, e.g., WhatsApp). Only smartphone interaction events (tap, long tap, writing, scroll, and text selection) for popular apps that at least half of the participants had used at least once were evaluated in this study. The number of interaction events was used as a measure of usage rather than time spent on a certain app to consider active usage only [18] (as opposed to passive usage where the user might not be interacting with their phone e.g., while listening to music or viewing content on Netflix). Due to privacy concerns, no data deemed too personal (e.g., content of received or sent messages, search history, GPS location, etc.) was collected.

In this study, we considered the mood reports which participants were prompted to answer once per day in the evening as a summary of how they felt prevalently during the day. Participants had the choice between the following options: Tense, Excited, Happy, Relaxed, Calm, Bored, Upset, Stressed, and Neutral. An overview of average frequency of reported moods is given in Figure 2. For each participant, a score

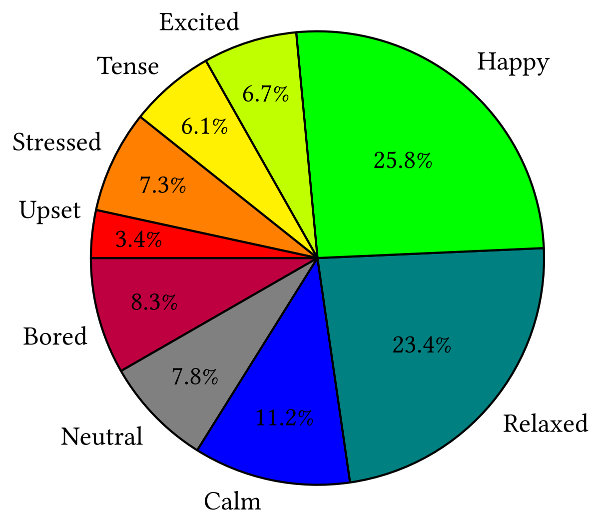

Figure 2: Mean percentage of reported daily moods across all users, N = 64

for each mood was obtained by dividing the number of occurrences of this mood by the total number of daily mood reports accumulated over the total duration of the study. Although subject to memory biases [17], a daily measure for mood was preferred for this study over the use of shorter intervals to take into account the mood the participant found most representative for their day.

Data analysis

To find predictors of Snapchat usage, survey data alone was first considered, followed by app interaction data alone, and finally, both types of data were analysed together.

Multiple regressions were performed with a log-transformed Snapchat variable so the parametric test could be used. The residuals of the regression were tested for normality using a Predicted Probability (P-P) plot. Homoscedasticity was tested by evaluating a scatter plot of the predicted values by the residuals and the Breusch-Pagan test. Multicollinearity was tested by evaluating the Variance Inflation Factor (VIF); variables with a VIF higher than 10 were excluded. No assumptions were violated.

Consistent with previous reports [9, 20], females in our sample ($M = 1157.03, SD = 2041.75$) used Snapchat significantly ($Z = -2.677, p = .007$) more than men ($M = 264.81, SD = 506.77$) on a daily basis and age had a high negative association with Snapchat usage ($r = -.467, p < .001$), therefore the demographic variables gender and age were considered confounding factors and inserted as a first block in analyses using survey data. A forced entry model regression was therefore used.

Table 2: Regression results for model 2 for the relationship between Snapchat usage and survey data.

Predictors	β
Smartphone Addiction	.341**
Happy	.248*
Boredom	.255*
Age	-.346**
Gender	.179
Model statistics	
BIC	86.539
ANOVA	F (57,5) = 8.389***

†p<.10, *p<.05, p**<.01, p***<.001

To determine in what order the remaining variables should be entered into the forced entry model, a backward elimination regression was performed. The order in which the variables were deleted from the backward elimination model regression was the reverse order they were entered (in blocks of 2 to 6 variables) into the forced entry model regression. Model 1 subsequently consisted of block 1, model 2 of block 1 and 2, and so forth. The full list of variables and entry blocks can be found in the appendix. Only the results of the model with the best fit (i.e., lowest Bayesian Information Criterion (BIC) value [26]) are reported in this study.

3 RESULTS

Survey data as predictors of Snapchat usage

The model that could most accurately predict Snapchat usage based on survey data according to the Bayesian Information Criterion values was model 2 (comprised of blocks 1 and 2) with a BIC value of 86.539 and a R^2 value of .424 (see Figure 3). The control variable gender was not a significant predictor for Snapchat use. However, age, Smartphone Addiction score, feeling bored, and feeling happy were significant predictors for Snapchat usage. More details can be found in Table 2.

Smartphone interaction data as predictors of Snapchat usage

The model that could most accurately predict Snapchat usage based on app usage data was model 2 (comprised of blocks 1 and 2) with a BIC value of 86.991 and a R^2 value of .383 (see Figure 3). All variables were significant predictors for Snapchat usage: WhatsApp, Facebook Messenger, Instagram, and BBC News, and Messaging. More details can be found in Table 3.

Table 3: Regression results for model 2 for the relationship between Snapchat usage and smartphone interaction data.

Predictors	β
WhatsApp	.449***
Facebook Messenger	.352**
Instagram	.236*
BBC News	-.227*
Model statistics	
BIC	86.991
ANOVA	F(59,4) = 9.157***

†p<.10, *p<.05, p**<.01, p***<.001

Table 4: Regression results for model 4 for the relationship between Snapchat usage and the smartphone interaction and survey data.

Predictors	β
Age	-.657***
Gender	-.124
WhatsApp	.406***
BBC News	-.365***
Smartphone Addiction	.411***
Gmail	.334**
Wake up frequency	-.214*
Sleep amount	-.209*
Amazon Shop UK	.172†
Conscientiousness	.219*
Facebook Messenger	.199*
Happy	.188*
Model statistics	
BIC	82.685
ANOVA	F(50,12) = 8.018***

†p<.10, *p<.05, p**<.01, p***<.001

Smartphone interaction and survey data as predictors of Snapchat usage

Google Music, Google Keep, Bored, Relaxed, and Sleep quality were excluded from the analysis due to multicollinearity with other variables.

The model that could most accurately predict Snapchat usage based on survey data was model 4 (comprised of blocks 1, 2, 3 and 4) with a BIC value of 82.685 and a R^2 value of .658 (see Figure 3). All variables except gender and Amazon Shop UK were significant predictors for Snapchat usage: age, WhatsApp, Facebook Messenger, BBC News, Smartphone Addiction score, Gmail, wake up frequency, amount of sleep, Conscientiousness and feeling happy. More details can be found in Table 4.

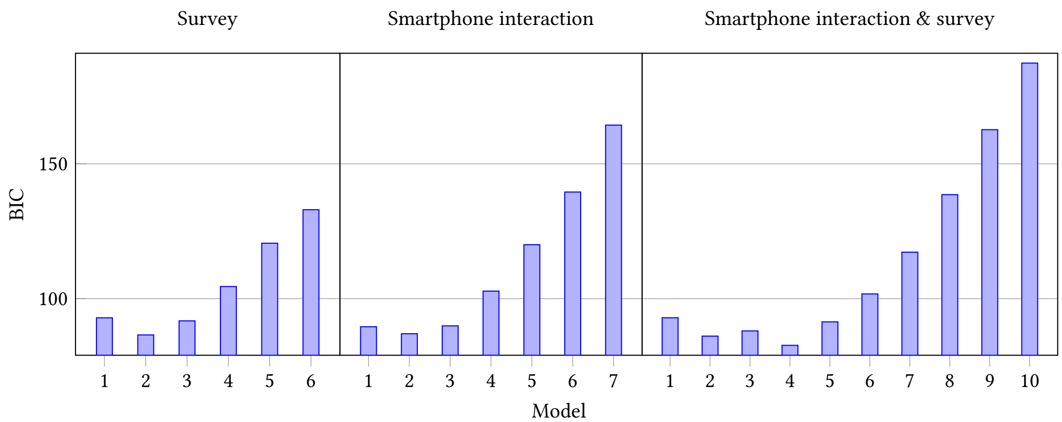

Figure 3: Bayesian Information Criterion (BIC) values for each model

Overview

All significant predictors had a positive relationship with Snapchat usage, except age, BBC News app usage, wake up frequency and amount of sleep which were negatively associated with interactions with the Snapchat app. Table 5 shows an overview of these results.

4 DISCUSSION

In this study, we have identified predictors of Snapchat usage based on passively collected smartphone interaction events and user surveys. We then combined both approaches to determine which predictors were most important overall. It is worth noting that most of the significant predictor variables in the former analyses recurred in the latter analysis. Furthermore, while none of the variables relating to personality or sleep were found to be predictors of Snapchat usage when looking at survey data only, they were relevant when considered together with smartphone interaction data.

Although gender effects have been reported in previous studies [2, 21, 30] and we found a significant difference in usage levels with women interacting significantly more with Snapchat than men, gender does not appear to be a significant predictor for Snapchat use in our sample. In contrast to gender, age was consistently a significant predictor for Snapchat usage with a high beta weight. The importance of age as a predictor is consistent with reports of the popularity of the app amongst young adult and teenage age groups while being sparsely used in older generations. This phenomenon reflects also the faster speed at which young people adopt new social media and new technology [15]. This plays a particularly large role for Snapchat as it is only available as an app, contrary to other popular social media such as Facebook, Instagram and Twitter which can be accessed as websites on other devices as well.

The use of social media has been linked to smartphone addiction in the wider literature [5, 22, 23, 25] and we have identified Snapchat use as a particularly strong correlate in a previous study [18] using the same dataset. It is therefore unsurprising that this relationship comes forward again in this study. As a type of behavioural addiction, smartphone addiction is an indicator of dependence for users that experience using their phones as rewarding despite it resulting in negative consequences on their health, social relationships and/or other aspects of their lives [8].

We have also identified that interactions with several other apps are predictors for the use of Snapchat. WhatsApp, Facebook Messenger, Gmail and Instagram were positive predictors, while the BBC News app was linked negatively to Snapchat usage. WhatsApp and Facebook Messenger are the two most popular chatting apps worldwide. As a notable part Snapchat's functionality surrounds chatting (with pictures), it is not unexpected that high levels of communication using these apps are predictors of high interaction with Snapchat. The email client Gmail is also arguably a communication app. It differs from either of the 3 previously mentioned apps in several aspects and thus makes for a more unexpected predictor of Snapchat use. While chats are a generally casual way to interact with friends and family through short messages, emails are commonly longer and used more in professional, educational, or generally formal settings where conversation partners are not necessarily close to each other [4]. It thus starkly contrasts with Snapchat, which could be described as the opposite in many aspects. We posit that it therefore serves a complementary function rather than being a predictor of Snapchat use due to its similarity with the app.

Waking up less frequently during the night was a significant predictor for Snapchat use. This is perhaps surprising as the app pushes towards more increased user engagement

Table 5: Significant predictors for Snapchat usage based on survey data, smartphone use data, and both.

Type of data	Survey	Smartphone use	Survey and Smartphone use
Demographics	*Age*		*Age*
Addiction	Smartphone Addiction		Smartphone Addiction
Mood	Happy		Happy
	Bored		
Sleep	-		*Wake up frequency*
			Sleep amount
Personality	-		Conscientiousness
Apps		WhatsApp	WhatsApp
		Facebook Messenger	Facebook Messenger
		BBC News	*BBC News*
		Instagram	Gmail

Italics indicate a negative association

through notifications and gamification elements aimed at pairs of users maintaining a minimum snapping frequency. However, sleeping less was also a predictor of Snapchat use. This finding is consistent with results of Mark et al. [16], who examined Facebook usage in relation to sleep and attention. They proposed sleep debt as a possible cause of increased Facebook usage, as sleep deprived individuals would seek out activities requiring a lower cognitive cost, such as social media use.

Conscientiousness was a significant positive predictor of Snapchat use. This finding is of interest as the literature has been inconsistent concerning its link with social media use: both negative [10, 12] and positive associations have been reported [19]. In our study, no correlation is found between Conscientiousness and Snapchat usage ($r = .004$, $n.s.$). As a significant predictor of Snapchat usage, this means that it could play a moderating role rather than influencing Snapchat usage directly. This would be consistent with the findings that conscientious individuals tend to refrain from using social media [24], but if they do, show consistency in their behaviour. Similarly, research examining check-in behaviour on Foursquare, a location based social network app, found a weak correlation with Conscientiousness, which the authors attribute to diligence and persistence, key characteristics of this personality facet [7]. On Snapchat, perseverance is also required: notably to maintain *Snapstreaks* scores by snapping back and forth with friends at least once per 24 hours. This result is worthy of further examination.

Lastly, Snapchat use was positively predicted by both high number of reports of daily happiness and boredom. In their examination of motivations for usage of a number of social media platforms, Alhabash & Ma [1] note that the primary reason behind Snapchat use is entertainment, followed by convenience, medium appeal and passing time. Vaterlaus et al. [33] have reported that when asked what type of content they shared on Snapchat, 98.7% of the user group they surveyed responded they sent "funny things". Snapchat therefore seems to be a prominent go-to app when experiencing boredom and might be successful in eliciting positive emotions in users.

5 CONCLUSION

Examining both survey and smartphone interaction data, we have identified significant predictors for Snapchat usage. This has involved deploying a bespoke app to collect the number of user-interface interactions with the smartphone, along with survey data. We found significant demographic (age) and behavioural (Smartphone Addiction score) predictors, but also predictors relative to sleep (sleep amount and wake up frequency), mood (happiness and boredom), personality (Conscientiousness), and app interaction (WhatsApp, Facebook Messenger, BBC News, Instagram, and Gmail).

To the best of our knowledge, the approach undertaken in this study is unique in respect to its methodology combining the smartphone interaction data collected over an extensive period of time with survey data gathered both periodically and through validated psychometric tests. Our findings reveal some novel predictive variables which have not previously been linked to Snapchat usage. Towards future work, further investigation of Conscientiousness as a possible moderating factor would be worth pursuing to determine under what circumstances the personality facet that is usually characterised by low social media use is positively associated with Snapchat usage.

ACKNOWLEDGMENTS

We thank the Wellcome Trust for funding this project through an Institutional Strategic Support Fund to Cardiff University and all participants who took part in our study.

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A REGRESSION MODELS

Snapchat usage and survey data

Predictors were entered in the following blocks:

(1) Block 1 (confounding factors): Age, Gender
(2) Block 2: Smartphone Addiction, Happy, Bored
(3) Block 3: Tense, Agreeableness, Impulsivity, Sleep amount
(4) Block 4: Calm, Upset, Extraversion, Openness to Experience,
(5) Block 5: Conscientiousness, Excited, Stressed, Wake Up
(6) Block 6: Sleep quality, N, Neutral, Relaxed

Snapchat usage and smartphone interaction data

Predictors were entered in the following blocks:

(1) Block 1: WhatsApp, Facebook Messenger
(2) Block 2: Instagram, BBC News
(3) Block 3: Messaging, Google Quick Search Box, YouTube
(4) Block 4: Google Calendar, Amazon Shopping, Phone, Google Play Store, Twitter
(5) Block 5: Google Maps, Google Keep, Amazon Shop UK, Outlook, Skype
(6) Block 6: Google Hangouts, WeChat, Settings, Chrome, Facebook
(7) Block 7: Google Photos, Calculator, Gmail, Spotify, Tinder, Contacts

Snapchat usage and survey and smartphone interaction data

Predictors were entered in the following blocks:

(1) Block 1 (confounding factors): Age, Gender
(2) Block 2: WhatsApp, BBC News, Smartphone Addiction
(3) Block 3: Gmail, Wake Up, Sleep amount, Amazon Shop UK
(4) Block 4: Happy, Conscientiousness, Facebook Messenger
(5) Block 5: Agreeableness, Neuroticism, Google Quick Search Box, Spotify, Outlook
(6) Block 6: Tense, Calm, Openness to experience, Google Calendar, Chrome
(7) Block 7: Facebook, Youtube, Calculator, Google Play Store, Phone
(8) Block 8: Tinder, Google Hangouts, Instagram, Impulsivity, Google Photos, Contacts
(9) Block 9: Settings, WeChat, Skype, Messaging, Excited, Extroversion
(10) Block 10: Google Maps, Twitter, Amazon Shopping, Stressed, Upset, Neutral