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Less is Not Always More: Investigating the Impact of Goal Difficulty and Immediacy of Social Media

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Less is Not Always More: Investigating the Impact of Goal Difficulty and Immediacy of Social Media Blockers on Productivity

Completed Research

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Abstract

Social media overuse is becoming prevalent across the globe, hurting users' mental health and productivity. To reduce social media usage and improve productivity, many users turn to social media blockers that rely on users to specify a social media reduction goal. However, as there is no empirical evidence and guidance on how users should choose the goal optimally, the user-chosen goals may not produce the intended benefits. In this study, we introduce two new dimensions of social media reduction goals — goal difficulty and goal immediacy. We found that the relationship between goal difficulty and productivity is of an inverted-U shape. In addition, the effect of goal difficulty further depends on the prior social media consumption level. We also found that changing goal immediacy from radical to incremental significantly improves the performance of relatively difficult goals, especially for users with higher prior social media consumption levels. Practical implications are discussed.

Keywords: Social media blocker, goal-setting, goal immediacy, goal difficulty

Introduction

Globally, social media has become a prominent part of contemporary life. Close to 60% of the world's population are social media users. On average, these 3.8 billion users spent about 2.5 hours daily on social media in 2019 (DataReportal, 2020). Because of its ubiquity and rich functionality, social media connects people like never before. Given its connectivity, it is not surprising that social media enhances social ties (Ali-Hassan et al., 2015; Sheer & Rice, 2017), leads to higher job satisfaction (Robertson & Kee, 2017), enables better knowledge integration (Robert et al., 2008), and increases perceived social support (Best et al., 2014). Despite these benefits (Ali-Hassan et al., 2015; Allcott et al., 2020; Robertson & Kee, 2017), social media can be detrimental to productivity because of its distracting nature (Bucher et al., 2013; Marotta & Acquisti, 2020; Yu et al., 2018). Social media costs employers trillions of dollars in the US each year as employees access social media during work hours[1]. Employees and students also regard social media use during work hours as counterproductive, whereas over half of surveyed employers restrict social media at work, according to the industry report by Udemy[2].

[1] https://www.nbcnews.com/tech/social-media/time-wasted-facebook-could-be-costing-us-trillions-lost-productivity-n511421
[2] https://research.udemy.com/research_report/udemy-depth-2018-workplace-distraction-report/

Social media blocking apps are an accessible means to improve productivity and are used by users to block off access to social media during work hours. Most social media blockers allow users to adjust social media access based on user-defined goals. For example, *Freedom*, a social media blocker used by more than 2 million users, allows users to set how much social media time is allowed during a specified period. Since users with different social media consumption levels and consuming habits tend to benefit from a personalized blocking strategy, it is pertinent to gain a better understanding of the optimum blocking strategy based on individual social media usage traits. However, no guidelines on the optimum blocking parameters are offered in practice. As a result, existing social media blockers have high attrition rates (Andreassen, 2015; Collins et al., 2014; Greenfield, 2012; Kovacs et al., 2018), and the effects on productivity were suboptimal, particularly for heavy social media users (Marotta & Acquisti, 2020).

Motivated by this knowledge gap, we seek to provide insights into a fundamental set of questions related to the design of social media blocking apps: (1) Would the use of a partial block produce better user outcomes (in terms of productivity) relative to that of a complete block? (2) If so, what should be the optimum reduction goal for different users? (3) What additional features should be considered to enhance the effectiveness of social media blockers towards these goals?

To answer these questions, we embark on a research agenda with two main objectives. First, we examine the effect of varying social media reduction goal difficulty on productivity. Existing literature has only considered the impact of completely blocking social media during work hours. In other words, past studies have only considered one goal difficulty level (completely blocking). As such, we currently do not have a good understanding of how other levels of goal difficulty levels influence productivity. In addition, we aim to shed light on the heterogeneous impacts of goal difficulty, knowing that "one size fits all" is unlikely to hold true in the use of social media blocking apps. Second, informed by the literature on goal-setting and behavioral change, we further examine the dimension of *goal immediacy* in addition to *goal difficulty* to have a more holistic understanding of how these two features work in conjunction. Existing literature has only examined the effect of immediately enforcing the social media reduction goal (i.e., radical goals). To this end, we propose a novel social media blocker design that gradually increases the level of social media restriction over time (i.e., incremental goals). We evaluate the effectiveness of incremental goals and examine how the choice of goal immediacy may interact with goal difficulty.

In this work, we designed and conducted a randomized experiment on Amazon Mechanical Turk (AMT) to address the questions we have set forth. To do so, we developed a Chrome browser extension that incorporates goal difficulty and goal immediacy. We randomly assigned participants from AMT to different conditions and assess how their productivity levels are affected by the various blocker features. To have an objective view of how productivity has changed for AMT workers under different conditions, we measured the proportion of time participants spent on work-related software and activities on their workstations (e.g., tasks on AMT, Qualtrics surveys, Microsoft Office, etc.).

We found that the effect of *goal difficulty* on productivity is highly nuanced. Specifically, the most restrictive goal of completely blocking all access to social media reduces the productive time during work hours, while the use of partial block increases the productive time. However, a more difficult social media reduction goal (reducing 75% of users' prior social media consumption compared to reducing 50%) can have a positive impact on productivity. Thus, the impact of goal difficulty is of an inverted-U shape. We further find that the positive impact of increasing the block intensity of a partial block strategy diminishes with the users' prior social media consumption. For instance, a difficult partial block involving a 75% reduction in social media access time does not increase the productivity of heavy social media users, compared to a partial block involving a 50% reduction. Therefore, a more restrictive social media blocking strategy does not always improve productivity.

We also found that incremental goals can significantly improve the performance of users who are placed under difficult blocking goals. While the use of incremental goals relative to radical goals does not help in situations with easy goals, incremental goals can help users be more productive when high block intensity is used. At the same time, this effect is found to be most pronounced for heavy social media users, which goes to show that the combination of *goal difficulty* and *goal immediacy* must be carefully chosen based on individual characteristics.

This paper makes several theoretical contributions. First, we challenge the existing one-sided view of social media use at work, in that usage of social media is nuanced and can bring positive effects when used in moderation. In particular, our results indicate that the complete block of social media is detrimental to productivity, while a partial block of social media can benefit productivity. With this study, there is a need to examine the optimal partial restriction strategy of social media more deeply.

Second, we highlight the importance of incorporating goal difficulty in designing interventions to curtail cyberloafing behaviors. Existing studies and practices have only considered a complete social media blocking goal, which is enforced immediately. In contrast to the prior belief that a complete block of social media would be the best solution to improve productivity, we theorize that there are benefits in *reducing* social media blocking intensity, as the impact of goal difficulty on productivity is non-monotonic. Contrary to the popular phrase "less is more", we show that "less social media does not always lead to better productivity levels". As the relationship between goal difficulty and productivity is characterized by an inverted-U shape, users must utilize the optimum goal difficulty to achieve the most desirable effect.

Finally, we add a new temporal dimension of goals – goal immediacy – to the literature. Prior literature has only considered enforcing goal difficulty immediately, neglecting the effects of gradually increasing goal difficulty over time on productivity. Our results highlight the theoretical importance of incorporating goal immediacy by showing its nuanced interaction with goal difficulty and user's prior social media usage.

Our results also provide important practical implications for users, employers, and app developers. For users and employers, our work provides guidelines to help optimize their goal difficulty setting decisions on social media blockers. App developers should consider providing incremental goal-setting as a native feature in their social media blockers, improving user retention and satisfaction for heavy social media users. If implemented properly, improvements in social media blocker design may allow a substantial productivity boost for millions of social media blocker users.

Background & Hypotheses

Effects of Social Media Use and Restrictions on Productivity

A review of the literature suggests that there are two contrasting views on the effect of social media blockers on productivity. On the one hand, consuming social media at work takes away the time that is supposed to be spent on productive activities. While it is necessary to take breaks during work, because of the distracting nature of social media, it may occupy more time than necessary (Gonidis & Sharma, 2017). The loss of productive time due to social media usage contributes directly to a loss of productivity (S. Kim & Christensen, 2017). On the other hand, consuming social media can potentially benefit productivity. Correlational studies have found that cyberloafing is positively associated with productivity (Garrett & Danziger, 2008). For example, studies have shown that social media provide mental breaks (Coker, 2013; Lim & Chen, 2012) and help individuals cope with stress (Ali-Hassan et al., 2015; Hu et al., 2021). While unregulated internet access is correlated with more cyberslacking activities, it is also associated with higher job satisfaction (Canaan Messarra et al., 2011). With two countervailing effects that are potentially at work, the effect of restricting social media usage is not immediately apparent. This uncertainty calls for a closer examination of the effects of restricting social media on productivity.

Despite the two contrasting views, *restricting* social media and other cyberloafing activities at work is a popular practice. A set of studies have primarily relied on surveys or observational data to study the antecedents of cyberloafing and evaluate the effects of organizations' cyberloafing-related policies. Khansa et al. (2017) compare the differences of antecedents of cyberloafing before and after a cyberloafing curbing policy using surveys. In another survey-based study, Khansa et al. (2018) found that although introducing technological interventions (such as monitoring employee network traffic in the workplace) reduce cyberloafing, these restrictions are associated with a perception of unfairness that hurts employee loyalty. Similarly, Jiang et al. (2020) found that internet monitoring and internet usage policy may curb cyberloafing but will reduce job satisfaction and employees' intrinsic work motivation. While the findings of these studies suggest a connection to productivity, only a limited number of studies have directly examined the effect of cyberloafing on productivity. For example, Glassman et al. (2015) examined the effectiveness of a firm-imposed internet restriction policy, which utilized an internet traffic filtering system to block access to social media. They found that such policy is associated with a higher level of traffic volume of work-related websites, which is in turn associated with productivity.

Other studies explored the effects of social media consumption restrictions in more general settings, with many highlighting potential withdrawal symptoms. For example, Stieger and Lewetz (2018) examined the effect of instructing individuals not to use social media entirely for a week. They observed an overall high relapse rate (where the participants use social media against the instruction) and withdrawal symptoms including heightened craving, boredom, and social pressure to use social media during the social media abstinence period. Baumer et al. (2015) found that social media users experience similar withdrawal symptoms within the first few days of a long-term abstinence. These studies rely on conventional methods such as following the participants on social media to ensure abstinence and do not involve the use of social media blockers.

Another set of studies rely on social media blockers to limit social media usage. Kim et al. (2017) used a social media blocker (which also blocks games) in a field experiment to investigate the coping strategies of self-interruptions. They found that social media blocker reduces the mental effort required to manage self-interruptions compared to manual blocking. However, these studies did not consider the effects on productivity. Marotta and Acquisti (2020) add to this set of findings by studying the causal impacts of blocking social media on productivity under a randomized control trial using social media blockers. They found that the benefits of blockers on productivity were short-lived and disappeared in the second week of usage. However, they only focus on a complete block of social media during work hours and did not consider goal immediacy.

To summarize, social media use at work can have both positive and negative effects on productivity. It is believed that social media usage within a certain threshold may enhance productivity, whereas usage above this threshold may hurt productivity (Andel et al., 2019; She & Li, 2022). Therefore, there is a need to investigate the impact of partially blocking social media access on productivity. However, existing studies that considered the effect of social media restrictions (either via social media blockers or manual intervention) on productivity only examined the effect of *completely* blocking social media (either during work hours or the entire day over weeks), while neglecting the possibility that users may set *partial* blocking goals offered by social media blockers. As such, there is a void in the literature on how the users should set the social media reduction goal and how the goal should be achieved.

Goal Difficulty

Social media blockers do allow users to set their social media reduction goals. Users can set how much social media access time will be allowed (referred to as allowance) during a specified time period (referred to as blocking hours). In the context of blocking social media, goal difficulty correlates with the extent to which the focal user has to adjust their social media consumption habit in order to achieve the goal. In other words, the allowance is the user's goal for reducing social media during blocking hours. *Ceteris paribus*, the lower the allowance, the more difficult the goal is. Following the goal-setting literature (Wright, 1990), we define the goal difficulty as the percentage of social media time *reduced* during the treatment. For example, a goal that reduces social media consumption by 75% requires the user to change their consumption habit more drastically than a goal that reduces social media consumption by 50%. Naturally, the former goal is more difficult than the latter.

Existent literature has highlighted the importance of the difficulty of goals in behavioral change contexts. More difficult goals, by definition, allow individuals to achieve a better outcome than easy goals. However, the performance only increases with the difficulty of goals to a certain point (Garland, 1983; Locke, 1966), showing an inverted-U shape and curvilinear relationship between goal difficulty and outcomes. According to the strength model of self-control, an individual has a finite amount of self-control to regulate one's behavior (Baumeister et al., 2007). When the difficulty of the behavioral change goals exceeds one's self-control capacity, such goals can negatively affect the outcome, as supported by both theoretical models (Jain, 2009) and empirical evidence (Baron et al., 2016). For example, prior studies show that when dieters perceive that they cannot achieve the goal, they tend to give up and even eat more than non-dieters (Polivy & Herman, 1985). The negative effect on the outcome induced by overly difficult goals can be found in studies using self-determined goals and assigned goals (Cochran & Tesser, 1996). In addition, when one fails to achieve a difficult goal, one may lose self-control and induce frustration, forming a negative feedback cycle that is detrimental to subsequent performance (Soman & Cheema, 2004).

Specifically, a higher goal difficulty induces two countervailing effects. First, there is a direct effect on productivity. Increasing social media reduction goal difficulty releases more time occupied by social media.

When more time is released from social media use during work hours, a user can then spend more time on productive activities. However, it may also induce indirect effects. As mentioned in the last section, consuming social media is not always counterproductive. A moderate amount of social media consumption is beneficial to productivity (Coker, 2013; Lim & Chen, 2012). These benefits diminish as goal difficulty increases. In addition, given the degree of social media's integration with modern society, most users will find such a goal hard to attain. As mentioned in the last section, prior studies have shown that social media abstinence has been unsuccessful and led to withdrawal-like symptoms, including heightened craving and boredom (Bányai et al., 2017; Baumer et al., 2015; Stieger & Lewetz, 2018). Being in such a withdrawal-like state is detrimental to the attention concentration (Cleary et al., 2016; Hunter & Eastwood, 2018). As goal difficulty increases, these indirect negative effects could be more pronounced.

While the direct benefit on productivity (i.e., the freed time) increases linearly with goal difficulty, the cost (or the self-control required) of achieving such goal difficulty follows a convex functional form (Jain, 2009). When goal is overly difficult, the cost exceeds the direct benefit on productivity. Therefore, the net effect of the two countervailing effects should depend on goal difficulty, resulting in a non-monotonic relationship between goal difficulty and productivity. Given the inverted-U shape relationship between goal difficulty and the outcomes, we expect that:

H1: The effect of goal difficulty on productivity is first increasing then decreasing.

Because completely blocking social media is the only goal difficulty level discussed in the prior literature and applied as a default option in many off-the-shelf social media blockers, we first test whether an overly difficult goal can decrease the productivity. We start by evaluating a social media reduction goal of 100%. For most users, completely blocking social media not only remove all the potential benefits of social media on productivity but also could potentially induce the "what-the-hell" effect and withdrawal-like symptoms that negatively affect productivity. To this end, we hypothesize that:

H1a: Completely blocking social media generally decreases productivity.

On the other hand, we expect setting less difficult goals (i.e., partially blocking social media) can be beneficial because (1) it consumes a lower amount of self-control capacity, reducing the likelihood of and "what-the-hell" effect and withdrawal-like symptoms, and (2) it regulates the use of social media in a way that retains the benefits of social media without allowing users to indulge excessively in social media. Therefore, we expect that:

H1b: Partially blocking social media generally increases productivity.

To further quantify the effect of goal difficulty, we evaluate the effects of two different levels of *partial* block goal difficulties. This range of goal difficulty is on the left-hand side of the inflection point on the inverted-U curve, where the performance is increasing with goal difficulty.

H1c: Relatively difficult partial blocking goals increase more productivity than relatively easy partial blocking goals.

Simply put, *H1c* and *H1b* together support the first half of *H1* (i.e., the effect of goal difficulty on productivity is first increasing). *H1a* supports the second half of H1 (i.e., the "then decreasing" part).

However, given the same goal difficulty, the relative strengths of these two forces may shift depending on individuals' prior social media consumption levels. First, the same social media reduction goal frees up more time for heavy social media users than light social media users. In other words, given the same goal, heavy social media users had more free time to potentially spend on productivity activities. As such, Ceteris paribus, a heavy social media user's performance-difficulty curve is generally higher than a light user's[3], as illustrated in **Figure 1 (a)** and **(b)**.

Second, as mentioned above, goal difficulty only increases the outcome to a certain point, forming an inverted-U shape curve. Given the same objective goal (i.e., easy or difficult goal, shown as dotted vertical

[3] Unfortunately, there is no existing definition of light or heavy social media users in the literature. As prior social media usage is a continuous spectrum, it is inherently difficult to define a single threshold to classify users as light or heavy social media users. Yet, for ease of discussion, we refer to a user who is using a relatively lower (greater) amount of prior social media consumption time as a light (heavy) social media user. We later define a working definition for a light (heavy) social media user in the results section.

lines in **Figure 1**), heavy social media users *perceive* this goal to be more difficult than light users because they tend to have lower self-control capacity (Brevers & Turel, 2019; Du et al., 2019). Therefore, the inflection point for heavy social media users is associated with a lower goal difficulty than for light social media users. As a result, the effect of goal difficulties depends on its relative location with respect to the inflection point. To this end, we expect that there exists an interaction effect between goal difficulty and users' prior social media usage level:

H2i: Users' prior social media consumption level moderates the effect of goal difficulty on productivity.

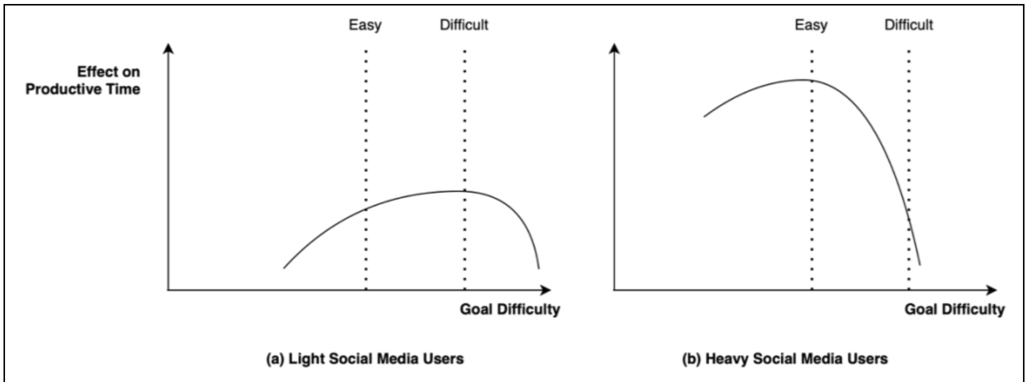

Figure 1: Heterogeneous Treatment Effect of Easy and Difficult Goals.

More specifically, for light social media users, because the "what-the-hell" effect is less likely, a difficult goal provides more benefits than an easy goal:

H2a: For light social media users, a difficult social media consumption reduction goal increases productive time more than an easy goal.

While difficult goals may generally increase productivity more than easy goals, difficult goals are more likely to induce the "what-the-hell" effect for heavy social media users, for whom an easier goal may provide more benefits than a relatively difficult goal. As such, we hypothesize that:

H2b: For heavy social media users, an easy social media consumption reduction goal increases productive time more than a difficult goal.

Goal Immediacy

Our review of goal-setting literature shows that overly difficult goals can hurt productivity. However, for many social media users, improving productivity is not the only objective for achieving difficult social media reduction goals. As excessive social media usage is shown to be associated with various mental health issues, heavy social media users may need a more difficult goal for their well-being. Is it possible for heavy social media users to achieve a difficult goal while still achieving optimal effects on productivity? While most prior literature on goal setting focuses on the difficulty of the goals, we do not know much about the temporal dimension of goals. To the best of our knowledge, existing literature has only examined the effect of a fixed social media reduction goal difficulty that is enforced immediately as blocking starts. We refer to this approach as setting a *radical goal*. In contrast, an alternative approach is setting an *incremental goal*, where the users set an *ultimate goal difficulty* that will be achieved gradually over time by dividing the ultimate goal into incremental, temporary sub-goals. For example, a user may specify a social media reduction goal difficulty to be achieved over two weeks. We refer to this temporal property of goals as *goal immediacy*.

Incremental change has been shown to be effective in behavioral change contexts. For example, a qualitative study showed that incremental goals are effective in limiting online gaming behavior (Zhou et al., 2021). They argue that the gradual process allows users to anticipate incremental goals, making the upcoming goals more acceptable. Another study found that incremental goals can effectively reduce the sitting time for adults (Lewis et al., 2016). They postulate that setting incremental goals allows individuals to feel more competent by making subgoals modest and achievable, thereby facilitating enduring behavioral change. While these studies suggest that incremental goals can reduce perceived goal difficulty, they did not offer a counterfactual comparison with radical goals.

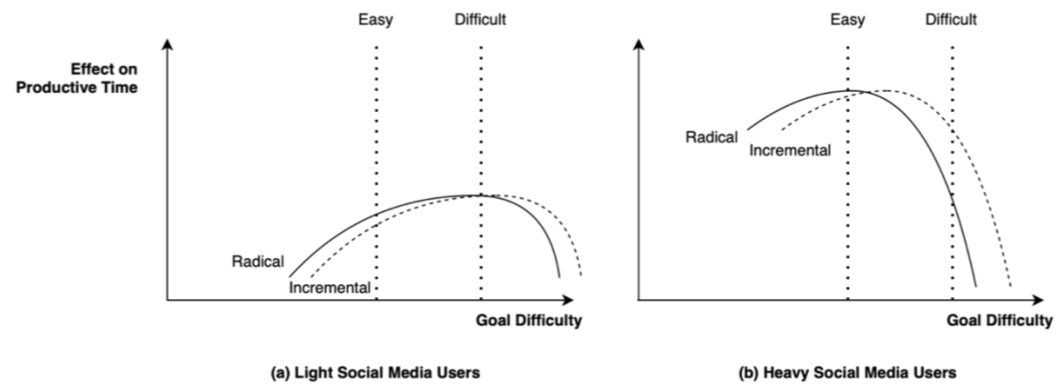

Figure 2. Combined effects of goal difficulty and goal immediacy

Incremental goals may bring two additional effects. First, as incremental goals start with easy temporary sub-goals, users adapt to the incremental goal difficulty during the process, allowing the users to achieve more difficult ultimate goals without inducing the "what-the-hell" effect. Second, as incremental goals start with easy subgoals, their blocking intensity is lower than radical goals, given the same ultimate goal difficulty. The first effect shifts the inverted-U curve for an incremental goal to the right (see **Figure 2**). An incremental goal increases the goal difficulty value associated with the inflection point on the curve due to the first effect. However, the direction of the second effect on productivity may depend on the user's prior social media consumption:

H3i: Users' prior social media consumption level moderates the effect of goal immediacy.

Specifically, for light social media users who are more likely to be on the left-hand side of the inverted-U curve (see **Figure 2a**), incremental goals may be "too easy", especially in the initial period where the temporary subgoals are modest. Light social media users may be better off achieving the ultimate goal immediately with radical goals. As such, we expect that:

H3a: For light social media users, radical goals increase more productive time than incremental goals.

In contrast, heavy social media users are more likely to be on the right-hand side of the inflection point. For these users, incremental goals can still be a better choice as it moves the inflection point to the right, reducing the risk of the "what-the-hell" effect. As such, we expect the following heterogeneous effects of goal immediacy:

H3b: For heavy social media users, incremental goals increase more productive time than radical goals.

Joint Effects of Goal Difficulty and Goal Immediacy

Thus far, we have separately discussed the related literature and the mechanism by which goal difficulty and goal immediacy may affect the treatment effect of social media blocking goals. To capture a complete picture of how these two effects may interact with each other, in this section, we discuss how goal immediacy can moderate the effect of reducing social media for different goal difficulties.

For easy goals, the benefit of reducing the risk of the "what-the-hell" effect is relatively low. Because incremental goals reach the ultimate goal gradually over time, the treatment strength is expected to be lower than radical goals before the ultimate goal is reached. As such, the benefits of incrementally increasing goal difficulty are limited or even negative, as illustrated in **Figure 2a**. Therefore, for easy goals, the incremental goals tend to have a lower effect on productivity than radical goals. We expect that:

H4a: For easy goals, the incremental approach does not increase productive time compared to the radical approach.

On the other hand, because difficult goals may be within the "what-the-hell" effect spectrum for some users (particularly for heavy social media users), difficult goals can benefit significantly from the incremental approach, as illustrated in **Figure 2** (b). By increasing the goal difficulty threshold associated with the inflection point, incremental goals allow difficult goals to be more attainable. Therefore, we expect that, in general, users with difficult goals will benefit the most from the incremental approach:

H4b: For difficult goals, the incremental approach increases productive time compared to the radical approach.

Experimental Design

In this paper, we focus on studying the impact of restricting social media usage *at work* using social media blockers on *productivity*. We do not restrict the "at work" definition to the physical workplace or in organizational contexts. Therefore, we can examine the effect on productivity in richer contexts (such as studying, self-improvement, in addition to job performance) and therefore capture more occupations such as students and freelancers. To this end, we opt for an online experiment on Amazon Mechanical Turk to examine the effects of social media reduction goal difficulty and immediacy on general productive activities during work hours.

Participants

We conducted an experiment on Amazon Mechanical Turk (AMT) with 125 (N=25 per cell, described later) participants ("Turkers") recruited to participate in our 4-weeks study. Amazon Mechanical Turk is a crowdsourcing marketplace where individual freelancers can accept jobs on the platform, to be completed remotely. Typical jobs on AMT are standardized jobs, which include survey participation, data labeling, and content moderation. AMT is an ideal place for our experiment as the "Turkers" work predominantly on their PCs. Following the Amazon Mechanical Turk reliability guidelines in the literature (Peer et al., 2014), we only recruit Turkers who have more than 95% approval rate[4].

In our recruitment material, we describe our study as "Increase your productivity by installing and using a Chrome extension and RescueTime app to limit social media usage for four weeks" under the title of "Chrome Extension for Reducing Social Media Usage". Our recruitment message attracts individuals who are relatively interested in reducing their social media usage. By targeting individuals who are willing to reduce their social media usage, our sample will be similar to the users who are actively searching for social media blockers in the real world. The participant also has to reside in the US and above 18 years old, in order to comply with regulations. We also exclude Turkers who may take tasks involving social media usage, such as scraping data from social media platforms. To control for smartphone usage, we require that the participants use an iPhone as their personal smartphone. We require users to enable the native "Screen Time" feature on iOS and submit screenshots throughout the experiment.

Chrome Extension Focus and RescueTime

To test the effect of different blocking strategies, we developed a Chrome Extension called *Focus*. It blocks social media sites during a specified period of time of the day, or "work hours", which will be described at the end of this section in detail. The participants install *Focus* and sign in with their designated pre-created accounts at the beginning of the experiment. After the treatment starts, they will see a pop-up blocking social media if they access social media during work hours. Each user will be given a certain amount of allowance time based on the condition they are assigned to. *Focus* will keep track of the time that participants spend actively engaging with social media (for example, we do not count the time when social media is in the background). The "Dismiss" button is enabled when the participants do not exceed their hourly allowance. They are able to close the prompt and continue using social media as usual if they click the dismiss button. However, if the hourly allowance is exceeded, the "Dismiss" button will be disabled and the participants will not be able to access social media. Since *Focus* only works with Chrome browser, we ensured that users only use Chrome during the entire study. We took two measures: first, in the recruitment material, we only allow Chrome users to participate. Users need to agree that their work does not involve

[4] The work of the Turkers needs to be approved by the job posters before getting paid. The approval rate refers to the ratio of lifetime approved jobs and the total jobs submitted.

using other browsers and will comply with our requirements. Second, we ask the users to install a third-party software, *RescueTime,* to track their activities on PC. *RescueTime* runs in the background with minimal user interaction after users log in with our pre-created accounts. By monitoring the data from these pre-created accounts, we are able to know if users are trying to use other browsers to bypass our extension.

Work Hours

To determine the work hours of each participant, we utilize the fine-grained data collected before the treatment. RescueTime automatically collects activities on the participants' PCs and classifies the activities as productive (e.g., Microsoft Office, Qualtrics) or social media use (e.g., Facebook, Instagram), among other categories (e.g., "Utility" for activities like system settings and "Entertainment" for video games and video streaming). RescueTime also assigns a productive score for each activity, which is positive if the activity is classified as productive and negative if classified as non-productive. For each participant, we calculate the time-weighted productivity scores for each hour in each day in week 1 (i.e., before the intervention). We then select the eight consecutive hours with the highest productive score as individual-specific work hours.

Procedure & Conditions

The first week of the experiment is an observational period. At this time, the users will install the *Focus* extension and RescueTime. We collect user activities on their PCs. The participants need to install *Focus* but the blocking function is disabled remotely by the researchers. The data collected in this stage will serve as a baseline for each participant. In weeks 2 to 4, the participants are randomly assigned to one of the treatment cells (See **Table 1**), wherein their social media blocker will update the daily allowance based on the schedule specified in **Figure 4** and **Table 1**. We check the balance among the three groups and found that the five groups have similar distributions of demographics, prior social media usage, and prior productive time. The blocking functions (as well as the attention redirection add-on depending on the treatment cells) in *Focus* will then be activated according to the treatment groups. At the end of each week, the participants are asked to complete a short dummy survey to claim weekly rewards. This stage lasts for two weeks. The experiment ends at the end of the third week.

Group	R-100	R-50	R-75	I-50	I-75
Immediacy	Radical	Radical	Radical	Incremental	Incremental
Difficulty (Reduction)	100%	50% of baseline	75% of baseline	50% of baseline	75% of baseline

Table 1. Overview of Experimental Conditions

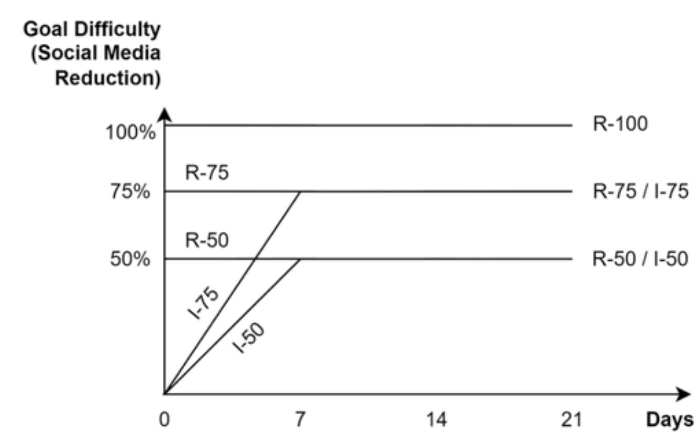

Figure 4. Social Media Blocking Schedules for each condition (after treatment)

We block the top web-based social media sites ranked by their pre-treatment total usage time across all participants. The final block list includes YouTube (43 hours), Facebook (19 hours), Reddit (14.2 hours), Twitter (8.4 hours), and Instagram (1.2 hours). LinkedIn (1.6 hours) was excluded as it can be considered work-related. The literature does not offer a widely agreed standard for operationalizing goal difficulty. We utilize the pre-treatment behavioral data to inform our operationalization choices. On average, participants spent 53.71 minutes on social media per day on their computers. A study suggests that 30 minutes of social media consumption per day correlates with desirable mental health outcomes (Hunt et al., 2018). Guided by this study, reducing 50% of user's total social media usage seems reasonable. In addition, we would like to test the effect of a relatively difficult goal. Therefore, we operationalize the relatively "easy goal" as a reduction of 50% social media consumption and the relatively "difficult goal" as a reduction of 75% social media consumption, which is a middle ground between the easy goal and completely blocking social media.

Variables and Measurements

Dependent Variable

Our dependent variable is the time the users spend on their computers doing productive activities during work hours when the social media blocker is enabled. For example, completing tasks on AMT, filling out surveys on Qualtrics, and using Microsoft Office are all classified as productive activities. To account for the fact that individuals have different working habits and social media consumption patterns, we measure productive time on an hour level. $ProductiveTime_{i,h,d}$ represents the hourly productive time (measured in minutes) of participant i in the h-th hour of the work hours on the d-th day since the start of treatment (d > 0 for after-treatment, $d < 0$ for pre-treatment). Note that when a participant did not use their computer in a particular hour, there will no corresponding observation for that hour in our data. As such, not all users will have an equal number of observations.

Alternatively, we define $\Delta ProductiveTime_{i,h,d}$ as the difference between the post-treatment and prior-treatment hourly productive time for participant i in the h-th hour of d-th workday after treatment. The value of $\Delta ProductiveTime_{i,h,d}$ directly reflects the direction and size of the treatment effect. Specifically,

$$\Delta ProductiveTime_{i,h,d} = ProductiveTime_{i,h,d} - ProductiveTimeBefore_{i,h}$$

where $ProductiveTimeBefore_{i,h}$ measures the *average* hourly productive time before the treatment (d < 0):

$$ProductiveTimeBefore_{i,h} = \sum_{d=-7}^{0} ProductiveTime_{i,h,d}/7$$

Other Variables

To investigate the heterogeneous treatment effects on individuals with different social media consumption level, we rely on an objective measurement of users' social media browsing habits, *Prior Social Media Consumption*. Before the treatment starts, our Chrome extension captures the social media consumption in the background and reports the statistics to our server. We then use these fine-grained social media consumption stream data to calculate $PriorSocial_{i,h}$, *which* measures the time that participant i spent on social media sites in the h-th work hour prior to treatment. In addition, we also control for the participants' age and gender.

Results

Effects of Goal Difficulty on Productive Time

In this section, we present our findings on the effects of different goal difficulty levels on productive time. To test H1a and H1b, we run two linear regressions comparing the treatment effect of different levels of goal difficulties on the radical-goal groups:

$$ProductiveTime_{i,h,d} = post_{i,h,d} + PriorSocial_{i,h} + age_i + gender_i$$

This model is separately evaluated using samples from the complete block group (i.e., 100% reduction goal) and partial block groups (i.e., 50% and 75% reduction groups). The results are reported in **Table 2**. The coefficients of the *post* dummy variable reflect the treatment effects. We find that when the goal is too difficult (i.e., complete reduction), the treatment effect is negative. In contrast, easier goals (partial reduction) achieve positive treatment effects. Therefore, both *H1a* and *H1b* is supported.

DV	**Productive Time (Minutes)**	
	Complete Reduction	**Partial Reduction**
(Intercept)	12.310***	14.648***
	(2.828)	(1.495)
post	−7.888***	2.330***
	(0.986)	(0.590)
prior_social	-0.012	0.084**
	(0.149)	(0.039)
age	0.496***	0.032
	(0.076)	(0.033)
gender	−5.587***	2.605***
	(1.016)	(0.602)
Num.Obs.	927	1866
R2	0.116	0.021
R2 Adj.	0.112	0.019
* p < 0.1, ** p < 0.05, *** p < 0.01 (same below)		

Table 2. Regression on Radical Groups

The above results show the average treatment effect on productivity. However, this model does not account for the fact users may have different productivity patterns over the workday. For example, the post-treatment productivity of 9 AM is compared against the average productivity over the day in the pre-treatment period instead of the productivity of 9 AM pre-treatment. To address this issue, instead of using the productive time as the dependent variable and using the *post* dummy as the treatment effect indicator, we change our dependent variable from $ProductiveTime_{i,h,d}$ to $\Delta ProductiveTime_{i,h,d}$. By using this dependent variable, we ensure that productivity is compared on a user-hour level.

To test *H1c,* we use the following model to compare the treatment effect within the partial block groups:

$$\Delta ProductiveTime_{i,h,d} = Goal75_i + PriorSocial_{i,h} + Age_i + Gender_i$$

where $Goal75_i$ is a dummy variable indicating whether the user is assigned to the 75% reduction group. Since the sample is limited to the partial block groups, $Goal75_i = 0$ means the user is assigned to the 50% reduction group.

The result is reported in **Table 3 (1)**. We find a more difficult goal (75% reduction compared to 50% reduction) results in a higher treatment effect on productivity. On average, users in the 75% reduction group increased 3.14 minutes of productive time compared to users in the 50% reduction group. Therefore, *H1c* is supported. Next, we examine the heterogeneous effects on individuals with different prior social media consumption levels.

Heterogeneous Effects of Block Intensities

To study the moderating role of prior social media consumption, we add an interaction term to the model. Since we have identified the main treatment is negative for 100% reduction, we only focus on easier goals and limit our scope of analysis to 50% and 75% social media reduction groups. Our interaction model is specified as follows:

$$\Delta ProductiveTime_{i,h,d} = Goal75_i \times PriorSocial_{i,h} + Goal75_i + PriorSocial_{i,h} + Age_i + Gender_i$$

The regression results are shown in **Table 3**.

DV	$\Delta ProductiveTime_{i,h,d}$			
	(1)	**(2)**	**(3)**	**(4)**
	Main Effect	**Heterogeneous Effect**	**Light Users**	**Heavy Users**
(Intercept)	−7.825***	−9.164***	−10.137***	−3.828*
	(1.565)	(1.606)	(2.324)	(2.232)
75% Reduction	3.140***	5.254***	3.958***	2.364***
	(0.603)	(0.832)	(0.931)	(0.808)
prior_social	0.210***	0.389***	1.448***	0.040
	(0.039)	(0.067)	(0.448)	(0.054)
age	0.278***	0.274***	0.157***	0.300***
	(0.038)	(0.038)	(0.056)	(0.053)
gender	−2.491***	−2.342***	-0.614	−3.589***
	(0.576)	(0.581)	(0.913)	(0.767)
75% × prior_social		−0.291***		
		(0.081)		
Num.Obs.	3183	3183	1238	1945
R2	0.043	0.047	0.038	0.034

Table 3. Heterogeneous Effects of Goal Difficulty on Productive Time

While generally a more difficult goal improves the effect of social media blocker (see coefficient for 75% Reduction dummy variable in model 1 and model 2), we find that such improvement is diminishing for individuals with higher social media consumption levels (see 75% Reduction × prior_social in model 2). Therefore, *H2i* is supported. We further conducted a subsample analysis by splitting the users into light and heavy social media users by median prior social media consumption level. We find that heavy social media users indeed enjoy fewer additional benefits from a more difficult goal than light social media users (i.e., 2.364 versus 3.958 in model 3 and model 4, respectively). Despite the diminishing effect, the main effects of a more difficult goal are still positive. As such, while *H2a* is supported, *H2b* is not supported.

Effects of Goal Immediacy on Productive Time

To evaluate the effect of goal immediacy, we now include the two incremental groups in our sample. As we have two goal difficulty levels, we include the goal dummy variable as a control variable. Our regression model is therefore specified as follows:

$$\Delta ProductiveTime_{i,h,d} = Incremental_i \times PriorSocial_{i,h} + Incremental_i + PriorSocial_{i,h} + Goal75_i + Age_i + Gender_i$$

where $Incremental_i$ is a dummy variable indicating whether the user is assigned to an incremental goal (as opposed to radical goals). The regression results are reported in **Table 4**. We first find that the coefficient for $Incremental_i \times PriorSocial_{i,h}$ is positive and statistically significant, suggesting that *H3i* is supported. However, incremental goals, in general, have a lower positive treatment effect on productive time compared to radical goals (see the negative coefficient for $Incremental_{\ i}$ in model 1). Given the same end goal, the incremental goal's difficulty is lower than radical goals in the incremental period (i.e., the first week). As such, the effective goal difficulty in the first week is lower than radical goals. This is consistent with the findings that more difficult goals do perform better in the last section. As such, *H3a* is supported. We further conducted a subsample analysis, shown in model 2 and model 3. While model 2 confirms *H3a*, model 3 does not support *H3b*. We note that the effect of incremental goals becomes positive but insignificant for heavy users in model 3. This result may be because incremental goals may only be beneficial to certain goal configurations, masking the main effect shown in model 3. We next study the potential interaction effect between goal immediacy and goal difficulty.

DV	$\Delta ProductiveTime_{i,h,d}$		
	(1)	(2)	(3)
	Base	Light User	Heavy Users
(Intercept)	−3.169***	−4.428***	-0.459
	(1.176)	(1.639)	(1.765)
Incremental	−3.346***	−2.463***	0.388
	(0.580)	(0.616)	(0.583)
prior_social	0.223***	0.862***	0.060
	(0.039)	(0.311)	(0.045)
75% Reduction	0.673	0.490	0.753
	(0.432)	(0.659)	(0.578)
age	0.143***	0.051	0.174***
	(0.028)	(0.038)	(0.042)
gender	−1.768***	-0.378	−2.505***
	(0.430)	(0.652)	(0.577)
Incremental × prior_social	0.289***		
	(0.063)		
Num.Obs.	5946	2846	3100
R2	0.037	0.012	0.015

Table 4. Effects of Goal Immediacy on Productive Time

Interaction Effects between Goal Difficulty and Goal Immediacy

To examine the interaction between goal difficulty and goal immediacy while taking their heterogeneous treatment effects (based on users' prior social media consumption level) into account, we further extend the model to a three-way interaction model as follows:

$$\begin{aligned}\Delta ProductiveTime_{i,h,d} &= Goal75_i \times Incremental_{\ i} \times PriorSocial_{i,h} + Goal75_i \times Incremental_{\ i} \\ &+ Incremental_{\ i} \times PriorSocial_{i,h} + Goal75_i \times PriorSocial_{i,h} + Goal75_i \\ &+ Incremental_{\ i} + PriorSocial_{i,h} + Age_i + Gender_i\end{aligned}$$

The results are shown in **Table 5**.

DV	$\Delta ProductiveTime_{i,h,d}$		
	(1)	(2)	(3)
(Intercept)	-1.289	-1.630	-4.371^{***}
	(1.146)	(1.153)	(1.236)
Incremental	-2.288^{***}	-0.118	0.531
	(0.421)	(0.640)	(0.853)
75% Reduction	0.738^{*}	2.515^{***}	4.567^{***}
	(0.437)	(0.590)	(0.830)
age	0.135^{***}	0.150^{***}	0.150^{***}
	(0.028)	(0.029)	(0.029)
gender	-1.730^{***}	-2.561^{***}	-2.600^{***}
	(0.431)	(0.457)	(0.464)
Incremental × 75% Reduction		-3.929^{***}	-7.407^{***}
		(0.905)	(1.201)
prior_social			0.393^{***}
			(0.067)
Incremental × prior_social			0.006
			(0.094)
75% Reduction × prior_social			-0.299^{***}
			(0.081)
Incremental × 75% Reduction × prior_social			0.564^{***}
			(0.130)
Num.Obs.	5946	5946	5946
R2	0.014	0.017	0.043

Table 5. Effects of Goal Immediacy on Productive Time

For interpretability, we discuss the predicted treatment effect shown in **Figure 5** based on model (3). First, incremental goals do not have significant effect on easy goals, regardless of the users' prior social media consumption level, as shown on right-hand side of the **Figure 5** and an insignificant coefficient for "Incremental" dummy variable. Interestingly, we found heterogeneous effects of incremental goals on difficult goals, as shown on the left-hand side of **Figure 5**. Compared to radical goals, incremental goals reduce the performance of *difficult* goals for *light* social media users ("Incremental × 75% Reduction"). However, it significantly improves the performance of *difficult* goals (75% reduction) for *heavy* social media users (see "Incremental × 75% Reduction × prior_social"). Therefore, *H4a* is supported but *H4b* is only supported for heavy social media users. Interestingly, we observe a negative impact of social media reduction on productivity for users with minimal social media usage (e.g., users who use less than 5 minutes of social media per hour during work hours). This negative impact exists for all combinations of goal difficulty and goal immediacy except for radical-difficult goals. We offer several possible explanations for this observation. First, by enforcing social media reduction goals by a percentage of the focal user's prior social media consumption level, users with prior minimal social media usage is effectively receiving a restriction that is similar to a complete block. However, this explanation does not explain the exception of the non-negative effect of radical-difficult goals. A second possible explanation is that users are only "hooked" to social media after a certain amount of exposure to social media content. Although partial blocks for minimal social media users are similar to hard block, it still provides enough exposure for users to get "hooked", except for the radical-difficult goals.

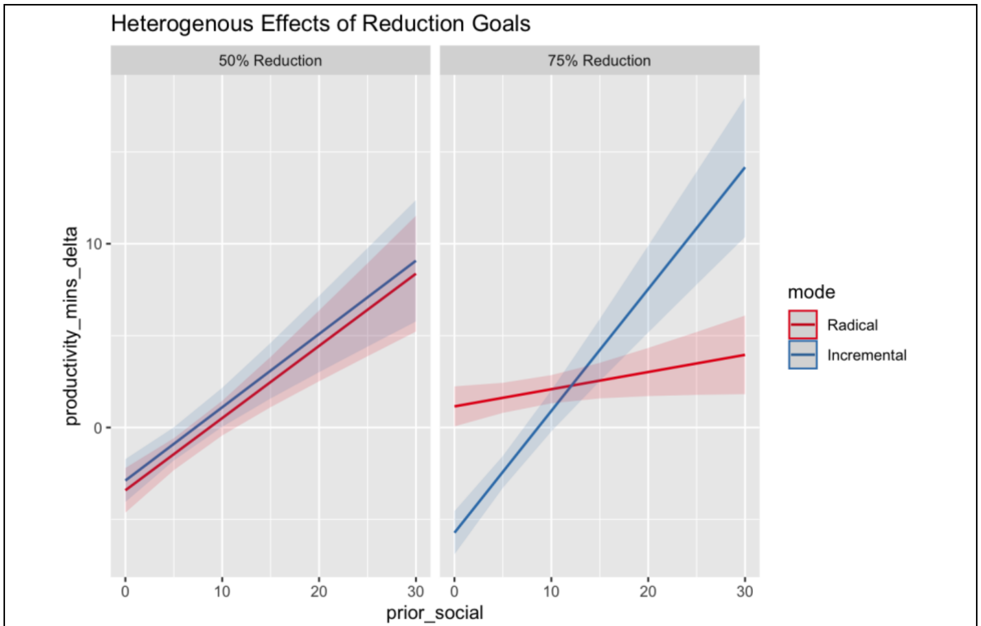

Figure 5. Predicted Margins of Block Intensity and Block Immediacy

Discussion and Conclusions

In this paper, we contribute to the literature by quantifying the effects of different goal difficulties, goal immediacy, and the interaction of the two dimensions. Our analysis deepens our understanding of how goal-setting affects the outcome, particularly in the social media usage reduction context. Each of our insights provides practical implications to individual social media users, employers, and social media blocker developers.

First, we shed light on the two-sided effects of social media consumption – some consumption can be beneficial (e.g., 50% or 75% reduction in social media), but too much consumption hurts productivity (i.e., 100% reduction in social media). However, completely blocking social media can result in a net negative impact on productivity. As such, less social media consumption is not always "more" in terms of productivity. Second, we study the heterogeneous treatment effects of goal difficulties on individuals with different prior social media consumption levels. This line of insights creates opportunities for personalization of social media blocking goals to improve the effects on productivity further. For example, developers of social media blockers can provide personalized goal difficulty suggestions according to users' prior social media consumption levels. Providing such a reference guideline makes it less likely for the users to "overshoot" or "undershoot" the goal, which undermines the effects on productivity. Finally, by studying the interacting effects of goal difficulty and goal immediacy, we found that goal immediacy can be particularly beneficial to heavy users who are trying to set a difficult goal. This result calls for the implementation of features that enable users to use incremental goals. For example, social media blockers can suggest heavy social media users enable incremental goals that will automatically be updated over time.

This research is not without limitations. First, although we monitored users' social media usage on smartphones, we did not block social media usage on smartphones due to feasibility reasons. However, our analysis did not show a significant difference in mobile social media usage using user-uploaded screenshots of their mobile usage statistics from iOS's Screen Time. Second, due to the experimental constraint, we were not able to test goal immediacy and goal difficulty in a more granular manner (e.g., more goal difficulty levels). We encourage future research to address this limitation by using larger-scale field experiments to provide more specific, personalized recommendations to individuals.

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