



Effect of Abstinence from Social Media on Time Perception: Differences between Low- and At-Risk for Social Media “Addiction” Groups

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Abstract

Time distortion is a hallmark feature of addictive behaviors including excessive technology use. It has clinically significant implications for diagnosis and treatment. Additional information on such distortions after prolonged abstinence from technology use is needed. We seek to examine differences in the effects of several days of abstinence on time-distortion in two groups: social media users who are at-risk and those who are at low risk for social media “addiction.” To examine this, we employed a randomized, two group, pre (t1) - post (t2) design. Both groups completed survey tasks that cued social media use at t1 and at t2. Between t1 and t2, the treatment group ($n = 294$) abstained from social media use for up to one week (less if they “broke” and decided to resume use), and the control group ($n = 121$) did not. Results indicated that low-risk individuals in both the treatment and control groups presented downward time bias at t1; at-risk individuals presented non-significant upward bias. After abstinence, both low- and at- risk individuals in the treatment group presented upward time distortion. This effect did not take place in the control group; low-risk users still presented significant downward bias at t2. The post-abstinence increase in time distortion was significantly more pronounced in at-risk users. These differences between pre- and post-abstinence time distortion patterns in normal and at-risk-for-“addiction” social media users can be used for adjusting and interpreting self-reports related to addictive uses of technologies.

Keywords Abstinence · Addictive use of social media · Internet addiction · Time distortion · Time perception

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Introduction

Time distortion is dissociation between actual and perceived time intervals. It is a hallmark feature of many substance use disorders [1], as well as of impulse disorders that involve addictive use of smartphones [2], videogames [3], and social media sites [4]. It is important for three primary reasons. First, it can motivate frequent repetition of technology use; when the last session is perceived to be in the distant past when it was not too long ago, psychological barriers for repetition in the present are removed. Similarly, when technology use session duration seems shorter than it actually is, it can motivate continuance [3]. Second, time distortion can be used as a diagnostic marker for impulse control disorders, as it often efficiently separates cases that may require treatment from those that may not [4]. Third, impulse control disorders are diagnosed based on self-reports that involve time estimates (e.g., the “tolerance” aspect of addictive use of technologies). Such estimates can be biased under risk for “addiction” conditions [2, 3].

In the realm of compulsive use of technology, two types of time distortion have been observed. The first involves a downward bias in the perceived duration of technology use among people who are at risk for technology “addiction”; that is, usage sessions seem shorter than they really are [2, 3]. The second involves an upward bias of time intervals of relatively short tasks (20–30 min) that cue the use of the addictive technology but prevent its use; these tasks seem longer than they actually are for people who are at-risk for addictive use of technologies [4].

The effects of lengthier (e.g., several days or weeks) deprivation/abstinence from technology use on time distortion in this context, though, are still unknown. It is important to examine whether time distortion changes after abstinence, because long-lasting abstention attempts are common in self-recovery efforts, as well as in treatment plans related to addictive technology use [5–8]. Understanding the effect of abstinence/deprivation on technology users’ time perception may help to account for biases in during- and post-treatment self-reports that involve time.

Here, we seek to make first strides toward understanding how time distortion is affected by several days of abstinence, in normal vs. at-risk for social media “addiction” users. We focus on Facebook as a common instance of social media and a platform the use of which for some university age users can be associated with addiction symptomology [9–11]. Social media “addiction” (also can be termed excessive or problematic use of social media) is a psychological state of dependence in which users are overly preoccupied with social media activities, and are driven by an uncontrollable motivation to use social media sites, to such an extent that it interferes with normal functioning and generates behavioral addiction-like symptoms [4]. It is a potential disorder that has not yet been formalized in the DSM or ICD (these include references to Internet gaming disorder, but not social media). Nevertheless, there is a growing corpus of academic works that illuminate the potential adverse effects of excessive and compulsive social media use on some individuals [12, 13]. Studies also demonstrate that the use of such sites can be associated with functional and morphological brain changes that resemble in some cases those observed in other addictive behaviors [14, 15].

Studies of adolescents point to about a 4.5% prevalence rate of strong addiction-like symptoms in relation to social media use; given the non-existent formal diagnosis criteria, this group is conceptualized as “at-risk for social media addiction” [13]. Studies of young-adults point to a 15.2% prevalence rate of “at-risk for social media addiction” [4]. In both populations, many others present addiction-like symptoms in relation to social media use but do not meet at-risk for addiction criteria.

In line with prior research [4], we expect that during a short survey task, people at-risk for social media addiction will present an upward time bias, in contrast to people with low-risk, who are expected to present a downward time perception bias. The reasons is that low-risk people will likely enjoy the task and accelerate their mental time perception (time “flies” under such circumstances); but for at-risk individuals, the task will violate their homeostasis by invoking an urge to use social media while at the same time preventing its use, and by so doing, slow down the perceived time (the task will seem longer than it actually is).

We also expect that after several days of abstinence, both the at-risk and low-risk groups will increase their time estimates such that they become upward biased in both groups (the task will seem longer compared to pre-abstinence). This is likely given that experiences of abstinence are stressful and can prevent the focus and attention that are needed for time estimates [16]. Under such conditions (e.g., as demonstrated in the case of smoking), upward bias of time perception forms, and non-use periods seem longer than they are [17, 18].

Lastly, we also expect that the post-abstinence time bias will be accentuated more so in those at-risk for “addiction” than in the low-risk cases. Among those at risk for addiction, homeostasis violations resulting from abstinence are likely to be much stronger than they are among low-/no risk cases, which should result in an even greater disturbance in their time perception [19]. At-risk cases likely have an impaired interoceptive awareness brain system (insular cortex dependent), which underlies the development of strong uncontrollable urges to use the technology [20] and “hijacks” the prefrontal cortex. As such, the expected strong urges may further reduce attention, disturb time estimates, increase stress and make the task seem longer than it is [16].

Method

Procedure

Participants were recruited via class announcements in separate sections of the same class; some sections (about 80%) were randomly assigned to be the treatment group and others (about 20%) were randomly assigned to be the control group. To be included participants had to be at least 18 years of age, use Facebook as their primary social networking site and consent their participation. Participation was voluntary and was encouraged with extra credit points. Study procedures were approved by the institutional review board of the university.

The treatment group was asked to complete an online survey, to try to abstain from social media use for up to one week, and to complete a second online survey right before they resumed social media use (either after one week or before, if they “break”). The first survey captured demographic, perceptual and social media use information, and time perception (expected completion = 30 min). The second survey captured abstinence experience and time perception (expected completion = 18 min). The control group was asked to complete two online surveys, one week apart. The first survey was identical to the treatment group survey. The second survey resembled the second treatment group survey, but instead of asking about actual abstinence it asked about hypothetical abstinence experiences.

The study description did not disclose the objective of this study; the study was presented as focused on examining social media use habits. Instructions guided participants to complete the survey in one take with no breaks. The surveys served three purposes. First, they captured information needed for our analyses. Second, they invoked social media use reflections while

preventing social media use for several minutes, with the hope to elicit time distortion [4]. Third, they prevented time counting [21].

Sample

Participants were recruited via announcements to 874 university students in the United States. A total of 709 were selected at random to be recruited to the treatment group, of which 294 (41.47%) completed both surveys and the abstinence task. A total of 165 were selected at random to be recruited to the control group, of which 121 (73.33%) completed both surveys. The fact that the response rate in the treatment group is lower is reasonable, given that the request to abstain from Facebook use for one week may have deterred participation in some users. Both groups were divided into at-risk of social media addiction vs. low-risk based on a commonly used (though, not formal) cutoff [4, 13]. Groups' attributes are given in Table 1.

The treatment and control groups did not differ in sex distributions, distribution of at-risk for addiction, average GPA and social media use. Consistent with prior research [e.g., [4]] the at-risk of addiction cluster comprised of over 10% of the groups. In both treatment and control groups, the extent of Facebook use was higher in the at-risk cluster compared to the low-risk cluster (all $p < 0.001$). In the treatment group, the number of contacts was significantly higher in the at-risk cluster compared to the low-risk cluster ($p < 0.05$). It was not significantly higher in the control group ($p < 0.60$). Lastly, in the treatment group, abstinence days were higher in the low-risk cluster compared to the at-risk cluster ($p < 0.001$) (i.e., low-risk individuals were less likely to “break” early), and difficulty to abstain was higher in the at-risk cluster compared to the low-risk cluster ($p < 0.05$).

Measures

The study captured the following descriptive variables: sex (Woman = 1), age (years), extent of Facebook use (four items from [22], each of which rated a facet of use on a 1 = “very low” to 7 = “very high” scale; the scale was reliable in both the case and control groups [$\alpha = 0.94$ and $\alpha = 0.95$, respectively]), GPA (seven bands: from 1 = “< 2.4” to 7 = “3.9–4.0”), and number of contacts on Facebook (seven bands: from 1 = “0–10” to 7 = “more than 1,000”).

The Bergen Facebook Addiction Scale [BFAS, see [23]] was used for capturing Facebook “addiction” symptoms and consequent risk. Scores on this scale capture the overall level of experiencing the range of typical addiction symptoms in relation to Facebook use. It includes six items, each capturing the frequency of one key, core symptom of addiction (tolerance, mood modification, salience, withdrawal, conflict, and relapse). Each item was rated on a 1 = “rarely/never” to 7 = “very often” scale. While there is no agreed upon cutoff point for classifying people to “at-risk for addiction” or “low-risk” clusters, it has been suggested that 26.6 [4] is an acceptable cutoff for the 1–7 Likert scale.¹

Time distortion was operationalized as the ratio of estimated time over actual time [24] where ratios of 1, < 1 and > 1 represented no-, downward-, and upward-biases, respectively. Actual time [minutes] was calculated by subtracting the beginning time stamp of the survey

¹ In the original cutoff study [13], Latent Profile Analysis detected this cutoff as the lower bound of a cluster of social media users with significantly elevated levels of symptoms, social media use, and depressive symptoms compared to the rest of the population, as well as reduced self-esteem compared to the rest of the population. The cutoff produced 83% sensitivity, 99% specificity, 73% positive predictive value, 99% Negative Predictive Value, and 98% accuracy.

Table 1 Characteristics of groups

	Treatment group (<i>n</i> = 294)		Control group (<i>n</i> = 121)		Comparison of groups
	Low Risk	At Risk	Low Risk	At Risk	
	All	All	All	All	
<i>n</i>	260 (88.44%)	34 (11.56%)	294	105 (86.78%)	121
Sex [Male/Female]	147/113	18/16	165/129	57/48	64/57
Age [Mean, Range, SD]	24.20, 20–49, 4.95	23.91, 20–36, 4.07	24.16, 20–49, 4.85	23.46, 20–38, 3.38	23.21, 19–38, 3.26
GPA [Modal range]	3.0–3.2	2.5–2.7	3.0–3.2	3.0–3.2	3.0–3.2
Extent of facebook use [Mean, SD]	2.67, 1.36	5.55, 1.05	3.00, 1.62	3.06, 1.53	3.37, 1.67
Facebook contacts [Mean, SD]	4.47, 1.53	5.09, 1.40	4.54, 1.52	4.89, 1.21	4.92, 1.21
Social media addiction score [Mean, SD]	11.88, 5.34	30.65, 3.61	14.05, 7.92	12.10, 5.58	14.50, 8.14
Abstinence days [Mean, SD]	6.15, 1.79	4.76, 1.57	5.99, 1.76	None	None
Difficulty to abstain [Mean, SD]	51.69, 26.29	61.40, 23.50	52.92, 26.11	None	None

Cutoff *p* value adjusted for multiple comparisons with Bonferroni correction is 0.008

from the end one. Estimated time [minutes] was operationalized using a sliding bar scale that allowed selecting integer values from 1 to 60 by dragging a bar along a visual scale. The bar used 3 min intervals between gridlines, had a granularity of 1 min, and presented the selected values to users as they drag the bar. The description of the question read: “Without looking at your watch, computer or cellphone time or any other indicator of time, how much time do you estimate that it took you to complete this survey? Drag the bar to indicate your estimated number of minutes. There is no right or wrong estimates here; we just seek your honest estimate.”

Change in time distortion was operationalized as the ratio of time distortion at t2 over time distortion at t1. Ratios of 1, <1 and > 1 represented no-, downward-, and upward-changes in time distortion over the time period between t1 and t2, respectively.

Statistical Analyses

SPSS 24 was used for all analyses. We employed bootstrapping with 1000 re-samples and 95% bias-corrected confidence intervals (CI) as a means to avoid distributional assumptions. First, time distortion values in each group and cluster were compared to 1 with one-sample t-tests, as a means to detect significant upward or downward biases. Second, ANCOVA models controlling for sex, age, and GPA were employed for (a) examining differences in time distortion between the two risk clusters in both the case and control groups, and to (b) compare the case and control groups. Two-Way ANCOVA was used to examine interaction (sample x addiction risk group) effects on time distortion change. This comparison of the time distortion change between the two groups is mathematically equivalent to a difference-in-differences analysis. Third, paired-samples t-tests were employed for examining differences in time distortion between the pre- and post- surveys (surveys 1 and 2), in both the treatment and control groups. Last, partial (with age, sex and GPA controls) correlations between time distortion and “addiction” scores were calculated in both the treatment and control groups.

Results

In the treatment group, the majority (187, 63.6%) managed to abstain the whole week; 74 (25.2%) abstained for 4–6 days, and very few (24, 8.2%) abstained for less than 3 days. Abstinence time was not correlated with time distortion at t1 ($p < 0.83$) or t2 ($p < 0.17$), but was correlated with the change in time distortion between t1 and t2 ($r = -0.14$, $p < 0.02$). This implies that when people do not handle abstinence, the change in time distortion was larger.

Completion times, time distortions for the different surveys, as well the changes in time distortion between t1 and t2 for the different groups and risk clusters, are given in Table 2. It also presents ANCOVA results for the comparison of the treatment and control groups in terms of completion time and time distortion. Lastly, the Table also presents bootstrapping-based one sample t-tests (see p values in parentheses) comparing each time distortion value to 1. As expected, time distortions differed between the “addiction” risk clusters. In both treatment and control groups the low-risk cluster presented a significant downward time distortion, while the at-risk cluster presented a slight upward distortion that was not statistically significant. While this significant downward time distortion was maintained in the control group after one week (t2), it reversed in the treatment (abstinence) group. At-risk individuals in both the treatment and control groups also presented a significant upward time distortion at t2.

Table 2 Completion times (in minutes), time distortion, and time distortion change by group and risk cluster

	Treatment group (n = 294)			Control group (n = 121)			Comparison of groups
	Low Risk		All	Low Risk		All	
	At Risk	All	At Risk	All	At Risk	All	
Completion time - survey 1 (pre) [Mean, SD]	28.53, 10.07	26.61, 11.60	28.31, 10.26	31.14, 12.40	26.48, 12.34	30.52, 12.45	$p = 0.059$
Completion time - survey 2 (post) [Mean, SD]	16.79, 8.32	15.82, 8.25	16.68, 8.31	24.21, 14.98	20.00, 12.25	23.65, 14.67	$p < 0.001$
Time distortion at t1 [Mean, SD, (p of < >1)]	0.83, 0.28, (0.001)	1.06, 0.45 (0.439)	0.86, 0.31, (0.001)	0.76, 0.2, (0.001)	1.04, 0.25 (0.514)	0.80, 0.24 (0.001)	$p = 0.053$
Time distortion at t2 [Mean, SD, (p of < >1)]	1.14, 0.44 (0.001)	1.67, 0.79 (0.003)	1.20, 0.52, (0.001)	0.91, 0.33 (0.009)	1.15, 0.26 (0.045)	0.94, 0.33 (0.043)	$p < 0.001$
Change in time distortion [t2 over t1] [Mean, SD, (p of < > 1)]	1.40, 0.40 (0.001)	1.61, 0.49 (0.001)	1.43, 0.41 (0.001)	1.28, 0.62 (0.001)	1.18, 0.49 (0.155)	1.27, 0.60 (0.001)	$p = 0.002$

Paired sample *t*-tests showed that the *t*₂ time distortion in both the treatment and control groups (regardless of addiction risk) were significantly (all $p < 0.001$) larger than the *t*₁ time distortion. This may reflect a general fatigue when taking a second a survey. ANCOVA revealed that the growth in time distortion was much more pronounced ($p < 0.001$) in the treatment group (95% CI [1.42–1.59]) than in the control group (95% CI [1.10–1.36]) (See also Table 2); this illuminated the abstinence effect. ANCOVA models revealed that growth in time distortion is larger in the at-risk cluster compared to the low-risk cluster in the treatment group (corresponding 95% CI [1.45–1.78] and [1.35–1.46], $p < 0.008$) but not in the control group (corresponding 95% CI [0.94–1.41] and [1.19–1.38]).

A two-way ANCOVA revealed non-significant age, sex and GPA effects, non-significant main addiction risk classification effects, but significant ($p < 0.001$) group (treatment or control) effect and significant group \times addiction risk cluster interaction ($p = 0.045$) effects on changes in time distortion (Fig. 1).

Next, in support of the general association between social media addiction symptoms and time distortion scores, a partial correlation of 0.26 (95%CI = [0.106–0.381], $p < 0.001$) was observed at *t*₁ and a partial correlation of 0.36 (95%CI = [0.221–0.486], $p < 0.001$) was observed at *t*₂, in the treatment group. In the control group a partial correlation of 0.37 (95%CI = [0.197–0.530], $p < 0.001$) was observed at *t*₁ and a partial correlation of 0.35 (95%CI = [0.197–0.506], $p < 0.001$) was observed at *t*₂. These results indicate that there is a general upward time distortion increase as a function of one's experience of social media addiction symptoms.

Discussion

This study extends observations regarding time distortion among social media users and differences in such distortion between addiction risk clusters, to the case of lengthy abstinence.

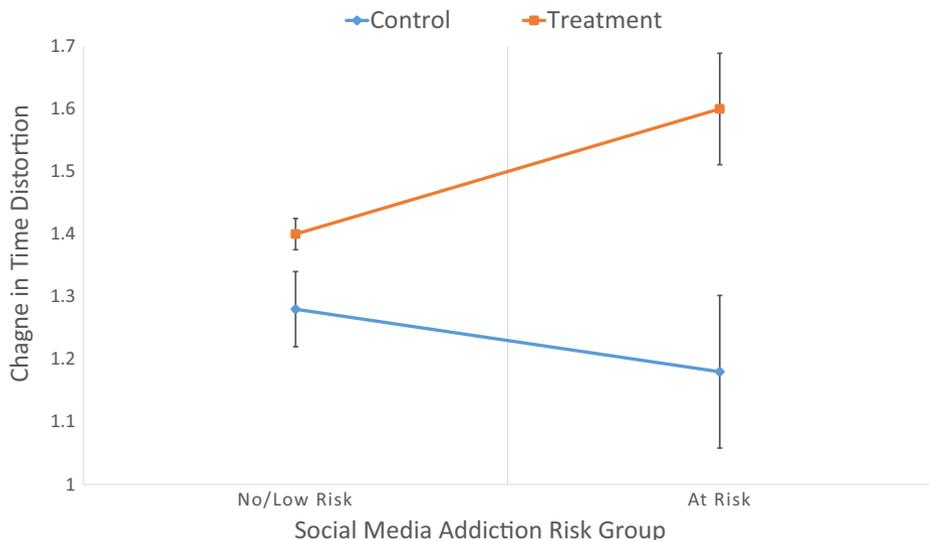


Fig. 1 Estimated marginal means for change in time distortion

Such biases are important to understand given that time estimates and abstinence are essential to many diagnostic and treatment procedures related to addictive use of technologies [25, 26].

As a first step, our findings partially replicated prior findings regarding the existence of time distortion among social media users and differences between low-risk and at-risk users in terms of time distortion. In line with Turel et al. [4], they demonstrated that (1) Facebook users distort time during tasks that invoke social media use reflection but prevent use, (2) time distortion differs between the “addiction” risk clusters, and (3) time distortion is positively associated with scores reflecting the levels of addiction-like symptoms in relation to Facebook use.

The findings specifically showed that low-risk users present a significant downward time distortion at t1, whereas at-risk users present a slight (but non-significant) upward time distortion. While the differences between the time distortion of the risk clusters are significant, the non-significant upward time distortion (in both the case and control groups) at t1 diverges from the upward significant time distortion in Turel et al. [4]. The disparity may be attributed to differences in the task. While in Turel et al. [4] the task required deep reflection on self-control attempts (many likely to be failed in the at-risk group), the task in the current study was likely less stressful as it mostly required reflections on normal social media use. This implies that while the between-group difference in time distortion and directions of time distortion may be consistent across studies, their magnitude can differ and possibly depend on the sample and the task.

The idea that perhaps the task in this case did not induce sufficient stress to violate homeostasis and produce significant upward time estimates in at-risk individuals at t1 is supported by the findings at t2. In all groups there was an upward update of the time distortion, in line with the notion that an additional task that further prevents social media use can make the relative time of the task longer. Consequently, the t2 task managed to replicate Turel et al. [4] in the control group (i.e., with no abstinence). In line with our expectations, the t2 task produced a significant downward time distortion in the low-risk cluster, and a significant upward time distortion in the at-risk cluster, in the control group.

Consistent with research on the effect of smoking abstinence on time distortion [16–18], our findings indicated that an abstinence from social media use for up to one week generated a significant increase in time distortion in the treatment group; both risk clusters developed an upward time distortion after abstinence. Moreover, in line with our expectations for larger disturbance in the at-risk cluster, this post-abstinence bias was significantly more pronounced in the at-risk cluster compared to the rest. This indicates that abstinence from social media use accentuates time distortion, especially in those who are at-risk for social media “addiction”.

From a practical standpoint, the findings imply that when social media users seek treatment for excessive or addictive use, self-reports of non-use epochs should be viewed with caution. Clinicians can expect downward-biased estimates from those who are less at-risk for social media addiction, and upward-biased estimates from those who are more at high risk. Lengthy abstinence, such as during quit attempts, can especially accentuate the upward-bias in those who are at high-risk for addiction. One potential solution to such issues is the reliance on both self-reports and subjective use data in the process of diagnosing and treating people at-risk for addictive use of social media [2, 4].

Several limitations of the study should be acknowledged. First, the concept of social media “addiction” does not yet have clear boundaries and diagnostic criteria; and the term “addiction” may not be the most appropriate one to describe the collection of symptoms associated with this phenomenon [27]. Our findings should therefore be interpreted with caution, and adjusted as the concept of social media addiction is fine-tuned. Second, we used specific tasks to cue and prevent social media use. While replicating key aspects in Turel et al.

[4] increases confidence in the robustness of the hypothesized time distortion patterns, more research is needed in order to extract the task elements that influence the magnitude of the time distortion. Third, the study relied on a trust system regarding abstinence, and whether users actually abstained or not could not be tested. While between-group differences in abstinence difficulty and duration imply that it is likely that most people abstained as expected, future research should consider finding subjective measures of abstinence. Lastly, although our research question is about social media in general, we test the question with one popular social media site. Future studies could extend our findings to other social media sites. Moreover, even though abstinence from one social media produced the expected time distortion effect, it would be interesting to consider in future research whether abstinence from multiple or all social media produces even a larger time distortion effect.

Author Contributions OT and DC designed the study, collected data, ran analyses and wrote a draft. It was edited and approved by OT and DC.

Compliance with Ethical Standards

Conflict of Interest Ofir Turel declares that he has no conflict of interest. Daniel Cavagnaro declares that he has no conflict of interest.

Ethical Approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

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