Time distortion when users at-risk for social media addiction engage in non-social-media tasks

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Abstract

Background: There is a growing concern over the addictiveness of Social Media use. Additional representative indicators of impaired control are needed in order to distinguish presumed social media addiction from normal use.

Aims: (1) To examine the existence of time distortion during non-social-media use tasks that involve social media cues among those who may be considered at-risk for social media addiction. (2) To examine the usefulness of this distortion for at-risk vs. low/no-risk classification.

Method: We used a task that prevented Facebook use and invoked Facebook reflections (survey on self-control strategies) and subsequently measured estimated vs. actual task completion time. We captured the level of addiction using the Bergen Facebook Addiction Scale in the survey, and we used a common cutoff criterion to classify people as at-risk vs. low/no-risk of Facebook addiction.

Results: The at-risk group presented significant upward time estimate bias and the low/no-risk group presented significant downward time estimate bias. The bias was positively correlated with Facebook addiction scores. It was efficacious, especially when combined with self-reported estimates of extent of Facebook use, in classifying people to the two categories.

Conclusions: Our study points to a novel, easy to obtain, and useful marker of at-risk for social media addiction, which may be considered for inclusion in diagnosis tools and procedures.

Keywords: Social media addiction, Internet addiction, Time distortion, Time perception

1. Introduction

The addictive use of social media (e.g., Facebook, Snapchat, Twitter) can be seen as a specific form of technology addictions, which shares common phenomenology with "Internet gaming disorder," recently included in *Section 3* of the DSM-5 (American Psychiatric Association, 2013). It manifests in addiction-like symptoms, including salience (preoccupation with the behavior), mood modification (performing the behavior to relieve or reduce aversive emotional states), tolerance (increasing engagement in the behavior over time to attain the initial mood modifying effects), withdrawal (experiencing psychological and physical discomfort when the behavior is reduced or prohibited), conflict (putting off or neglecting social, recreational, work, educational, household, and/or other activities as well as one's own and others' needs because of the behavior), and relapse (unsuccessfully attempting to cut down or control the behavior) (Andreassen et al., 2016). Hence, it can be conceived as a state in which the individual is overly concerned about social media activities, driven by an uncontrollable motivation to perform the behavior, and devotes so much time and effort to it, so that it interferes with other important life areas (Dong and Potenza, 2014).

There is mounting behavioral and neuro-physiological evidence showing that such possible addiction-like symptoms are prevalent, can adversely impact the lives of many individuals, and can be similar in many respects to symptoms manifested in more established addictions (Banyai et al., 2017; Dong et al., 2012). While the boundaries of what exactly constitutes such addictions are still controversial (Widyanto and Griffiths, 2006), the appropriate terminology (e.g., disorder, addiction, problematic use) is not agreed upon (Lortie and Guitton, 2013), and there are no established clinical classification criteria for social media addiction (Kuss and Griffiths, 2017), studies largely agree that many social media users present addiction-like symptoms that cause some impairment in other life domains (Turel and Serenko, 2012). Moreover, studies of adolescents point to about 4.5% prevalence rate of at-risk for addiction, and show that most adolescent social media users present some degree of addiction symptoms (Banyai et al., 2017). It is important to study such presumed addictions because they can adversely impact the wellbeing, social functioning, sleep, academic and work performance and health of large cross-sections of social media users (De Cock et al., 2014; Karaiskos et al., 2010; Kuss et al., 2013).

Social media addiction is often captured by means of self-reports (as a continuous concept that encapsulates the level of symptoms) and clinical interviews (Andreassen et al., 2016). Recent research indicates that there is a growing need to find objective markers for such addictions, to supplement rather than replace surveys and clinical interviews. This need stems from the idea that self-reports, especially as related to core symptoms that involve time estimates: compulsion, overuse and tolerance, can be biased (Lin et al., 2015; Rau et al., 2006). Such studies show that in line with time perception theories (Takahashi et al., 2008; Wilson et al., 2015; Wittmann and Paulus, 2008), time distortion is a marker that can help classifying people to addiction and no-addiction groups. They specifically show that the stronger the addiction is, the greater the temporal misperception of users is; users underestimate the time intervals in which they engage in the addictive behavior, and this contributes to addictive behaviors (Lin et al., 2015). One explanation for this is that Internet (and presumably also social media) addictions can be conceived as a special type of an impulse control disorder; a condition under which people lose track of time (i.e., their psychological clock runs slow) and their self-consciousness is impaired (Rau et al., 2006). Viewed this way, it is possible that social media addiction shares similar time distortion features, with more common impulse control disorders, such as compulsive sexual behavior, in which time distortion is a common feature of dissociation (Birchard, 2015).

Two psychological processes underlie such time perception biases: an attention mechanism that can be impaired when people engage in highly rewarding behaviors, and an arousal mechanism that distorts how people accumulate temporal units (Wittmann et al., 2006; Wittmann and Paulus, 2008). Consequently, there tends to be downward-biased time estimates of use epochs in presumed technology addicts, and these can be used for screening and research purposes, as supplements for self-reports (Lin et al., 2015; Rau et al., 2006).

In this study we contend that distortion of time regarding tasks that prevent the use of the addictive technology but involve reflections on it, can too be indicative of social media addiction and serve as another marker for signaling risk for such disorders. Specifically, a period of non-social-media use and in which there is exposure to social media cues might trigger a deprivation state in people at risk for addiction. Hence, one may expect that these individuals will overestimate the completion time of task where they do not have access to social media, especially when the task requires social media reflections. For instance, when people with obesity are deprived of food (e.g., while dieting), they perceive the time intervals between meals to be longer than they are, and hence allow themselves to eat sooner and more often; this bias has been shown to prevent recovery and to contribute to obesity etiology (Faulkner and Duecker, 1989). Similarly, it has been shown that deprivation of smoking and drug use when people try to quit, result in impaired (upward) time perception (Merson and Perriot, 2011; Sayette et al., 2005). Indeed, cognitive time passes more slowly in stressful (e.g., under deprivation when an addict is exposed to cues related to the addictive substance/behavior and homeostasis is disrupted) than in less stressful situations (Fraisse, 1984). In contrast, people with no/low risk of addiction will likely have no or negative time distortion, because they are likely to find reflections on social media to be enjoyable, without being stressed by the deprivation the task induces (Turel and Bechara, 2016).

We follow the same logic here and suggest that (1) one's level of social media addiction as manifested via the degree of addiction-like symptoms will be positively associated with upward time distortion during this task, and (2) this time distortion can be used as one marker (out of many) that can separates people at-risk for social media addiction from those who are not. In essence, we expect that tasks that prevent social media use but involve social media cues will produce upward time distortion for people who meet common at-risk for addiction criteria, and possibly downward time distortion for people who do not meet these criteria. This proposed time distortion can be easy to measure and may extend the battery of manifestations in technology addiction research and practice.

2. Methods

2.1. Participants

A total of 274 university students who use Facebook were recruited from statistics classes at a university in the United States (response rate of 88%), in July 2017. The recruitment strategy was based on the idea that university students can be heavy users of social media and present varying degrees of addiction-like symptoms in relation to Facebook use (Kuss et al., 2013). The split at-risk of social media addiction vs. no- or low-risk was done based on a suggested cutoff point (Banyai et al., 2017) applied to the addiction scores. Sample attributes are given in Table 1:

Table 1: Sample characteristics

	No/low Risk	**At Risk**	**All**
n	232 (84.7%)	42 (15.23%)	274

Sex [Male/Female]	151/81	28/14	179/95
Age [Mean, Range, SD]	25.55, 18-54, 5.69	23.52, 18-32, 3.15	25.24, 18-54, 5.42
GPA [Modal range]	3.0-3.2	3.0-3.2	3.0-3.2
Extent of Facebook Use [Mean, SD]	3.89, 1.19	4.92, 0.95	4.04, 1.22
Social Media Addiction Score [Mean, SD]	2.77,0.87	5.07, 0.66	3.13, 1.18
Big-5 personality profile [Mean, SD]			
Openness	4.31,1.11	4.65,1.45	4.36, 1.18
Conscientiousness	5.16,1.14	4.92,1.03	5.12, 1.13
Extraversion	4.38, 1.28	4.70, 0.99	4.43,1.25
Agreeableness	5.03,1.03	5.23, 0.97	5.06,1.02
Neuroticism	3.51,1.29	3.93, 1.50	3.58,1.33

The range and means of the addiction scores imply that many respondents experienced addiction-like symptoms in relation to social media use, but on average these were experienced somewhat rarely, as expected in the case of problematic behaviors.

2.2. Procedures

The study was approved by the institutional review board of the university; participation was voluntary and was encouraged with class bonus points. Inclusion criteria included Facebook use and age>18. Twelve records were excluded because they met the exclusion criteria; the sample was consequently reduced from 286 to 274. The study was conducted in a computer lab from which time elements (e.g., clock) were removed.

The study followed the method of retrospect verbal estimation of duration. The fact that time is a key aspect in the study was not disclosed, and a concurrent task (survey completion) prevented time counting (Wittmann and Paulus, 2008). To operationalize this, the study was presented to students as a study that solicits approaches regarding and opinion of self-control strategies related to Facebook use. They were asked to complete an online survey in one attempt; the survey collected data relevant for this study as well as a range of open ended questions that asked participants to write the strategies they use for controlling their level of Facebook use and rate the frequency, difficulty and efficacy of these strategies. The nature of this task served two purposes. First, it prevented people from using Facebook on the computer while working on it. It was hence expected to induce some agitation and carvings in Facebook users who are at-risk for addiction. Second, the nature of the task encouraged self-reflection on one's self control behaviors related to Facebook use; these are presumed to be unpleasant especially for those who are at-risk for addiction and can serve as cues that motivate use. Moreover, we assumed that this facet of the task can also be efficacious in inducing craving and violate the homeostasis of those who are at-risk for social media addiction (Michalowski and Erblich, 2014). These are the needed conditions for eliciting upward time distortion (Wittmann and Paulus, 2008). The study was designed to take about 20-25 minutes (it took about 27 minutes in a pilot study, n=10). On the last screen of the survey, participants were asked to do their best to estimate the time it took them to complete the task.

2.3 Measures

The study captured age, sex self-reported GPA, extent of Facebook use and big-five personality for descriptive and control purposes. Age was reported with an open ended numerical question, sex was measured with a binary choice variable (men coded as 0), and GPA was measured with seven bands, ranging from 1 = "< 2.4" to 7 = "3.9-4.0". The extent of Facebook use was measured with four items from Turel and Bechara (2016) on a 1 = "very low" and 7 = "very high" scale; it was reliable (α=0.90). Sample item: "How do you consider the extent of your Facebook use, in terms of time?". Personality was measured with a short-form big-five survey that included three items per trait (Srivastava et al., 2015), on a 1 = "extremely small extent" to 7 = "extremely large extent". All scales were reliable (α = 0.77 to 0.83). Sample item that measures neuroticism: "I see myself as anxious". The survey included three trap questions (one in each page) for exclusion purposes. Example question: "All of my friends are aliens from Mars".

Study variables included Facebook addiction and time distortion. Facebook addiction was measured with the six-item Bergen Facebook Addiction Scale (BFAS, see Andreassen et al., 2012) using a 1-7 Likert scales (1=very rarely/never, and 7=very often)[1]. Each item captured the frequency of one key core symptom of addiction (salience, tolerance, mood modification, relapse, withdrawal, and conflict). This scale has been shown to work well in various samples (Steenackers et al., 2016). Such self-reported scales represent the best-practice of capturing social media addictions as the communal variance of the range of the examined symptoms represent the level of addiction (as a continuous variable) a person has; and then a cut-off point can determine who meets presumed at-risk criteria for social media addiction (Kuss and Griffiths, 2017). Even though there is no formal cutoff point for this scale, recent research suggests that 19 on a 1-5 scale, as a cutoff point, separates “at-risk for addiction” from those with “low- or no-risk” (Banyai et al., 2017). Since we use a 1-7 Likert scale here, the cutoff was adapted to be 26.6.

Time distortion was captured in line with many prior studies as the ratio of estimated time over actual time (Wittmann, 2015). Actual time was measured in seconds by subtracting the beginning from the end time stamps of the task. Estimated time was measured on a 1-8 scale [in minutes: 1="5-8", 2="9-12", 3="13-16", 4="17-20", 5="21-24", 6="25-28", 7="29-32", 8="over 33"]. Small time bands rather than precise time were used here since it is unreasonable to expect precise estimates for long tasks (Grondin, 2010). In order to produce the ratio, actual time was converted to the same time bands (i.e., to an identical 1-8 scale), and the estimated time score

[1] We used a 7 point scale rather than a 5 point scale in order to obtain better granularity and reduce biases in responses, as well as to be able to have less concerns regarding treating this variable as continuous rather than ordinal (which is recommended for many 5-point scales). We have successfully used this 7-point version in several studies.

was divided by the actual time score. One represented no-bias, ratios below one represented downward bias, and ratios above one captured upward time bias.

2.4. Statistical Analyses

SPSS 24 was used in all analyses; bootstrapping with 1,000 re-samples and 95% bias-corrected confidence intervals (CI) was used in order to avoid distributional assumptions. MEdCalc was used for enriching the ROC analysis. First, mean estimated-to-actual time ratio was compared to one (i.e., the ratio that is interpreted as no time distortion) using a one-sample t-test. Second, ANCOVA (after accounting for controls: age, sex, GPA and Facebook use extent) was used for checking if time distortion differs between the at-risk group and others. Third, partial correlation (after accounting for controls) between addiction scores and estimated-to-actual time ratio was calculated. Fourth, logistic regression and Receiver operating characteristic (ROC) curve were used for assessing the classification efficacy of time distortion on the examined task.

3. Results

The average time it took to complete the survey was 1,753 seconds (SD = 700 sec). Average time distortion (estimated-to-actual) was 0.99 (SD=0.72); it was not significantly different from 1 (t_{273} = -0.35, $p < 0.73$, 95%CI for mean difference = [-0.09;0.08]). This implies that on average, there was no upward time distortion in the sample. Repeating this analysis for the two groups (at-risk and not) separately revealed that while the low/no risk group had a mean ratio of 0.91 (SD=0.55) that was significantly below 1 (t_{231}=-2.53, $p < 0.01$, 95%CI for mean difference = [-0.16;-0.02]), the at-risk group had a mean ratio of 1.40 (SD=1.28) that was significantly above 1 (t_{41}=2.05, $p <$ 0.047, 95%CI for mean difference = [0.07;0.85]). ANCOVA revealed that the groups differ in upward time distortion (F = 16.63, $p < 0.001$, 95%CI for estimated marginal mean of time distortion in "low/no risk" group = [0.84;0.97] and in "at risk" group = [1.07;1.82]). This implies that the upward distortion effect is pronounced in the at-risk group, that a downward time distortion is pronounced in the no/low risk group, and that the groups differ in time distortion during tasks that provide Facebook cues and prevent Facebook use.

Next, we observed a significant partial correlation between Facebook addiction score and time distortion (r = 0.33, p < 0.001, 95%CI for correlation = [0.21;0.42]), after controlling for age, sex, GPA and Facebook use. This implies that the stronger one's addiction level is, the stronger his or her time distortion (estimated-to-actual) on tasks that prevent Facebook use. Repeating this analysis for the two groups separately revealed that while the correlation in the no/low-risk group was significant (r = 0.27, p < 0.001, 95%CI= [0.09;0.39]), it was not significant in the at-risk group (r = 0.13, p < 0.45, 95%CI= [-0.22;0.58]). This implies that there may be a ceiling effect on the growth of time distortion, which may be an artifact of the binning approach we employed.

Next, classification tests were performed. Logistic regression revealed that the extent of Facebook use t (B = 0.88, p < 0.001, 95%CI= [0.61;1.24]; odds-ratio=2.40, 95%CI= [1.68;3.43]) and time distortion (B = 0.729, p < 0.001, 95%CI= [0.34;1.59]; odds-ratio=2.07, 95%CI= [1.35;3.18]) are significant classifiers that produce Nagekerke pseudo r-square of 0.27 and Cox & Snell r-square of 0.16. This implies that a one unit increase in time distortion, after accounting for controls, increases the odds of meeting at-risk criteria more than two-fold. The percentage of correct classification was 85.8% for all categories and 19% for the at-risk category. ROC curve produced asymptotically significant (p < 0.011) area under the curve of 0.62 (0.52-0.73). Maximal values were: sensitivity = 40.48%, specificity = 86.21%, Youden Index=0.27 with classification criterion of time distortion > 1.17. These indices imply that the observed time distortion has some diagnostic value.

Lastly, given the logistic regression results, an ROC curve with the extent of Facebook use was estimated. It produced an area under the curve of 0.75 (0.68-0.82). Maximal values were: sensitivity = 92.86%, specificity = 46.12%, Youden Index = 0.390. We next combined the two predictors (SNS use extent and time distortion) by using the predicted probabilities from a logistic regression model. Using this variable, the area under the curve was 0.80 (0.75-0.84) and significantly above 0.5 ($p < 0.001$). Youden's index was 0.530 with 85.71% maximum sensitivity and 67.24% maximum specificity. The potential predictors (time distortion, use extent and the combined variable) were compared with DeLong et al pairwise comparison procedures. The ROC curves are depicted in Figure 1. The comparison tests indicated that use extent is a slightly better classifier than time distortion (z = 1.88, $p < 0.061$) and that the combined index is better than time distortion ($z = 3.552$, $p < 0.001$) and slightly better than extent of use ($z = 1.870$, $p < 0.062$).

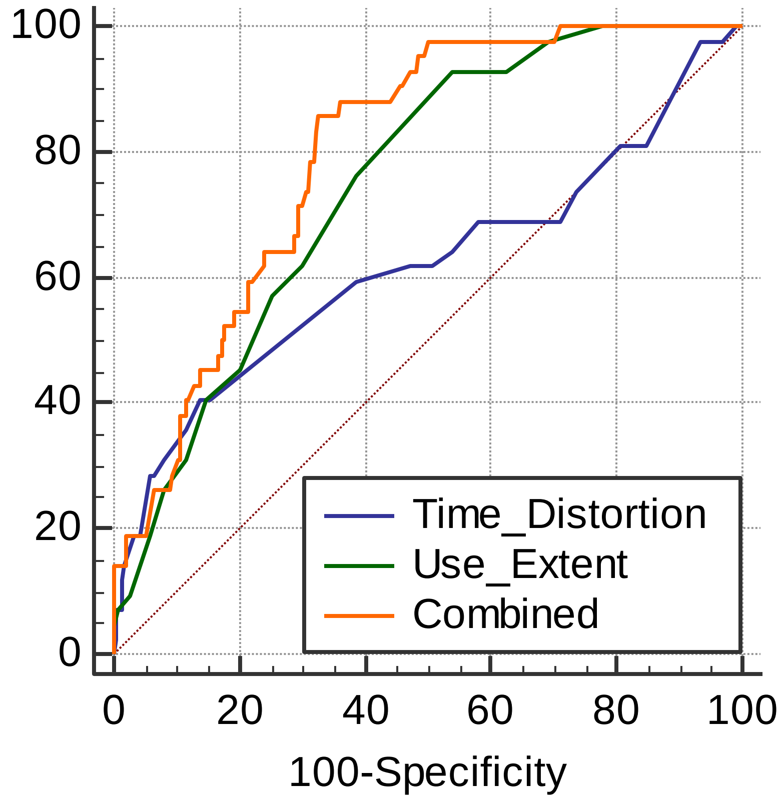

Figure 1: ROC Curves

4. Discussion

The study sought to examine the ideas that (1) people at risk of social media addiction distort upward time estimates of tasks that do not involve the use of the addictive application, but provide cues related to it, more than others, and (2) this distortion is a manifestation of such so-called addictions, that can help in distinguishing people at-risk of social media addiction form those who have no/low risk.

The findings first indicated that on average, social media users who engage in about 30-minute task that prevents them from using social media do not distort time. One viable explanation for this, which we confirm here, is that the upward bias of people who meet at-risk for Facebook addiction criteria may counterbalance the downward bias that most people who do not meet at-risk criteria feel. The findings also indicated that in line with research on time perception of addicts and impulsive people (Merson and Perriot, 2011; Takahashi et al., 2008; Wilson et al., 2015; Wittmann and Paulus, 2008) and specifically research on upward time bias of periods between rewarding-behaviors (Faulkner and Duecker, 1989), people at risk of Facebook addiction present distorted time assessments that are longer than actual for tasks that cue but do not involve Facebook use. Prior research in the areas of technology addiction have focused on time distortion during the rewarding task, such as while playing videogames (Rau et al., 2006) or using smartphones (Lin et al., 2015). We extend this line of research on time perception by showing that the time during which one is prevented from using the rewarding technology (and in which he or she is exposed to technology use cues) is also distorted, and in a different direction.

Moreover, the finding demonstrated some classification power to the time distortion we focus on. The use of time distortion in the task we employed produced an area under the ROC curve, which is similar to these observed by Lin at el. (2015), as measured with a self-developed app that captured actual smartphone use. The classification was substantially improved once a combination of time distortion and self-reported extent of use were employed. Hence, the findings provide initial evidence regarding the potential utility of these manifestations for supplementing (but not replacing) screening tools. This has important implications since it can, for some researchers and therapists, be easier to measure time distortion during non-use tasks as compared to, for example, measuring social media use with an app. The latter option may not be accessible to all and may compromise ecological validity (the installation of an application may lead to behavior change). Note that we do not suggest that using time distortion on such tasks is better and should replace other measures if available. Instead, we introduce another equally powerful manifestation that can be used in conjunction with previously validated markers for research and diagnosis.

It is interesting to note that time distortion predicted at-risk potential with higher specificity (86.21%) than sensitivity (40.48%). In contrast, combined SNS use extent and time distortion predicted at-risk potential with higher sensitivity (85.71%) than specificity (67.24%). This suggests that time distortion combined with SNS use extent is efficient in detecting at-risk cases at the expense of misclassifying no/low risk cases. In contrast, time distortion alone is more efficacious in detecting no/low risk cases at the expense of misclassifying at-risk cases. Hence, the use of these classifiers should not be guided solely by the reported DeLong et al pairwise comparisons, but also by misclassification costs.

There are several limitations that should be acknowledged and can serve as a basis for future research. First, the existence, exact boundaries and diagnosis of social media addiction are still not fully agreed upon (Kuss and Griffiths, 2017). We used here the term "addiction" out of convenience and to be consistent with prior research. Nevertheless, future research may revisit our findings as the definition, boundaries and diagnosis of social media addictions are further developed. Second, the sample included university students, focused on one potentially addictive technology, and used a specific task. Future research should extend the generalizability of our findings and/or test the relative efficacy of other tasks, such as asking people about social media friends and activities while avoiding social media use. Third, this study focused on a task that prevented use of social media but invoked thoughts related to it. Future research may examine the value of combining time distortion during this task with time distortion during social media use epochs; it should also consider testing whether time distortion is a task-specific or general individual difference, account for possible existence of underlying differences in time perception, and examine the usefulness of including potential time distortions from other life domains as classifiers. Fourth, we assumed that the time distortion is mediated in part via urge/craving processes. These were not captured in this study and can extend our finding in future research. Similarly, we assumed no social media use during the task; even though participants were supervised, we could not fully validate it. Lastly, the classification we employed was based on a scale score and did not involve formal interviews. Tools like the Structured Clinical Interview for DSM-5 (SCID-5) and Clinical Global Impression (CGI) can be used in future research to produce formal clinical diagnoses, at least for those subjects who meet at-risk for addiction criteria.

In conclusion, this study indicates that upward time distortion exists in people who may be considered at-risk for Facebook addiction, during tasks that prevent Facebook use and invoke Facebook reflections; and that this time distortion, especially when combined with self-reported extent of Facebook use, can be useful for classifying people to at- vs. low/no-risk categories.

Conflict of interest: None.

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