

No Exceptions: Personal Rules and Self-Control

Amanda Ngo

Department of Psychology, The University of Pennsylvania

INSP 398: Senior Thesis

Advisor: Angela L. Duckworth, Ph.D.

May 12, 2020

Abstract

Personal rules such as “I *never* eat meat” and plans (“I will try not to eat meat”) are common. Whereas a plan expresses an intention, a personal rule is a categorical principle you vow to follow without exception. Despite the anecdotal accounts of the value of personal rules as a self-control device, experimental evidence is scarce. In this study ($N = 156$), we compared the effect of a personal rule versus a plan in increasing people’s daily step count over a week-long intervention. Both personal rules and plans increased step count significantly more than a comparison no-treatment control group, but there was no difference between personal rules and plans. While these findings may indicate that personal rules are no more effective than plans, they may also suggest that the efficacy of personal rules depends on conditions not established in this intervention.

Keywords: self-control, personal rules, plans, step count

No Exceptions: Personal Rules and Self-Control

Self-control conflicts—between immediately rewarding *wants* and more enduringly valuable *shoulds*—are a familiar struggle (Milkman et al, 2008). Failures are commonplace (Norcross & Vangarelli, 1988), and have significant negative consequences: self-control is as predictive of life outcomes as intelligence and family socioeconomic status (Moffitt et al., 2011). Specifically, self-control predicts academic grades, graduation rates, wealth, substance abuse, criminal activity, obesity, eating behaviors, subjective well-being, weight loss, and exercise (Crescioni et al., 2011; Duckworth et al., 2019; Fan & Yin, 2013; Moffitt et al., 2011; Wiese et al., 2017). In fact, self-control has been deemed a “hallmark virtue of human character” (Prelec & Bodner, 2003, p. 227) from which “human happiness is inseparable” (Rachlin, 2000, p. 8). Personal rules have been proposed as a potentially powerful self-control strategy (Ainslie & Haslam, 1992), yet experimental evidence is sparse. Synthesizing previous literature, we define personal rules as a categorical principle you vow to follow without exception and present results from an experiment comparing personal rules to plans as strategies for increasing physical activity.

Self-control

Self-control refers to “the capacity for altering one’s own responses, especially to bring them in line with standards such as ideals, values, morals, and social expectations, and to support the pursuit of long-term goals” (Baumeister et al., 2007, p. 351). The need for self-control arises because long-term goals often conflict with momentarily more gratifying goals. This leads to a phenomenon called *preference reversal*: although when asked in advance an individual prefers actions that align with a long-term goal, when the moment of choice arises, they change their mind and instead prefer the more rewarding, short-term goal (Berns et al., 2007). For example, at

the start of the week an individual may have a preference to go to the gym on Wednesday to get fit. However, when Wednesday arrives, the temptation to stay in and watch Netflix overrides the previous preference and the individual fails to act in alignment with their long-term goal. For many of our valued goals, rewards depend on consistent repetition over time of actions aligned with the goal (Rachlin, 2000; Prelec & Bodner, 2003). Working out once does not make you fit; but working out consistently and repeatedly for several months does. The benefit of self-control thus depends, in part, on the establishment of patterns of behavior over time (Rachlin, 2000).

Personal Rules

One strategy that can establish patterns of behavior is personal rules (Rachlin, 2000). Personal rules have been defined and used in a variety of different ways. In existing literature, personal rules have been defined as internal, or soft, commitment devices (Bénabou & Tirole, 2004; Bryan et al., 2010; Rachlin 2000), promises to oneself (Bénabou & Tirole, 2004; Kirby, 2014), self-enforcing contracts with future selves (Ainslie & Haslam, 1992), choices that align with the ‘best’ disposition one could have, regardless of the disposition one actually has (Prelec & Bodner, 2003), and categorical rules that link situational cues to a desired response (Duckworth et al., 2019). Consistent with these conceptualizations, we define personal rules as a categorical principle you vow to follow without exception. For example: “I never eat meat,” or “I always go to sleep before midnight.”

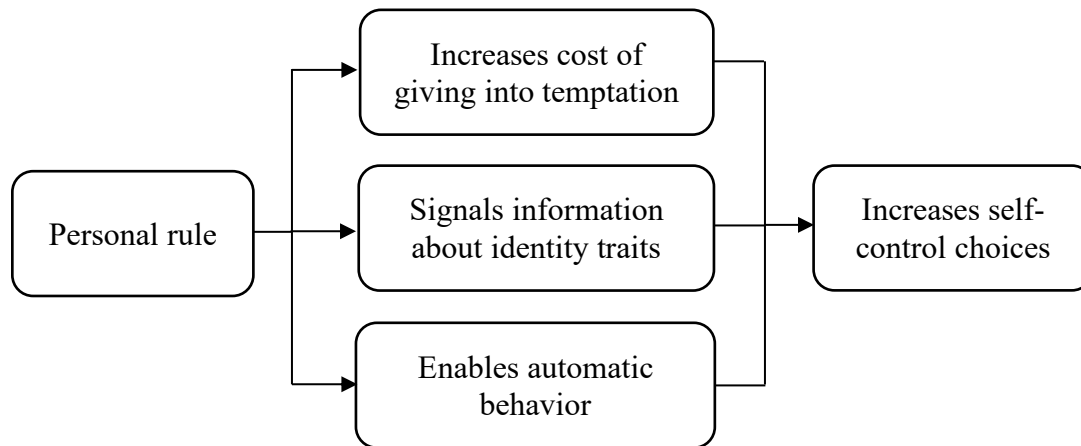
Rules are commonly used to guide behavior. Laws are rules enforced by an external authority, and principles such as the biblical ten commandments prescribe rules for moral action. Personal rules in particular have captivated thinkers throughout history. Adam Smith spoke of the need to master “passive feelings” with “active principles” (Meardon & Ortmann, 1996). Thomas Schelling urged: “Set yourself the kinds of rules that are enforceable. Use bright lines

and clear definitions, qualitative rather than quantitative limits if possible... Permit no exceptions.” (Schelling, 1984, p. 7). Mahatma Gandhi achieved fasting, celibacy, and the practice of non-violence throughout his life by following vows (Kirby, 2014). According to Gandhi, a vow is a promise to oneself that involves an “unalterable decision to do or not do a particular thing.” (Gandhi, p. 240). Benjamin Franklin, polymath and Founding Father, used resolutions in his relentless quest for self-improvement. On realizing the confused nature of his conduct, he determined: “Let me, therefore, make some resolutions...that, henceforth, I may live in all respects like a rational creature” (Franklin, 1726).

Personal rules are posited to increase self-control by increasing the cost of temptation, signaling information about identity traits, and enabling automatic behaviors.

Figure 1

Framework for the Effect of Personal Rules on Self-Control



Note. Framework of how personal rules lead to increased self-control choices. Increasing the cost of giving into temptation, enabling automatic behaviors, and identity signaling are three possible mediators.

Increasing the Cost of Giving into Temptation

Why are people motivated to avoid giving into temptation when they have a personal rule? First, personal rules make it more difficult to ignore or forget that one has given into temptation. Second, breaking a rule once undermines one's expectation of successfully exerting self-control in the future. Given the importance of repeating self-controlled behaviors over time, even one lapse can be damaging (Ainslie & Haslam, 1992).

Making Lapses Evident

A personal rule makes it clear when an action is a violation of the rule by using a categorical qualifier 'always' or 'never' and pairing it with a specific action. This creates a *bright line*, which is a boundary that "cannot be moved just a little bit" (Ainslie & Haslam, 1992, p. 195). For example, an individual who has a rule "I always go to bed before midnight" clearly violates their rule if they go to bed at 1:00 am. Personal rules are also accompanied by an implicit or explicit commitment to *self-monitor* (Bénabou & Tirole, 2004). Self-monitoring is the process of paying deliberate attention to one's behavior (Schunk, 1983) and has been shown to increase self-control (see e.g., Burke et al., 2011; Schmitz & Perels, 2011; Zimmerman & Paulsen, 1995). By forming a personal rule with a bright line and paying attention to their behavior, an individual is more likely to recall giving into temptation (Bénabou & Tirole, 2004). Awareness that one has broken an explicit commitment is aversive as it undermines one's desire to be internally consistent (Beshears et al., 2016; Festinger, 1962). Moreover, recalling that you have broken a rule means you are more likely to experience the cost of reduced expectation of self-control (Bénabou & Tirole, 2004).

Reducing Expectation of Future Self-Control

Personal rules do not permit exceptions. Breaking a rule even once undermines the force of the rule: one's expectation of exerting self-control in the future decreases. Two models specify

how this process occurs. In the *hyperbolic discounting model*, personal rules group choices into a category (Ainslie & Haslam, 1992). Linking a series of choices together means a current choice sets a *precedent* for future choices in that category, preventing an individual from allowing themselves to give into temptation “just this once” (Ainslie & Haslam, 1992; Rachlin, 2000). This changes the cost of giving into temptation relative to exerting self-control. In a self-control choice, an individual chooses between a large reward received later, and a small reward received sooner. However, if a rule is specified that makes a choice today indicative of similar choices in the future, then the rewards from the repeated choices are aggregated: an individual must choose between the sum of all smaller, sooner rewards and the sum of all larger, later rewards across the repeated choices. Giving into temptation is no longer preferred: an individual who caves to temptation loses the sum of larger, later rewards from every future choice in that category (Ainslie, 1975, 1992, 2012; Ainslie & Haslam, 1992).

Several theorists have compared the consequences of viewing choices as part of a broader series rather than individually. In *choice bracketing*, choices are grouped into sets; a choice is made by taking into account its effect on other choices in the set (Read, Loewenstein, Rabin, et al., 1999). Choice bracketing “reveals the broader patterns of behavior that are less apparent when each choice is considered in isolation.” (Fujita & Roberts, 2010, p. 1051). Similarly, Heyman (1996) differentiates between *local framing*, where one considers only the value of each isolated choice, and *global framing*, where future choices are taken into account. *High-level construal* involves abstracting the global features of a set of examples (Fujita & Han, 2009). Activating high-level construal by asking ‘why’ participants engage in behaviors rather than ‘how’ has been shown to increase participants’ likelihood of opting into self-control strategies, such as choice bracketing, for valued goals (Fujita & Roberts, 2010).

Researchers showed the efficacy of reward bundling based on a hyperbolic discounting model in both humans and animals (Ainslie & Monterosso, 2003). In one influential experiment, researchers calibrated a choice between a small, immediate reward and a large, delayed reward such that each participant impulsively preferred the smaller, sooner reward. A significant number of participants switched to choosing the larger, later reward when choices were repeated and linked together either by force (offering only one choice between the sum of all smaller rewards and all larger rewards), by suggestion (framing a choice today as “the best indication of how you will choose every time”), or by simply telling participants that a choice was the first in a series of similar choices (Kirby & Guastello, 2001, p. 159). Using a similar paradigm focused on smokers, Hofmeyr et al. (2010) demonstrated that when individual decisions between smaller, sooner rewards and larger later rewards were bundled into groups (either by forcing participants to make all decisions at once, or by suggesting that participants consider the decisions as part of a series), participants increased their preference for the larger, later rewards (Hofmeyr et al., 2010). Similar results have been observed when participants make choices requiring self-control simultaneously versus sequentially (Read, Loewenstein, Kalyanaraman, et al., 1999), and when choices are grouped into triplets by function of a delay after three choices (Kudadjie-Gyamfi & Rachlin, 1996).

In the *self-reputation model*, personal rules influence future choices by providing information about one’s self-control (Bénabou & Tirole). A person has imperfect knowledge of their self-control in the face of visceral temptations and can thus only infer their self-control from past actions. If a person gives in to temptation in an immediate self-control conflict and recalls the lapse, this signals poor self-control and lowers their expectation of successfully exhibiting self-control in future choices. Personal rules are self-enforcing because individuals

want to avoid the cost of signaling poor self-control and jeopardizing future self-control choices (Bénabou & Tirole).

Identity signaling

People are motivated to resist temptation not only because it signals likelihood of future self-control choices, but also because it sends a signal about the ‘kind of person’ they are (Prelec & Bodner, 2003). People are uncertain about the extent to which they possess desirable traits, and choose actions based on the information the action provides about these traits (Prelec & Bodner, 2003; Bodner & Prelec, 2003). Research suggests that identity signaling increases self-controlled behavior (see, e.g., Berger & Rand, 2008; Magen & Gross, 2007; Quattrone & Tversky, 1984; Touré-Tillery & Fisbach, 2015).

Personal rules may leverage the effect of identity signaling by making identities particularly salient. March & Olsen (2011) hold that rules and identities are intimately connected: people have a collection of identities, each of which entails rules of appropriate behavior in relevant situations. Rules, identities, and situations are matched through the process of asking: “What kind of a situation is this? What kind of a person am I? What does a person such as I do in a situation such as this?” (March & Olsen, 2011, p. 479). Patterns of repeated behavior created by strategies such as personal rules and habits foster self-identification as ‘the kind of person’ who engages in that behavior (Gardner et al., 2011; Rachlin, 2000; Verplanken & Sui, 2019). The more strongly an action influences an individual’s conception of their identity, the more they will tend towards ‘always’ or ‘never’ rules for that action (Prelec & Bodner, 2003; Bodner & Prelec, 2003).

Enabling Automatic Behaviors

Forming a personal rule links an environmental cue (such as time of day) with a response (such as going to bed). This increases the likelihood that when the situation arises, an individual will automatically act on their personal rule (Duckworth et al., 2019). This phenomenon can be understood using the *process model of self-control*. According to this model, behaviors are generated from four recursive stages: situation, attention, appraisal, and response (Gross, 1998; Duckworth et al., 2019). People find themselves in an objective *situation*. They direct their limited *attention*, subjectively *appraise* whether something is good or bad for them, and then enact a *response*.

Plans, habits, and personal rules bypass the appraisal stage of the process model by linking situational cues directly to a response (Duckworth et al., 2019). When an individual with the personal rule “I never eat meat” sees meat on the menu, they do not need to deliberate whether it would be good or bad to eat it; they simply enact their rule. Shortcutting the deliberation phase is helpful for self-control because in the moment, the reward from temptation is often greater than the reward from the self-controlled choice (Ainslie, 1975; Loewenstein, 1992). If behaviors prompted by a personal rule are repeated over an extended period of time, they may become habits (Duckworth et al., 2019). Habits are a valuable self-control strategy that are similarly triggered by context, but are acquired slowly and performed independently of a goal (Wood & Neal, 2007).

Personal Rules and Plans

Like personal rules and habits, plans enable automatic behaviors by linking an environmental cue to a desired response (Gollwitzer, 1999). Due to the robust evidence that plans increase goal attainment and goal striving, plans are a useful benchmark for the efficacy of personal rules (Gollwitzer, 1999; Milkman et al., 2012; Rogers et al., 2015; Yeomans & Reich,

2017). Plans bridge the gap between wishes and goal attainment by specifying when, where, and how to act (Gollwitzer, 1999; Gollwitzer & Bargh, 1996). Plans force people to consider logistical hurdles to their goals, combat forgetfulness, and link tasks to environmental, temporal or behavioral cues in an automatic way (Gollwitzer, 1999; Beshears et al., 2016; Rogers et al., 2015).

There are several important differences between personal rules and plans. First, personal rules are categorical by definition. Whereas a plan might state: “When I walk into my bedroom, I will study math,” a personal rule would state: “When I get home, I *always* do my homework” (Duckworth et al., 2019). Plans are often tailored to fit one-off circumstances such as attending an appointment (Milkman et al., 2012; Rogers et al., 2015). In contrast, personal rules apply to choices repeated over time (Ainslie & Haslam, 1992).

Current Investigation

Physical activity is a domain in which self-control conflicts abound. Health-related outcomes such as fitness and weight loss require many repetitions of self-controlled choices. However, it is often more tempting to stay at home than to go to the gym. The prevalence of self-control conflicts provides insight into why only half of Americans meet physical activity recommendations (Clarke et al., 2016), despite the benefit of physical activity for long-term outcomes such as coronary heart disease, cancer, diabetes, depression, weight loss, and quality of life (Bize et al., 2007; Richardson et al., 2008; Roumen et al., 2009; Sattelmair et al., 2011; Tardon et al., 2005; Teychenne et al., 2008).

Step count is a useful measure for physical activity because it is objective, easy to measure, and correlated with important health outcomes (Bassett et al., 2017; Morris & Hardman, 2012). Behavioral interventions such as planning, goal-setting, self-monitoring,

precommitment, and gamification have been shown to increase step count (Romeo et al., 2019; Kramer et al., 2020; Patel et al., 2019; Kanejima et al., 2018). Prior work indicates that increasingly ubiquitous wearables such as Fitbit accurately track step count (El-Amrawy et al., 2015).

This study provides empirical evidence on the effect of forming and following a personal rule. In a one-week intervention, we led participants through the generation of a personal rule related to step count, and compared the effect of personal rules with plans on step count over the course of the week. This study used a new method of collecting Fitbit data. Rather than partnering with costly third-party platforms, we developed a free web app which simply required users to log into their existing Fitbit account to grant access to their data for 30 days.

Method

Participants

Participants were $N = 156$ adults recruited via online task crowdsourcing platforms Prolific and Amazon Mechanical Turk (MTurk) in April 2020. The participants were 87% White, 8% Asian, 8% Hispanic, 4% Black, and 2% other racial-ethnic backgrounds; 74% were female. Participants were between the ages of 19 and 71 ($M = 34.29$, $SD = 11.75$). All participants were from the United States and owned a Fitbit which they used regularly. Participants completed the survey using the Prolific or MTurk platforms, which are crowdsourcing websites where remote workers can complete surveys posted by researchers in exchange for compensation. We excluded participants who reported being unable or unwilling to walk outside during the coronavirus outbreak, did not want to walk more, or did not wear their Fitbit daily. Participants were rewarded using a bonus scheme. They received \$0.15 if they

started and submitted the survey.¹ To motivate them to share their Fitbit data, they received a bonus of \$3.00 if they authorized access to valid step count data.

Measures

Step count

Participants authorized access to their daily step count history measured by the wearable device, Fitbit. We collected the total number of steps taken each day for each participant for 30 days prior to the intervention, and 30 days after the intervention began.

Demographic information

We collected participants' age, gender, and race at the end of the survey.

Procedure

Participants were prompted to log in to their Fitbit account and check a box to give researchers access to their activities and exercise history for a duration of 30 days. Activities and exercise data comprises multiple measurements, such as calories burned and floors climbed, but we communicated that only the step count measurement would be accessed (Fitbit, 2019). Next, a back-end web app verified self-reported frequency of Fitbit use by screening participants' data for the number of days with 0 step count. Only frequent users, who had a step count of 0 on fewer than 5 days in the 30 days prior to the intervention, continued in the survey.

Participants were then randomly assigned to two conditions: the personal rule condition ($n = 83$) and the planning control ($n = 73$). In the personal rule condition, subjects were given the definition of a personal rule as a principle you vow to follow without exception, followed by two comprehension checks. Participants who failed a comprehension check after two attempts were

¹ MTurk and Prolific allow participants to submit a survey even if they have not completed the full survey. Paying a base rate of \$0.15 to everyone who submitted the survey was logistically easier, as it ensured that we did not have a high rate of rejecting participants.

shown the correct answer, then continued in the survey. Participants then wrote their own personal rule to follow over the next week. They were first prompted to think of something they would like to do to increase their step count, then asked: “Now turn it into a rule that starts with ‘I always’”. Participants were required to include ‘I always’ in their response. In the planning control, participants were prompted to think of something they would like to do to increase their step count, then asked: “Now turn it into a plan that starts with ‘I plan to’”. Participants were required to include ‘I plan to’ in their response (see Appendix for full intervention text). Additionally, we compared both the planning control and the personal rule condition to a comparison no-treatment control group ($n = 52$). The group consisted of participants from previous pilot studies whose step count data we were still able to access during the time period of the study outlined above. We assumed that the no-treatment participants were no longer affected by our intervention after more than 3 weeks post-survey.

We then collected demographic information. Both conditions were reminded that over the next week they should try to increase their step count, wear their Fitbit daily, and sync their Fitbit app on their phone to ensure we could access their data. Participants were sent daily reminders with the text of their plan or rule and an encouragement to increase their step count.

At any point after the intervention week ended, participants had to sync their Fitbit with their mobile phone to update the step count data we had access to. If they did not complete this sync, our data indicated a step count of 0 on each of the days since the participant last synced their Fitbit and phone.

Analytic strategy

We used an intent-to-treat strategy. We define missing data as days with less than 2000 steps based on similar strategies in previous step count literature (Bachireddy et al., 2019). Days

with missing data were replaced with the participant's mean daily step count from the pre-intervention period for that specific day of the week. We did an additional sensitivity analysis in which we removed days with less than 2000 steps rather than replacing them with pre-intervention averages. We used ordinary least squares regression to determine the effect of the treatment and control conditions on participants' daily steps during the intervention period. We included person-by-day-of-week fixed effects to control for daily step count prior to the intervention and clustered standard errors by person-by-day-of-week to account for participants' variations in step count activity (e.g., walking more on the weekends than on the weekdays, or vice versa).

Results

Both personal rules and plans increased step count compared to a comparison no-treatment control group, but there was no difference between the effect of personal rules and plans on step count.

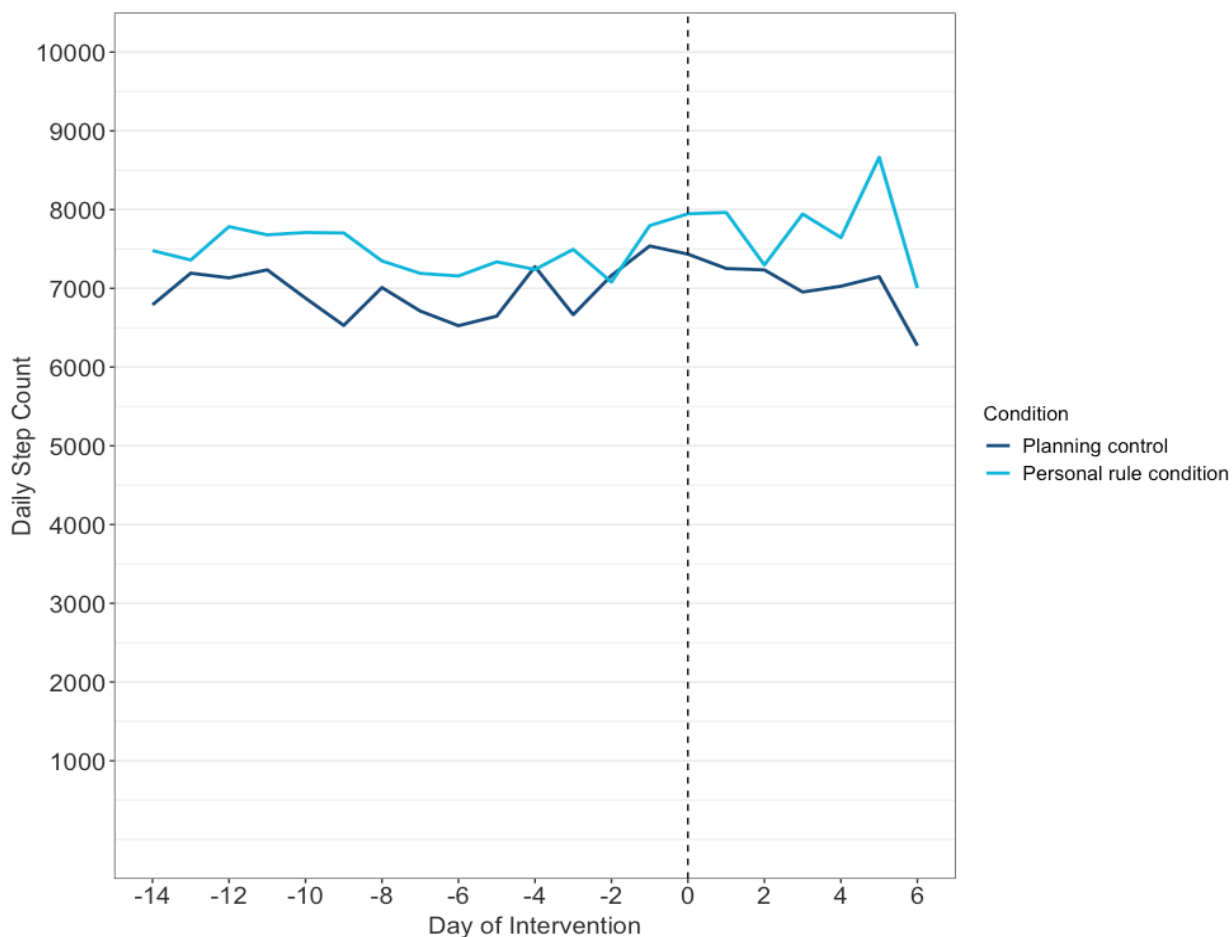
In total, 28% of the participants who began the survey provided Fitbit data, were randomized into conditions, and were included in the analysis (see Figure 2). Of the 565 online workers who began the survey, 339 participants (60%) dropped out prior to reaching the Fitbit data sharing instructions page, and 227 participants (40%) reached the instructions. Of these 227 participants, 20 dropped out upon reading the instructions (9%), 51 provided data that had more than five days of 0 step count (22%), and the remaining 156 participants (69%) provided valid data and proceeded to be randomized into the two conditions. Three people dropped out before completing the full survey and one participant revoked access to their step count data during the intervention week; all are still included in the analysis.

In the 30 days prior to the intervention, participants took an average of 7,288 steps (see Table 1). There was no difference between the mean pre-intervention daily step count for the planning control group and the personal rule condition (707.69, 95% CI: [-339.00, 1754.38]; $p = .184$). As context, the average American walks 5,117 steps per day (Bassett et al., 2010) and a typical day's step count for a healthy adult is between 6,000 and 7,000, excluding sports and exercise (Tudor-Locke & Bassett, 2004). One hundred and forty-nine participants walked every day and synced their Fitbit with their mobile after the intervention week ended – this meant they had no days with 0 step count. Seven participants had between one and seven days with 0 step count. There was no significant difference ($ps > .05$) between the treatment and control groups in race, age, gender. Baseline step count did not differentially affect during-intervention step count between conditions.

During the week of the intervention, the planning control group took 103.29 more steps than they did prior to the intervention (95% CI: [-161.05 to 367.63]; $p = .444$). The personal rule group took 183.54 more steps than they did prior to the intervention (95% CI: [-80.42 to 447.50; $p = .173$). Participants in the personal rule condition took 80.26 additional daily steps (95% CI: [-293.36 to 453.88]) relative to the participants in the planning control during the intervention period ($p = .674$). This difference was not significant (see Table 2).

Figure 3

Comparison of Step Count Change During Intervention Between Planning Control and Personal Rule Condition



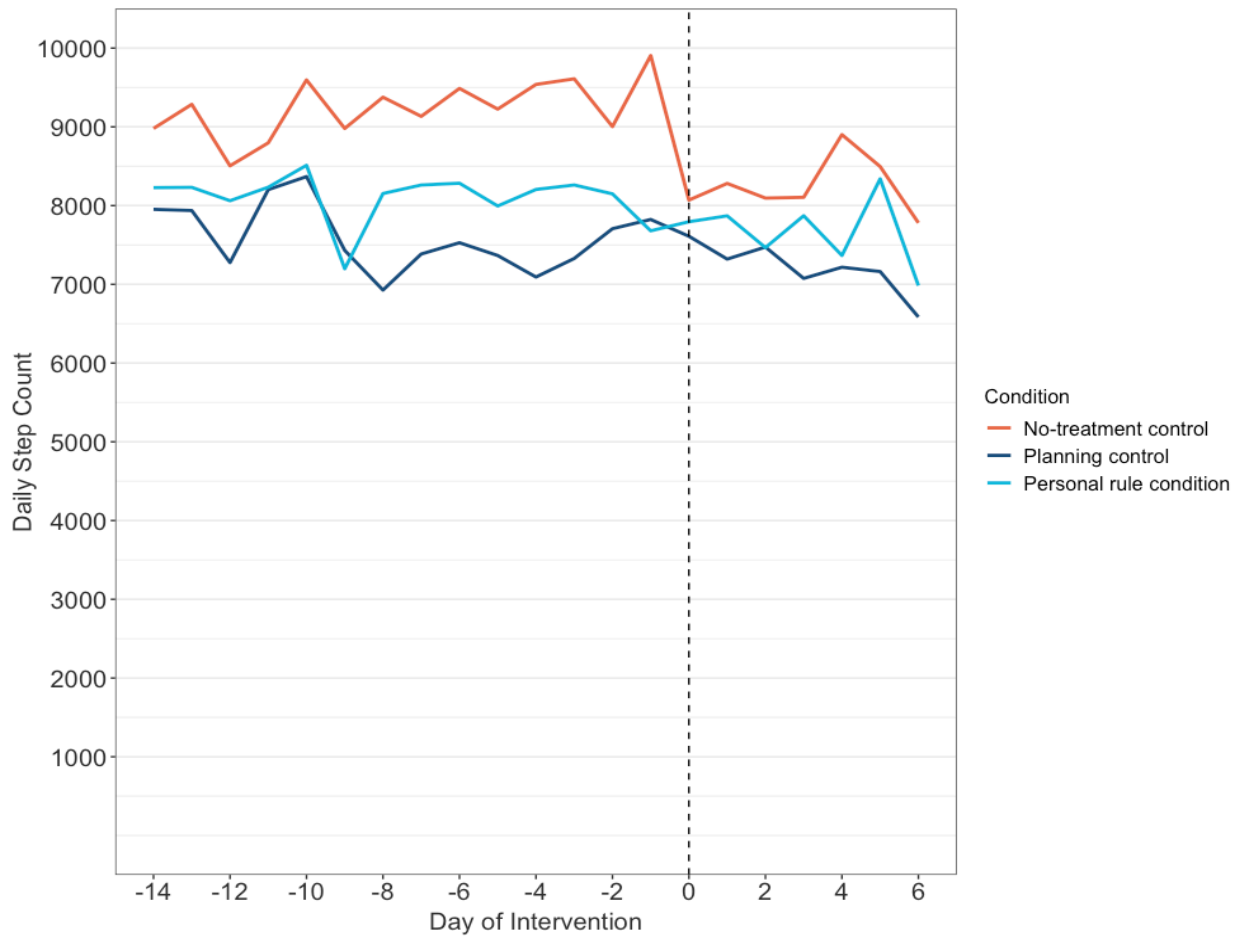
Note. The dotted line represents the first day of the seven-day intervention. Negative days indicate days prior to the intervention; two weeks of pre-intervention data is displayed.

Both the planning control and the personal rules condition increased step count compared to the no-treatment control group (planning control: 522.34; 95% CI: [20.49 to 1024.19 steps]; $p = .041$; personal rules condition: 463.58; 95% CI: [-23.22 to 950.37 steps]; $p = .062$); see Table 3.² We found qualitatively similar results when we removed step count data less than 2000 steps rather than imputing it (see Table 4).

² The no-treatment control group began their intervention before the coronavirus outbreak. To ensure the pre-intervention data did not systematically differ across conditions, we used a pre-intervention period based on the 30 days before the no-treatment control began their intervention. Because a different pre-intervention period is used, the results differ slightly from the analysis with just the planning control and the personal rule condition.

Figure 4

Comparison of Step Count Change During Intervention Between Planning Control, Personal Rule Condition, and No-treatment Control Group



Discussion

In a one-week intervention administered to online workers, we compared the effect of personal rules and plans on step count measured by Fitbit. Both personal rules and plans increased step count compared to a comparison no-treatment control group, but there was no difference between the effect of personal rules and plans on step count.

What theoretical inferences can be drawn from this study? The study replicated prior findings that plans increase self-control choices. The lack of significant difference between plans

and personal rules could be interpreted as evidence that personal rules are no more effective than plans. An alternative interpretation is that personal rules increase self-control choices more than plans, but this intervention did not capture their effect. This may be due to the limitations of a step count intervention, lack of social accountability, lack of iteration, and insufficient self-monitoring.

The domain of step count may have dampened the effect of personal rules. The coronavirus pandemic and weather constraints meant some actions to increase step count could not be consistently taken. This may have caused personal rules to backfire. Studies on dieting have demonstrated that deviating from a goal can cause people to abandon attempts to exert self-control; this is known as the “what the hell” effect (Cochran & Tesser, 1996; Polivy & Herman, 1985). Breaking a personal rule once may similarly induce participants to give up on the rule altogether (Ainslie & Haslam, 1992). Participants may not have been sufficiently motivated; at baseline, participants already had a higher average daily step count than that of a typical healthy adult. Low motivation may have prevented participants from forming a genuine internal commitment to their rule. Finally, walking is a relatively low-effort activity that may not have made identities such as healthiness salient. It may be necessary to form personal rules about behaviors that are strongly linked to one’s identity, or prime identities prior to rule formation.

This intervention did not require participants to share their rule with other people. However, the power of personal rules may stem from social accountability. Vegetarianism, which entails a rule of not eating meat, regulates self-control in part due to the social identity surrounding the label (Rosenfeld & Burrow, 2017). Many of Gandhi’s vows were public and provided justifications for not engaging in an easily observed behavior (Kirby, 2014). The potential to provide excuses, both internally and externally, is an appealing component of

personal rules. If an individual makes a rule to “Never respond to emails after 10pm,” they can easily excuse themselves from responding to emails by citing the rule to others. The individual can also stop responding to emails at 10pm *without* sending a signal to themselves about the kind of person they are; the rule exempts an action from self-signaling traits like laziness.

Personal rules may require iteration and a gradual increase in difficulty over time, a process which was not possible in this week-long intervention. Self-efficacy has been shown to be important for self-controlled behavior (Bandura, 1997). To follow personal rules, people need sufficiently high pre-existing self-efficacy to be willing to stake their perception of their self-control on a choice (Bénabou & Tirole, 2004). Given people’s tendency to be over-optimistic about their goals (Norcross & Vangarelli, 1988; Garon et al., 2015), it may be most effective to start with small rules, iterate to improve them, and increase the difficulty of rules over time.

Personal rules may require more explicit prompts to examine behavior. Bénabou & Tirole (2004) suggest that a behavioral rule such as “I will save at least \$500 each month” should be accompanied by a cognitive monitoring rule such as “I will check my savings account...every month” (Bénabou & Tirole, 2004, p. 879). Although the Fitbit app can facilitate self-monitoring, this study did not require participants to monitor themselves. More explicit prompts, such as a cognitive rule or a recommendation to check the Fitbit app daily, may be necessary to capture the effect of personal rules.

Limitations and Future Directions

This study has several limitations. The study was underpowered due to the coronavirus outbreak; it was not possible to run a large week-long study amid social distancing uncertainty. A larger sample size would be necessary to detect the small effect sizes often observed for step count interventions (Romeo et al., 2019). Only 27% of those who began the survey authorized

access to their Fitbit data and were randomized into conditions. Those who persisted in the intervention are likely to be different from an average member of the population. We sent participants daily reminders including the text of their rule and encouragement to increase their step count. However, outside of a study context, people do not receive reminders and indications that someone is observing their actions.

Much remains for future research to investigate. To explore the relationship between personal rules and social accountability, future studies could pair participants and determine the effect of publicly stated rules, or study personal rules in a socially observable domain such as social media communication. To attenuate the cost of rigidity, future interventions could use conditional rules that account for obstacles, such as: “I always go for a run except when it is raining.” Conditional rules can be consistently followed as they allow for extenuating circumstances (Kirby, 2014). Additionally, we developed a self-monitoring dashboard that participants could use to view their step count change during the intervention (although it was not used in this study). Future studies could employ similar methods to increase self-monitoring. To link personal rules more strongly to identity, future interventions could include questions such as: What kind of person am I? What behaviors would the kind of person that I am follow?

In addition, more clarity is needed on different types of personal rules, how personal rules increase self-control, and potential moderators. Future research could investigate the difference between rules related to one’s character such as “I never lie,” excuse-based rules such as “I never respond to emails after 10pm,” and concrete action-based rules such as “I always walk around the block every day.” Personal rules have been posited to both change the cost-benefit analysis in a self-control choice (by increasing the cost of temptation and identity signaling), and skip the cost-benefit analysis (by enabling automatic behaviors). Personal rules literature would benefit

from more research on whether and how these processes trade off. Finally, it would be valuable to test potential moderators of personal rules such as self-efficacy, motivation, and the extent to which the goal is valued.

Conclusion

Personal rules are a potentially valuable yet under-investigated self-control strategy. This study demonstrated that personal rules are as effective as plans in the domain of step count. However, the limitations and conditions of this study may have dampened the effect of personal rules. Future research is required to determine conditions under which the potential value of personal rules could be fully harnessed.

References

- Ainslie, G. (1975). Specious reward: A behavioral theory of impulsiveness and impulse control. *Psychological Bulletin*, 82(4), 463–496. <https://doi.org/10.1037/h0076860>
- Ainslie, G. (1992). *Picoeconomics: the strategic interaction of successive motivational states within the person*. Cambridge University Press.
- Ainslie, G. (2012). Pure hyperbolic discount curves predict “eyes open” self-control. *Theory and Decision*, 73(1), 3–34. doi: 10.1007/s11238-011-9272-5
- Ainslie, G., & Haslam, N. (1992). Self-control. In G. Loewenstein & J. Elster (Eds.), *Choice over time* (p. 177–209). Russell Sage Foundation.
- Ainslie, G., & Monterosso, J. R. (2003). Building Blocks Of Self-Control: Increased Tolerance For Delay With Bundled Rewards. *Journal of the Experimental Analysis of Behavior*, 79(1), 37–48. <https://doi.org/10.1901/jeab.2003.79-37>
- Bachireddy, C., Joung, A., John, L. K., Gino, F., Tuckfield, B., Foschini, L., & Milkman, K. L. (2019). Effect of Different Financial Incentive Structures on Promoting Physical Activity Among Adults. *JAMA Network Open*, 2(8). doi: 10.1001/jamanetworkopen.2019.9863
- Bandura, A. (1997). *Self-efficacy the exercise of control*. Freeman.
- Bassett, D. R., Toth, L. P., Lamunion, S. R., & Crouter, S. E. (2017). Step Counting: A Review of Measurement Considerations and Health-Related Applications. *Sports Medicine*, 47(7), 1303–1315. <https://doi.org/10.1007/s40279-016-0663-1>
- Baumeister, R. F., & Tierney, J. (2012). *Willpower: rediscovering the greatest human strength*. Penguin Books.
- Baumeister, R. F., Vohs, K. D., & Tice, D. M. (2007). The Strength Model of Self-Control.

- Current Directions in Psychological Science*, 16(6), 351–355. doi: 10.1111/j.1467-8721.2007.00534.x
- Bénabou, R., & Tirole, J. (2004). Willpower and Personal Rules. *Journal of Political Economy*, 112(4), 848–886. doi: 10.1086/421167
- Berger, J., & Rand, L. (2008). Shifting Signals to Help Health: Using Identity Signaling to Reduce Risky Health Behaviors. *Journal of Consumer Research*, 35(3), 509–518. <https://doi.org/10.1086/587632>
- Berkman, E. T., Livingston, J. L., & Kahn, L. E. (2017). Finding The “Self” in Self-Regulation: The Identity-Value Model. *Psychological Inquiry*, 28(2-3), 77–98. <https://doi.org/10.1080/1047840x.2017.1323463>
- Berns, G. S., Laibson, D., & Loewenstein, G. (2007). Intertemporal choice – toward an integrative framework. *Trends in Cognitive Sciences*, 11(11), 482–488. doi: 10.1016/j.tics.2007.08.011
- Beshears, J., Milkman, K. L., & Schwartzstein, J. (2016). Beyond Beta-Delta: The Emerging Economics of Personal Plans. *American Economic Review*, 106(5), 430–434. <https://doi.org/10.1257/aer.p20161100>
- Bize, R., Johnson, J. A., & Plotnikoff, R. C. (2007). Physical activity level and health-related quality of life in the general adult population: A systematic review. *Preventive Medicine*, 45(6), 401–415. doi: 10.1016/j.ypmed.2007.07.017
- Bodner, R., & Prelec, D. (2003). Self-Signaling and Diagnostic Utility in Everyday Decision Making. In I. Brocas & J. Carrillo (Eds.), *The Psychology of Economic Decisions. Volume I: Rationality and Well-Being* (p. 105–26). Oxford: Oxford University Press.
- Bryan, G., Karlan, D., & Nelson, S. (2010). Commitment Devices. *Annual Review of*

- Economics*, 2(1), 671–698. doi: 10.1146/annurev.economics.102308.124324
- Burke, L. E., Wang, J., & Sevick, M. A. (2011). Self-Monitoring in Weight Loss: A Systematic Review of the Literature. *Journal of the American Dietetic Association*, 111(1), 92–102. doi: 10.1016/j.jada.2010.10.008
- Case, M. A., Burwick, H. A., Volpp, K. G., & Patel, M. S. (2015). Accuracy of Smartphone Applications and Wearable Devices for Tracking Physical Activity Data. *JAMA*, 313(6), 625–626. <https://doi.org/10.1001/jama.2014.17841>
- Clarke, T. C., Norris, T., Schiller, J. S. (2016). *Early Release of Selected Estimates Based on Data From the 2016 National Health Interview Survey (05/2017)*. National Center for Health Statistics.
- Cochran, W., & Tesser, A. (1996). The “what the hell” effect: Some effects of goal proximity and goal framing on performance. In L. L. Martin & A. Tesser (Eds.), *Striving and feeling: Interactions among goals, affect, and self-regulation* (p. 99-120). New York: Psychology press
- Conn, V. S., Hafdahl, A. R., & Mehr, D. R. (2011). Interventions to Increase Physical Activity Among Healthy Adults: Meta-Analysis of Outcomes. *American Journal of Public Health*, 101(4), 751–758. doi: 10.2105/ajph.2010.194381
- Coughlin, S. S., & Stewart, J. (2016). Use Of Consumer Wearable Devices To Promote Physical Activity: A Review Of Health Intervention Studies. *Journal of Environment and Health Science*, 2(6), 1–6. doi: 10.15436/2378-6841.16.1123
- Crescioni, A. W., Ehrlinger, J., Alquist, J. L., Conlon, K. E., Baumeister, R. F., Schatschneider,

- C., & Dutton, G. R. (2011). High trait self-control predicts positive health behaviors and success in weight loss. *Journal of Health Psychology, 16*(5), 750–759. doi: 10.1177/1359105310390247
- Duckworth, A. L. (2011). The significance of self-control. *Proceedings of the National Academy of Sciences, 108*(7), 2639–2640. doi: 10.1073/pnas.1019725108
- Duckworth, A. L., Taxer, J. L., Eskreis-Winkler, L., Galla, B. M., & Gross, J. J. (2019). Self-Control and Academic Achievement. *Annual Review of Psychology, 70*(1), 373–399. doi: 10.1146/annurev-psych-010418-103230
- El-Amrawy, F., & Nounou, M. I. (2015). Are Currently Available Wearable Devices for Activity Tracking and Heart Rate Monitoring Accurate, Precise, and Medically Beneficial? *Healthcare Informatics Research, 21*(4), 315. <https://doi.org/10.4258/hir.2015.21.4.315>
- Fan, M., & Jin, Y. (2013). Obesity and Self-control: Food Consumption, Physical Activity, and Weight-loss Intention. *Applied Economic Perspectives and Policy, 36*(1), 125–145. doi: 10.1093/aep/ppt034
- Festinger, L. (1962). Cognitive dissonance. *Scientific American, 207*(4), 93–107. <https://doi.org/10.1038/scientificamerican1062-93>
- Fitbit Development: Activity & Exercise Logs. (n.d.). Retrieved from <https://dev.fitbit.com/build/reference/web-api/activity/>
- Franklin, B. (1726). Plan of Conduct. Retrieved from <https://founders.archives.gov/documents/Franklin/01-01-02-0030>
- Fujita, K., & Han, H. A. (2009). Moving Beyond Deliberative Control of Impulses. *Psychological Science, 20*(7), 799–804. doi: 10.1111/j.1467-9280.2009.02372.x
- Fujita, K., & Roberts, J. C. (2010). Promoting prospective self-control through abstraction.

- Journal of Experimental Social Psychology*, 46(6), 1049–1054.
<https://doi.org/10.1016/j.jesp.2010.05.013>
- Fujita, K., Trope, Y., Liberman, N., & Levin-Sagi, M. (2006). Construal levels and self-control. *Journal of Personality and Social Psychology*, 90(3), 351–367.
<https://doi.org/10.1037/0022-3514.90.3.351>
- Gandhi, M. (1930). Letter to J.C. Kumarapa, 31 Oct 1930. *CWMG*, 50, 240. Retrieved from
<https://www.gandhiashramsevagram.org/gandhi-literature/mahatma-gandhi-collected-works-volume-50.pdf>.
- Gardner, B., Bruijn, G.-J. D., & Lally, P. (2011). Habit, identity, and repetitive action: A prospective study of binge-drinking in UK students. *British Journal of Health Psychology*, 17(3), 565–581. <https://doi.org/10.1111/j.2044-8287.2011.02056.x>
- Garon, J.-D., Masse, A., & Michaud, P.-C. (2015). Health club attendance, expectations and self-control. *Journal of Economic Behavior & Organization*, 119, 364–374.
<https://doi.org/10.1016/j.jebo.2015.08.015>
- Gollwitzer, P. M. (1999). Implementation intentions: Strong effects of simple plans. *American Psychologist*, 54(7), 493–503. doi: 10.1037/0003-066x.54.7.493
- Gollwitzer, P. M., & Bargh, J. A. (Eds.). (1996). *The psychology of action: Linking cognition and motivation to behavior*. Guilford Press.
- Gross, J. J. (1998). The Emerging Field of Emotion Regulation: An Integrative Review. *Review of General Psychology*, 2(3), 271–299. doi: 10.1037/1089-2680.2.3.271
- Heyman, Gene. (1996). Resolving the contradictions of addiction. *Behavioral and Brain Sciences*. 19. 561 - 574. 10.1017/S0140525X00042990.
- Hofmeyr, A., Ainslie, G., Charlton, R., & Ross, D. (2010). The relationship between addiction

- and reward bundling: an experiment comparing smokers and non-smokers. *Addiction*, *106*(2), 402–409. <https://doi.org/10.1111/j.1360-0443.2010.03166.x>
- Joyce, B., Joyce, J., & Chase, P. (1989). Considerations for the Use of Rules in Academic Settings. *Education and Treatment of Children*, *12*(1), 82-92. Retrieved April 27, 2020, from www.jstor.org/stable/42899096
- Kanejima, Y., Kitamura, M., & Izawa, K. P. (2018). Self-monitoring to increase physical activity in patients with cardiovascular disease: a systematic review and meta-analysis. *Aging Clinical and Experimental Research*, *31*(2), 163–173. <https://doi.org/10.1007/s40520-018-0960-7>
- Kirby, K. N. (2014). Gandhi, vows, and the psychology of self control. *Gandhi Marg*, *35*(4), 519-540.
- Kirby, K. N., & Guastello, B. (2001). Making choices in anticipation of similar future choices can increase self-control. *Journal of Experimental Psychology: Applied*, *7*(2), 154–164. Doi: 10.1037//1076-898x.7.2.154
- Kramer, J.-N., Künzler, F., Mishra, V., Smith, S. N., Kotz, D., Scholz, U., ... Kowatsch, T. (2020). Which Components of a Smartphone Walking App Help Users to Reach Personalized Step Goals? Results From an Optimization Trial. *Annals of Behavioral Medicine*. <https://doi.org/10.1093/abm/kaaa002>
- Kudadjie-Gyamfi, E., & Rachlin, H. (1996). Temporal Patterning in Choice among Delayed Outcomes. *Organizational Behavior and Human Decision Processes*, *65*(1), 61–67. <https://doi.org/10.1006/obhd.1996.0005>
- Loewenstein, G., (1992). The Fall and Rise of Psychological Explanations in the Economics of

- Intertemporal Choice. In G. Loewenstein & J. Elster (Eds.), *Choice over time* (p. 3–34). Russell Sage Foundation.
- Magen, E., & Gross, J. J. (2007). Harnessing the need for immediate gratification: Cognitive reconstrual modulates the reward value of temptations. *Emotion*, 7(2), 415–428. Doi: 10.1037/1528-3542.7.2.415
- March, J. G., & Olsen, J. P. (2008). The Logic of Appropriateness. *Oxford Handbooks Online*. <https://doi.org/10.1093/oxfordhb/9780199548453.003.0034>
- Meardon, S. J., & Ortmann, A. (1996). Self-Command In Adam Smith’s Theory Of Moral Sentiments. *Rationality and Society*, 8(1), 57–80. doi: 10.1177/104346396008001003
- Milkman, K.L., Beshears, J., Choi, J.J., Laibson, D., & Madrian, B.C. (2012). Following through on Good Intentions: The Power of Planning Prompts. *National Bureau of Economic Research*.
- Milkman, K. L., Rogers, T., & Bazerman, M. H. (2008). Harnessing Our Inner Angels and Demons: What We Have Learned About Want/Should Conflicts and How That Knowledge Can Help Us Reduce Short-Sighted Decision Making. *Perspectives on Psychological Science*, 3(4), 324–338. doi: 10.1111/j.1745-6924.2008.00083.x
- Moffitt, T. E., Arseneault, L., Belsky, D., Dickson, N., Hancox, R. J., Harrington, H., ... Caspi, A. (2011). A gradient of childhood self-control predicts health, wealth, and public safety. *Proceedings of the National Academy of Sciences*, 108(7), 2693–2698. doi: 10.1073/pnas.1010076108
- Morris, J. N., & Hardman, A. E. (1997). Walking to health. *Sports Medicine*, 23(5), 306–332. <https://doi.org/10.2165/00007256-199723050-00004>
- Norcross, J. C., & Vangarelli, D. J. (1988). The resolution solution: Longitudinal examination of

- New Year's change attempts. *Journal of Substance Abuse*, *1*(2), 127–134. doi: 10.1016/s0899-3289(88)80016-6
- Patel, M. S., Small, D. S., Harrison, J. D., Fortunato, M. P., Oon, A. L., Rareshide, C. A. L., ... Hilbert, V. (2019). Effectiveness of Behaviorally Designed Gamification Interventions With Social Incentives for Increasing Physical Activity Among Overweight and Obese Adults Across the United States. *JAMA Internal Medicine*, *179*(12), 1624. doi: 10.1001/jamainternmed.2019.3505
- Polivy, J., & Herman, C. P. (1985). Dieting and bingeing: A causal analysis. *American Psychologist*, *40*(2), 193–201. <https://doi.org/10.1037/0003-066X.40.2.193>
- Prelec, D., & Bodner, R. (2003). Self-signaling and self-control. In G. Loewenstein, D. Read, & R. Baumeister (Eds.), *Time and decision: Economic and psychological perspectives on intertemporal choice* (p. 277–298). Russell Sage Foundation.
- Quattrone, G. A., & Tversky, A. (1984). Causal versus diagnostic contingencies: On self-deception and on the voters illusion. *Journal of Personality and Social Psychology*, *46*(2), 237–248. doi: 10.1037//0022-3514.46.2.237
- Rachlin, H. (2000). *The science of self-control*. Cambridge, MA: Harvard Univ. Press.
- Read, D., Loewenstein, G., & Kalyanaraman, S. (1999). Mixing virtue and vice: combining the immediacy effect and the diversification heuristic. *Journal of Behavioral Decision Making*, *12*(4), 257–273. [https://doi.org/10.1002/\(sici\)1099-0771\(199912\)12:43.0.co;2-6](https://doi.org/10.1002/(sici)1099-0771(199912)12:43.0.co;2-6)
- Read, D., Loewenstein, G., & Rabin, M. (1999). Choice Bracketing. *Journal of Risk and Uncertainty*, *19*(1/3), 171-197. Retrieved May 12, 2020, from www.jstor.org/stable/41760959
- Richardson, C. R., Newton, T. L., Abraham, J. J., Sen, A., Jimbo, M., & Swartz, A. M. (2008). A

- Meta-Analysis of Pedometer-Based Walking Interventions and Weight Loss. *The Annals of Family Medicine*, 6(1), 69–77. doi: 10.1370/afm.761
- Rogers, T., Milkman, K. L., John, L. K., & Norton, M. I. (2015). Beyond good intentions: Prompting people to make plans improves follow-through on important tasks. *Behavioral Science & Policy*, 1(2), 33–41. doi: 10.1353/bsp.2015.0011
- Romeo, A., Edney, S., Plotnikoff, R., Curtis, R., Ryan, J., Sanders, I., ... Maher, C. (2019). Can Smartphone Apps Increase Physical Activity? Systematic Review and Meta-Analysis. *Journal of Medical Internet Research*, 21(3). <https://doi.org/10.2196/12053>
- Rosenfeld, D. L., & Burrow, A. L. (2017). The unified model of vegetarian identity: A conceptual framework for understanding plant-based food choices. *Appetite*, 112, 78–95. <https://doi.org/10.1016/j.appet.2017.01.017>
- Roumen, C., Blaak, E. E., & Corpeleijn, E. (2009). Lifestyle intervention for prevention of diabetes: determinants of success for future implementation. *Nutrition Reviews*, 67(3), 132–146. doi: 10.1111/j.1753-4887.2009.00181.x
- Sattelmair, J., Pertman, J., Ding, E. L., Kohl, H. W., Haskell, W., & Lee, I.-M. (2011). Dose Response Between Physical Activity and Risk of Coronary Heart Disease. *Circulation*, 124(7), 789–795. doi: 10.1161/circulationaha.110.010710
- Schelling, T. C. (1984). Self-Command in Practice, in Policy, and in a Theory of Rational Choice, *American Economic Review* 74(2), 1-11.
- Schmitz, B., & Perels, F. (2011). Self-monitoring of self-regulation during math homework behaviour using standardized diaries. *Metacognition and Learning*, 6(3), 255–273. <https://doi.org/10.1007/s11409-011-9076-6>
- Schunk, D. H. (1983). Progress self-monitoring: Effects on children's self-efficacy and

- achievement. *Journal of Experimental Education*, 51, 89-93.
- Shimon, J. M., & Petlichkoff, L. M. (2009). Impact of Pedometer Use and Self-Regulation Strategies on Junior High School Physical Education Students' Daily Step Counts. *Journal of Physical Activity and Health*, 6(2), 178–184. doi: 10.1123/jpah.6.2.178
- Tardon, A., Lee, W. J., Delgado-Rodriguez, M., Dosemeci, M., Albanes, D., Hoover, R., & Blair, A. (2005). Leisure-time physical activity and lung cancer: a meta-analysis. *Cancer Causes & Control*, 16(4), 389–397. doi: 10.1007/s10552-004-5026-9
- Teychenne, M., Ball, K., & Salmon, J. (2008). Physical activity and likelihood of depression in adults: A review. *Preventive Medicine*, 46(5), 397–411. doi: 10.1016/j.ypmed.2008.01.009
- Touré-Tillery, M., & Fishbach, A. (2015). It was(n't) me: Exercising restraint when choices appear self-diagnostic. *Journal of Personality and Social Psychology*, 109(6), 1117–1131. <https://doi.org/10.1037/a0039536>
- Verplanken, B., & Sui, J. (2019). Habit and Identity: Behavioral, Cognitive, Affective, and Motivational Facets of an Integrated Self. *Frontiers in Psychology*, 10. doi: 10.3389/fpsyg.2019.01504
- Wiese, C. W., Tay, L., Duckworth, A. L., D'Mello, S., Kuykendall, L., Hofmann, W., ... Vohs, K. D. (2017). Too much of a good thing? Exploring the inverted-U relationship between self-control and happiness. *Journal of Personality*, 86(3), 380–396. doi: 10.1111/jopy.12322
- Wood, W., & Neal, D. T. (2007). A new look at habits and the habit-goal interface. *Psychological Review*, 114(4), 843-863. <http://dx.doi.org/10.1037/0033-295X.114.4.843>
- Yeomans, M., & Reich, J. (2017). Planning prompts increase and forecast course completion in

massive open online courses. *Proceedings of the Seventh International Learning Analytics & Knowledge Conference*. doi: 10.1145/3027385.3027416

Zimmerman, B.J. and Paulsen, A.S. (1995), Self-monitoring during collegiate studying: An invaluable tool for academic self-regulation. *New Directions for Teaching and Learning*, 1995: 13-27. doi:10.1002/tl.37219956305

Appendix

Table 1

Step Count Across Conditions Pre- and During-intervention

	N	Pre		During	
		Mean	SD	Mean	SD
Control	73	6,911	3,325	7,014	3,752
Personal Rule	83	7,619	3,277	7,778	3,456
Total	156	7,288	3,308	7,421	3,606

Table 2*Comparison of Step Count Change Across Planning Control and Personal Rule Condition*

	Estimate	SE	t-value	95% CI		p-value
				LL	UL	
During Intervention	103.29	134.83	0.77	-161.05	367.63	0.444
Personal Rule * During Intervention	80.26	190.57	0.42	-293.36	453.88	0.674

Note. OLS with person-by-day-of-week fixed effects and clustered standard errors by person-by-day-of-week.

Table 3

Comparison of Step Count Change Across Planning Control, Personal Rule Condition, and No-treatment Control

	Estimate	SE	t-value	95% CI		p-value
				LL	UL	
During Intervention Planning Control *	-853.71	193.22	-4.42	-1232.50	-474.92	<.001
During Intervention Personal Rule * During Intervention	522.34	255.99	2.04	20.49	1024.19	0.041
	463.58	248.31	1.87	-23.22	950.37	0.062

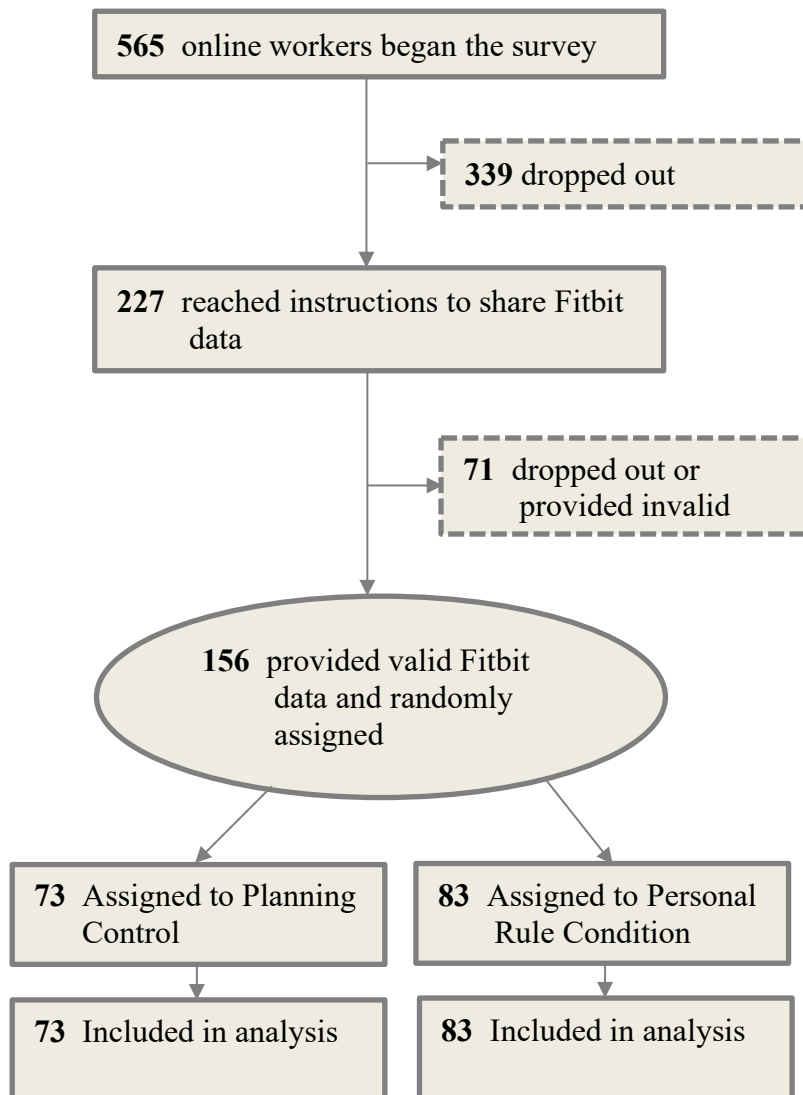
Note. OLS with person-by-day-of-week fixed effects and clustered standard errors by person-by-day-of-week.

Table 4







Comparison of Step Count Change Across Planning Control and Personal Rule Condition, Step Count < 2000 Removed



	Estimate	SE	t-value	95% CI		p-value
				LL	UL	
During Intervention	103.26	156.97	0.77	-187.50	428.02	0.444
Personal Rule * During Intervention	80.83	216.09	0.374	-342.83	504.48	0.708

Note. OLS with person-by-day-of-week fixed effects and clustered standard errors by person-by-day-of-week. Days with steps less than 2000 were removed rather than replaced with pre-intervention averages.

Figure 2*Study Flow Diagram*

Intervention Text

Personal Rule Condition	Planning Control
<p>With COVID-19 disrupting our lives, it can be hard to stay healthy. Luckily, this change is also a great opportunity to create new healthy behaviors.</p> <p>We want to help you to create healthy behaviors around step count using your Fitbit.</p> <p>Physical activity is associated with many positive outcomes, including:</p> <ul style="list-style-type: none">  Happier mood  Less stress  Less risk of disease  More energy  Weight reduction  Better sleep 	
<p>Currently, walking and running outside is:</p> <ol style="list-style-type: none"> 1. Safe (as long as you practice social distancing) 2. Exempt from "stay at home" and "lockdown" orders in the United States <p>Don't believe us? Check out these reputable news sources that are encouraging outdoor exercise (New York Times, Today, Insider).</p> <p>Are you able and willing to walk or run outside in the next week?</p> <ul style="list-style-type: none"> ● Yes ● No 	
<p>Great! This is a 5-minute survey to help you increase your step count.</p> <p>To earn \$3.00 today, you must log into your Fitbit account to share your step count history for 30 days. You must have a pre-existing Fitbit account – you will not get paid if you created a Fitbit account today!</p>	

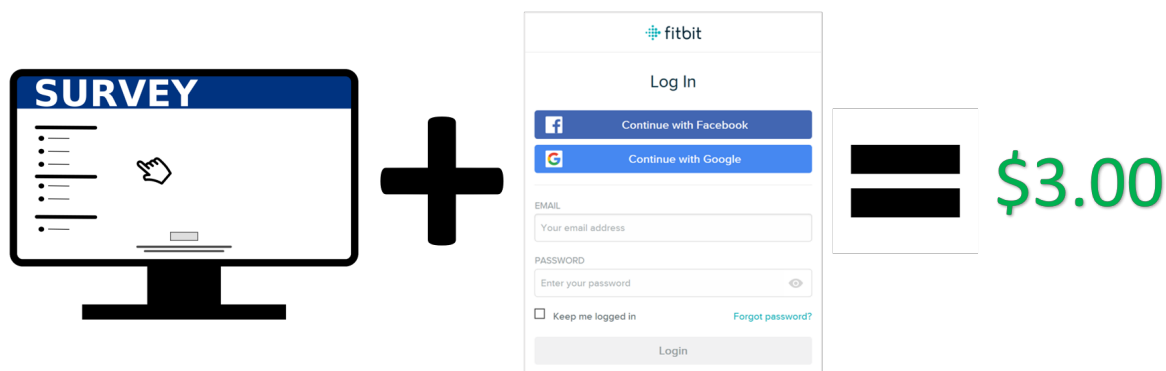
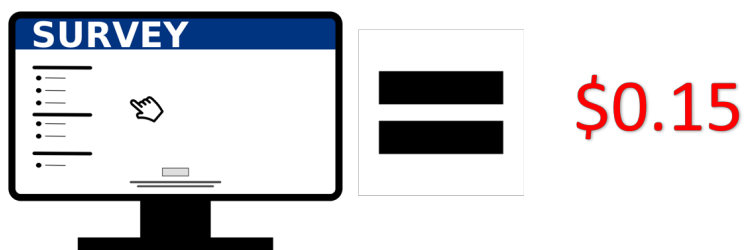
<p>What you are sharing from Fitbit</p> <hr/> <p> Step count history for 30 days before and 30 days after this survey</p>	<p>What you are not sharing</p> <hr/> <p> Name Email Password Profile Any health records</p>
<p><i>Your data will be confidential and strictly used for research purposes only.</i></p> <ul style="list-style-type: none"> • I own a Fitbit and agree to log into my Fitbit account to share my step count history • I do not meet these requirements 	
<p>Please enter your Prolific ID below. By entering your ID, you acknowledge that you have read the consent form below and are consenting to participate.</p>	
<p>[Textbox]</p>	
<p style="text-align: center;">Informed Consent</p> <p>We are researchers at the University of Pennsylvania studying decision making. The survey that linked you to this page will take you approximately 5 minutes to complete, and you will receive \$3.00 for completing the HIT. You must share your step count history from Fitbit for thirty days before and thirty days after the survey in order to complete the HIT. You have the right to revoke access to your step count history at any time, and researcher access to your step count history will automatically expire in 30 days. Every effort will be made to keep all the information you share during the study strictly confidential, except as required by law.</p> <p>Your participation in this research is voluntary. You have the right to withdraw from the study at any point and for any reason without penalty. This includes withdrawing any additional history of activity and exercise that you may authorize through Fitbit, such as previous history beyond thirty days, although researchers will not use that information for their analysis. Your name and other identifying information will never be connected with the responses you provide so no one will ever be able to identify you in any publications that will result from this research.</p> <p>If you have questions about your rights as a volunteer in this research study you can contact the Office of Regulatory Affairs at the University of Pennsylvania at (215)-898-2614.</p>	
<p>It is often difficult for people to motivate themselves to be active by walking. Would you like to walk more?</p> <ul style="list-style-type: none"> • Yes 	

- No

How often do you wear your Fitbit? You will **NOT** be paid the \$3.00 bonus if you forgot to wear your Fitbit for more than 5 days in the past 30 days.

- I wear my Fitbit daily
- I wear my Fitbit occasionally
- I wear my Fitbit rarely or never

Please read this page *carefully* on how to earn \$3.00.



IMPORTANT: You must complete the survey and log into Fitbit to earn \$3.00. We worked with Fitbit and an Ivy League university to build an advanced fraud detection algorithm that can instantaneously detect if you're cheating on the Fitbit login section.

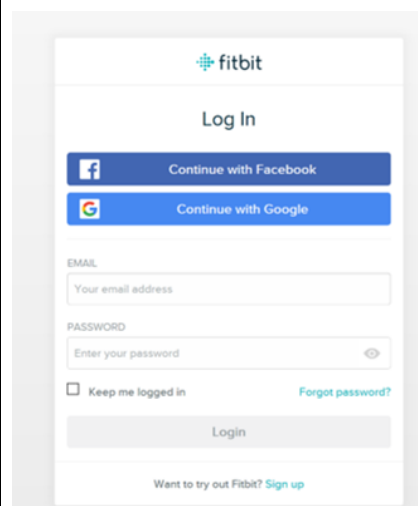
Please be honest with yourself: If you don't already use a Fitbit regularly, don't waste 5 minutes for a meager \$0.15. There are better HITS out there!

- I'm ready to earn the \$3.00 bonus by logging into my Fitbit account.
- I'm no longer interested in earning the \$3.00 bonus by logging into my Fitbit account.

You're almost halfway done with this survey—you **don't want to lose this \$3.00 bonus!**

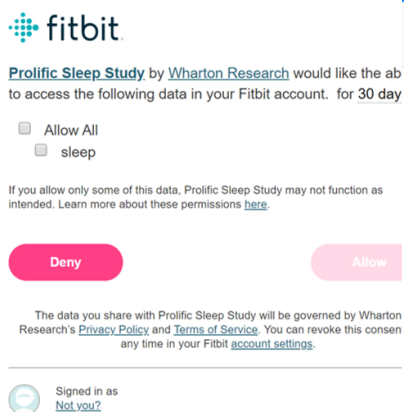
Now, **log into your Fitbit account HERE to share your step count history and receive the password to continue with the survey.** See the images below for help.

1. Login



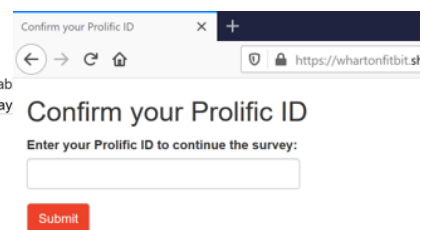
The image shows the Fitbit login page. At the top, there is the Fitbit logo and a "Log In" heading. Below this are two large buttons: "Continue with Facebook" and "Continue with Google". Underneath these are input fields for "EMAIL" (with the placeholder "Your email address") and "PASSWORD" (with the placeholder "Enter your password"). There is a checkbox for "Keep me logged in" and a link for "Forgot password?". A "Login" button is at the bottom, and a "Sign up" link is at the very bottom.

2. Select "Allow All"



The image shows a Fitbit permission screen. At the top is the Fitbit logo. Below it, text says "Prolific Sleep Study by Wharton Research would like the ab to access the following data in your Fitbit account. for 30 day". There are two checkboxes: "Allow All" (checked) and "sleep". Below this is a warning: "If you allow only some of this data, Prolific Sleep Study may not function as intended. Learn more about these permissions here." There are two buttons: "Deny" and "Allow". At the bottom, there is a note: "The data you share with Prolific Sleep Study will be governed by Wharton Research's Privacy Policy and Terms of Service. You can revoke this consent any time in your Fitbit account settings." and a "Signed in as Not you?" link.

3. Submit your MTurk ID



The image shows a browser window titled "Confirm your Prolific ID". The address bar shows "https://whartonfitbit.st". The main heading is "Confirm your Prolific ID". Below it, text says "Enter your Prolific ID to continue the survey:". There is an input field for the Prolific ID and a "Submit" button.

Need to reset your Fitbit password? Click the + button for additional help. + Your password can be reset by clicking on "Forgot password?" with the link provided in Step 1 of the instructions or through the main Fitbit website.

Enter the password to continue:

[textbox]

People we admire, like Benjamin Franklin and Mahatma Gandhi, used *personal rules* to achieve their goals.

A **personal rule** is a **principle you vow to stick to without exception**. It is something that you choose to *always* do, or *never* do.

So, what is a personal rule?

- Something that you choose to always or never do
- A preference you have about how to behave
- Something you wish you did more often

Which of the following is an example of a personal rule?

- Try to use the stairs as much as possible



People we admire, like Benjamin Franklin and Mahatma Gandhi, made *plans* to achieve their goals.

A **plan** is **something you intend to do**.

<ul style="list-style-type: none"> • Only buy baked goods when you get a good grade • Most nights, turn your phone off at 9pm • Never buy sugary drinks 	
<p>Now, let's form a personal rule for you to follow over the next week!</p> <p>1 Think of something you'd like to do that will increase your step count</p> <p><i>Think of something that you can do frequently and is easy to do. It's better to start small, and work your way up! For example, walk around the block. Make sure you think of something you can do while social distancing.</i></p> <p>Over the next week, I'd like to... [textbox]</p>	<p>Now, let's make a plan for you to follow over the next week!</p> <p>1 Think of something you'd like to do that will increase your step count</p> <p><i>Think of something that you can do frequently and is easy to do. It's better to start small, and work your way up! For example, walk around the block. Make sure you think of something you can do while social distancing.</i></p> <p>Over the next week, I'd like to... [textbox]</p>
<p>So you want to: {text}? Awesome! Now:</p> <p>2 Turn it into a rule that starts with 'I always'</p> <p><i>For example, 'I always walk around the block once per day'. The rule should be specific, and something you can follow without exception.</i></p>	<p>So you want to: {text}? Awesome! Now:</p> <p>2 Turn it into a plan that starts with 'I plan to'</p> <p><i>For example, 'I plan to walk around the block once per day'. The plan should be specific, and something you can follow.</i></p>
<p>Great! You've decided to follow the rule:</p> <p>{text}</p> <p>A rule is feasible if you think you can follow</p>	<p>Great! You've decided to follow the plan:</p> <p>{text}</p> <p>A plan is feasible if you think you can follow</p>

<p>it without giving up. How feasible is this rule?</p> <p>{Slider with options:</p> <ul style="list-style-type: none"> ● 1: Not at all feasible ● 2: Not very feasible ● 3: Somewhat feasible ● 4: Very feasible ● 5: Extremely feasible} 	<p>it without giving up. How feasible is this plan?</p> <p>{Slider with options:</p> <ul style="list-style-type: none"> ● 1: Not at all feasible ● 2: Not very feasible ● 3: Somewhat feasible ● 4: Very feasible ● 5: Extremely feasible}
<p>It looks like your rule is not very feasible.</p> <p>To make sure you can follow your rule, choose another rule that is more feasible.</p> <p>The rule should start with 'I always,' be specific, and something you can follow without exception.</p> <p>[textbox]</p>	<p>It looks like your plan is not very feasible.</p> <p>To make sure you can follow your plan, choose another plan that is more feasible.</p> <p>The plan should start with 'I plan to', be specific, and something you can follow.</p> <p>[textbox]</p>
<p>Good job making the feasible rule:</p> <p>{text}</p> <p>Just to <i>really</i> make sure you remember, type out your rule again below:</p> <p>[textbox]</p>	<p>Good job making the feasible plan:</p> <p>{text}</p> <p>Just to <i>really</i> make sure you remember, type out your plan again below:</p> <p>[textbox]</p>
<p>Please answer the following last few questions about your demographics.</p> <p>What is your age?</p> <p>What is your gender?</p> <ul style="list-style-type: none"> ● Male ● Female ● Other <p>What is your race? Select any that apply</p> <ul style="list-style-type: none"> ● American Indian/Alaskan Native ● Asian, Asian-American or Pacific Islander ● African-American/Black 	

- Caucasian/White
- Hispanic/Latino
- Other

 The ultimate reward is a healthier version of yourself, so try your best on the following:
{text} 

Remember to wear your Fitbit and sync it with your phone every day so your step count data is recorded!

If you fall off the wagon, don't worry – try again the next day. We'll send you daily reminders over the next 7 days!

Click the next button to claim your \$3.00 and a healthier you this week!

Daily Reminder Email

Hello! Thank you for taking the Fitbit survey about increasing your step count. You're actively moving towards a healthier you!

Remember to follow what you wrote to increase your step count: [[personalized text]] – and practice social distancing while you do.