Boredom-Computer Interaction: Boredom Proneness and The Use of Smartphone

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ABSTRACT

Mobile technology is becoming a loyal companion in our lives. It is used for increasing amounts of time during the day and night, enabling the development of intelligent user interfaces that characterize their users' traits and adapt to them. In this paper, we show how an individual's tendency to experience boredom, *i.e.* the personal trait called *boredom proneness*, affects the use of technology – specifically a smartphone. We develop machine learning models to automatically classify individuals into high/low boredom proneness from their typical daily patterns of smartphone use. We thus propose *boredom proneness* as a trait with high potential to enable the design of personalized mobile services that are more meaningful to their users.

Author Keywords

User Modeling; Boredom Proneness; Mobile Devices

ACM Classification Keywords

H.1.2. Models and Principles: User/Machine Systems – Human Factors.

INTRODUCTION

Boredom is a common human experience, both today and thousands of years ago [1]. Yet, people today appear to be more predisposed to boredom than ever before despite the fact that technology provides us with an ample source of stimuli at our fingertips [2][3]. This may sound paradoxical, though it might also be an indication of the intertwined connection between boredom and the use of technology, which we set to explore in two studies. In [26] we investigated this relationship with respect to a temporary experience *i.e.* the *state of boredom* whereas in this paper we explore it with respect to a personal trait – *boredom proneness*.

The predisposition to experience boredom of all types is a personal trait called *boredom proneness*, which is associated to a number of outcomes including behavioral and substance addictions, mood disorders and social problems [4]. Understanding boredom proneness has shown to be important as individuals with high propensity to chronic boredom can benefit from treatment strategies to alleviate its negative impact [5]. Furthermore, knowing one's boredom proneness can be a valuable input in a variety of use cases, from improving work productivity [6] to optimizing medical treatments [7] and potentially designing ubiquitous technologies. Boredom proneness is typically assessed with psychometric scales [4]. However, a wide practical application of such scales is limited for several reasons, including 1) the burden of filling out a questionnaire, 2) the need to answer questions related to private-life which can be uncomfortable for people, and 3) the requirement of repeated measurements as boredom proneness is a trait that can fluctuate over life-time.

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In this paper, we provide evidence that an individual's propensity to boredom is reflected in his/her patterns of using technology – particularly a smartphone, such that a user's proneness to boredom can be automatically classified by a machine learning algorithm. In this paper, we:

1) Propose a novel method to infer boredom proneness from smartphone usage patterns. We validate this method in an in-the-wild user study with 22 participants reaching over 80% accuracy in the classification of users with high *vs.* low boredom proneness;

2) Derive implications of using boredom proneness as an individual trait with value for the UbiComp community.

BACKGROUND

Definition of boredom proneness

The boredom trait, typically referred to as *boredom proneness*, is defined as the tendency towards experiencing boredom [8][4]. As it has been increasingly emphasized in the literature [4][9][10], it is important to make a clear distinction between situational and dispositional boredom: between a *boredom state* (the actual instantaneous experience of boredom) and a *boredom trait* (the predisposition to become bored). Although the boredom trait has been linked to personality traits (that are stable personal characteristics), it is considered to be an independent trait that can fluctuate during a lifetime to a certain extent [1]. To address the need to quantify individual differences in the predisposition to experience boredom, several psychometric scales [4] have been developed, out of which the Boredom Proneness Scale (BPS) [8] is considered to be the most influential over the last three decades [4]. Thus, this is the scale that we use in this paper to quantify the level of boredom proneness.

Correlates of boredom proneness and its relevance for technological research

Boredom proneness has been linked to a myriad of adverse behaviors including pathological gambling [11], drug [12] and alcohol consumption [13], and somatization [14]. In addition, it is also correlated with depression and anxiety [13], impulsivity [15], procrastination and a lack of autonomy (see [4] for a literature review of the implications of boredom proneness). Specifically, there are several correlates of boredom proneness that can be of particular interest to ubiquitous computing. Boredom proneness is directly associated with a more frequent need for sensation seeking [16] for which technology, and in particular a mobile phone, plays an important role as it is often used as a source of stimulation [17]. Boredom proneness is also associated with the personality traits of neuroticism [18] and extroversion [19] that in turn have an impact on the perceived usability and satisfaction with technology [20]. In addition, scholars in the human-computer interaction community have studied disruptions [21] and attention (*e.g.* related to the messages [22]) which are directly related to boredom proneness [4].

When it comes to the inference of personal characteristics, previous research has remained mostly focused on personality traits and their inference from social network characteristics [23], Call Detailed Records [24], and smartphone sensing [25]. To the best of our knowledge there have been no attempts to infer boredom proneness in an automatic manner and to explore how patterns of smartphone usage differ depending on this individual trait.

METHODOLOGY

To analyze how boredom proneness might get reflected in the patterns of smartphone usage, we carried out an in-the-wild study with 22 volunteers, who were asked to: 1) install a mobile sensing application (that we made available on Google Play Store) on their smartphones through which we captured their phone usage patterns, and 2) fill-out a Boredom Proneness Scale (BPS) questionnaire at the end of the study. The participants were also asked to answer probes related to their boredom state multiple times per day, which were used in another study [26] focused on automatically inferring the *state of boredom*. All participants received a 20 EUR Amazon gift card.

Participants

Participants were recruited through two mailing lists, one containing computer-science students at a German university, and the other one consisting of individuals that had signed up to participate in research studies in a large organization in Spain. Overall 22 participants (aged from 21 to 44, mean=30, SD=6, 13 males, 4 females, and 5 chose not to disclose their gender) successfully completed the study. That is, they installed the mobile application, had it running for at least 2 weeks, had at average 6 or more daily probe responses (related to the boredom state) with a standard deviation of the scores less than 0.25 (a threshold that we used to filter out presumably non-valid answers), and filled out the BPS questionnaire.

Data Collection

Phone usage patterns were captured through phone activity logs and sensor readings that were collected by the Android application developed for the purpose of this study. Energy consumption was optimized by deactivating parts of the sensors when the user was not active. Screen on/off status, phone unlock events, notifications, proximity, ring and network modes were logged continuously (every 5 to 60 seconds depending on a specific sensor). Cell tower information, amount of data traffic, foreground applications, and screen orientation were logged only when the screen of the phone was on and unlocked.

We used a refined experience-sampling method (rESM) [27] to obtain an insight into the participants daily variations of their boredom state: at semi-regular intervals[1], with an average of six times per day, the application probed participants to report their perceived level of boredom in a 5-point Likert scale by rating the statement: *"Right now, I fell bored"*. At the end of the 2-week study, participants were asked to fill out the 28-item BPS survey [8], which provided the ground-truth of boredom proneness.

Feature Extraction

The mobile phone is often used as a source of stimuli to deal with boredom [17], thus we expected that an individual's tendency towards boredom would have an impact on day-to-day phone usage. We extracted 61 features that characterize the type and patterns of typical daily phone usage. These features were descriptive statistics of the collected sensor data aggregated on a daily basis and related to 1) phone activity (such as calls, messages, application use, receiving and attending notifications, etc.), 2) intensity of usage (such as traffic amounts, battery levels, charging frequency, etc.), and 3) dynamics of phone usage (such as time periods since last activity, number of unlocks, screen on/off events, etc.).

Feature Selection and Model Building

From the 61 extracted features and given the ground truth of boredom proneness obtained with the BPS questionnaire, we formulate two problems: 1) *classification*, where the goal is to automatically classify whether a person has high or low proneness to boredom; and 2) *regression*, where the goal is to automatically infer the boredom proneness value of each individual. Feature selection is important to reduce the dimensionality of the feature space and to have an

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[1] The pop-up questionnaire was more likely to be triggered when a participant was interacting with the mobile phone, and not less than 30 min since the last report was provided.

insight into which features are the most correlated with boredom proneness. We applied SVM Recursive Feature Elimination (SVM-RFE) [28] that returns a ranking of the features by training an SVM and recursively removing the features with the smallest ranking criterion. To avoid overfitting, feature selection was performed using a randomly selected half of the entire sample.

RESULTS

Questionnaire Analysis

The results of the Boredom Proneness Scale survey show a satisfactory internal consistency with a *Cronbach's alpha* of α=0.82, which indicates a good reliability of the conducted questionnaire. This is in accordance with previous work [8] that demonstrated satisfactory levels of internal consistency (α=0.79) as well as of test-retest reliability (r=0.83). The scores were normally distributed (we consider both Q-Q plot analysis as well as Shapiro-Wilks test) with values ranging from 58 to 132 and with a mean of 95±17. These statistics are comparable to the descriptive statistics reported in the literature for considerably larger samples of subjects [5], [8], [29].

First, we analyzed if the obtained Boredom Proneness Scale values were correlated with the individuals' responses to the rESM probes as suggested in the literature. For two weeks we collected 122±33 subjectively reported boredom states *i.e.* rESM probes per participant, and we use the mean value as a measure of the central tendency to feel bored. As our sample size is small (N=22) and the level of boredom was reported on a 5-point Likert scale, the choice of using median instead of mean value as the measure of the central tendency was equivalent (thus, performing the normality test for the daily responses of each participants would be superfluous). The correlation between the mean values of the reported levels of boredom and the BPS scores was strong (**r = 0.63, *p*<0.005**). As expected, the correlation was identical for the median values. The strong correlation between boredom proneness scores (*trait*) and reported boredom levels (*state*) indicates that the BPS indeed captured the individuals' tendency to experience boredom despite the limited duration of our study (two weeks).

Boredom Proneness Inference

We tested several machine learning techniques (including SVMs, Random Forests and Gaussian Processes), out of which SVM (Support Vector Machines) outperformed the other methods and hereby we will provide only the results using SVMs. Using the SVM-RFE method we selected the 14 most predictive features (discussed in more detail below) out of the pool of 61 features. The performance of inferring boredom proneness –both for classification and regression– was computed through the leave-one-out method of sequentially selecting one individual (*i.e.* the features related to his/her phone usage) as a test point while using the rest as a training set. For the data analysis, we used *R* with the *kernlab*, *caret* and *pathClass* libraries.

Regression

Fig. 1 shows the cumulative distribution function (CDF) of the errors for BPS score regression.

The median estimation error (the 50th percentile) is 11 *i.e.* half of the prediction errors are within 14% of the whole range (74) of the observed boredom proneness values, whereas the 95th percentile error reaches 26 (the absolute error in predicting the score).

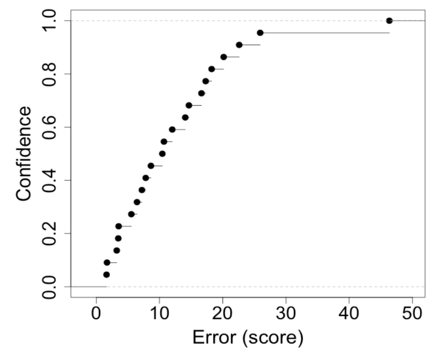

Figure 1 –Accuracy of Estimating the BPS Score

Further analysis of the errors with respect to the scores (Fig. 2) provides a more precise picture of the regression performance: the highest estimation errors correspond to the extreme values of boredom proneness. Although further tuning of the *epsilon*[2] parameter in the SVM model might have decreased the errors in the extreme values, we avoided this additional tuning due to the risk of overfitting, particularly considering the sample size.

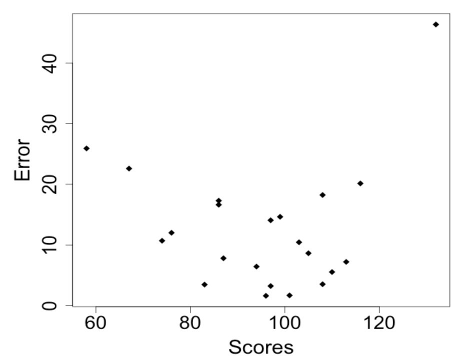

Figure 2 – BPS estimation errors *vs.* BPS scores

Classification

In order to evaluate the classification performance we split participants into two classes based on the median value of the boredom proneness score: median=97. Previous work reported a similar median score [4], [5]. Therefore, participants with a BPS score >=97 were labeled as "HIGH" whereas participants with a BPS score <97 were labeled as "LOW". The confusion matrix of the accuracy of

[2] Data points below this threshold do not contribute to the regression fit while data points with a greater absolute difference contribute linearly

the SVM classifier is presented in Tab. 1. The incorrectly classified instances (false positives and false negatives in Tab. 1) did not correspond to the instances with the highest regression errors (Fig 1. and Fig.2), with an exception of a participant with a BPS score of 132. Therefore, although the extracted features were not predictive enough to infer the extreme boredom proneness scores with high accuracy in the regression task, our classifier correctly classified such individuals as HIGH or LOW.

	Predicted LOW		Predicted HIGH	
	Percentage	# of subjects	Percentage	# of subjects
LOW	**80%**	8	20%	2
HIGH	17%	2	**83%**	10

Table 1. Confusion Matrix of SVM Classifier

Boredom Proneness and Phone Usage Patterns

The SVM-RSE algorithm provided an insight into which mobile phone usage features were the most predictive of boredom proneness, namely:

- The number of received *social network notifications* (*MAX* and *SD*)
- The frequency of opening the notification center (*MIN* and *SD*)
- Changes in screen status (*SD* of the number of screen-on events and of orientation changes).

Additional features that are important are related to the number of launched apps (*MEDIAN*), charging time in seconds (*MEDIAN* and *MIN*), and transmitted amount of data (*MAX*)[3].

The features related to *social network notifications* were top-ranked by the SVM-RSE. Although not directly triggered by the user him/herself, the number of received *social network notifications* is expected to reflect one's overall engagement in social networks.

Interestingly, the standard deviations of switching the screen on (the higher the value the higher the BPS scores) and of changing the screen orientation (the higher the value the lower the BPS scores) were more indicative of boredom proneness than the total time of having the screen on. The *screen* status events, together with features related to opening the notification center, might reflect the behavior characterized as "active search for stimuli". However, such interpretations remain speculative and though qualitative interviews with participants would have provided a better understanding of their behavior we avoided them due to the anonymity of the recruitment process.

The results of our study suggest that typical daily patterns of smartphone usage reflect boredom proneness, at least for the participants in our study. Therefore, boredom proneness can be automatically inferred from mobile phone usage. Due to the study limitations, we refrain from further generalizing our results until we carry out a larger user study.

[3] Note that *SD*, *MIN*, *MAX*, *MEDIAN* refer to standard deviation, minimum, maximum, and median values (respectively) extracted daily for the 2-week period.

IMPLICATIONS FOR UBICOMP COMMUNITY

Controlling for sample biases in user studies. When testing new technologies, the samples of individuals involved in user studies are typically controlled for biases related to gender, age, socio-economic status and other demographic features. We showed that boredom proneness impacts the way people use mobile phones –and possibly technology in general. Thus, the design and initial testing of mobile applications and services could benefit by achieving a balance sample according to boredom proneness (particularly for prolonged evaluations).

Adjusting the level of user engagement. When proactively engaging with users (e.g. through mobile phone notifications) people may easily start feeling overwhelmed. It was shown that overusing mobile services leads to lower satisfaction with mobile services [20]. Knowing a person's boredom proneness can thus help to personalize the level of proactive engagement to the extent where it will not be perceived negatively. In this respect, recommendation algorithms can help individuals with high boredom proneness manage the use of their phones in a more productive manner, or suggest more relevant content.

Large-scale and unobtrusive behavioral analysis. Todman [9] asserts that we still know little about the extent to which negative outcomes associated to boredom proneness (pathological gambling, depression, somatization, etc.) are actually induced by exposure to different types of boredom-inducing environments. Thanks to the automatic inference of boredom, mobile computing can help shed light onto this topic by combining it with the analysis of mobile phone daily usage patterns and the user's context. Identifying longitudinal correlations among these three elements at an individual level would enable the development of persuasive interfaces to help users improve their behavioral routines to minimize negative outcomes.

CONCLUSION

In this paper we study *boredom proneness* and its relation to mobile phone usage. We find that it is related to the daily frequency of opening the notification center and of activating the screen and changing its orientation, the use of social networks on the phone, the number of launched apps, charging time, and the transmitted amount of data. We build machine learning models to automatically classify users in high/low boredom proneness with over 80% accuracy. Ultimately, we suggest that boredom proneness has value for controlling for sample biases in user studies, for personalizing mobile services and for designing persuasive applications to help users improve their daily life routines.

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