

Gamification of behavior change: a mathematical principle and a field experiment

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Gamification of behavior change: a mathematical principle and a field experiment

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Abstract

Background: Many people want to build good habits to become healthier, live longer, or become happier but struggle to change their behavior. Gamification can make behavior change easier by awarding points for the desired behavior and deducting points for its omission.

Objective: Here, we introduce a principled mathematical method for determining how many points should be awarded/deducted for the enactment/omission of the desired behavior depending on when and how often the person has succeeded versus failed to enact it in the past. We call this approach optimal gamification of behavior change.

Methods: As a proof of concept, we design a chatbot that applies our optimal gamification method to help people build a healthy water drinking habit. We evaluated the effectiveness of this gamified intervention in a 40-day long field experiment with two control groups that used the same chatbot without points and without feedback and reminders, respectively.

Results: We found that, during the intervention, users who received feedback based on optimal gamification enacted the desired behavior more often than the active control group or the passive control group. After the intervention the experimental group enacted the desired behavior just as often as the two control groups.

Conclusions: Our findings suggest that optimal gamification can be used to make digital behavior change interventions more effective.

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Original Paper

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Abstract

Background: Many people want to build good habits to become healthier, live longer, or become happier but struggle to change their behavior. Gamification can make behavior change easier by awarding points for the desired behavior and deducting points for its omission.

Objectives: Here, we introduce a principled mathematical method for determining how many points should be awarded/deducted for the enactment/omission of the desired behavior depending on when and how often the person has succeeded versus failed to enact it in the past. We call this approach *optimized gamification of behavior change*.

Methods: As a proof of concept, we design a chatbot that applies our optimized gamification method to help people build healthy water drinking habits. We evaluated the effectiveness of this gamified intervention in a 40-day-long field experiment with one experimental group (n=43) that used the chatbot with optimized gamification and two active control groups for whom the chatbot's optimized gamification feature was disabled. For the first control group (n=48), all other features were available, including verbal feedback. The second control group (n=51) received no feedback and no reminders. We measured the strength of all participants' water-drinking habits before, during, and after the intervention with the Self-Report Habit Index and by asking participants how many days of the previous week they enacted the desired habit. In addition, all participants provided daily reports of whether they enacted their water-drinking intention that day.

Results: A Poisson regression analysis revealed that, during the intervention, users who received feedback based on optimized gamification enacted the desired behavior more often ($M=14.71$ times, $SD=6.57$ times) than the active ($M=11.64$ times, $SD=6.38$ times; $P<.001$; I.R.=0.80, 95% C.I. [0.71; 0.91]) or passive ($M=11.64$ times, $SD=5.43$ times; $P=.001$, I.R. =0.78, 95% C.I. [0.69; 0.89]) control groups. The Self-Report Habit Index significantly increased in all conditions (all $P < .001$) but did not differ between the experimental condition and the control conditions (all $P > .11$). After the intervention, the

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experimental group performed the desired behavior equally often as the two control groups (all $P \geq .17$).

Conclusions: Our findings suggest that optimized gamification can be used to make digital behavior change interventions more effective.

KEYWORDS: gamification; points; feedback; behavior change; habit formation; chatbot; digital interventions; mobile phone; artificial intelligence

Introduction

People often struggle to change their behavior in ways that would benefit them in the long run. For instance, many people could improve their health and life expectancy by building healthy habits, such as exercising [1], healthy eating [2], or drinking a glass of water before every meal [3,4]. People who want to adopt healthy habits because they know about their benefits nevertheless struggle to change their behavior accordingly.

Building a good habit is especially difficult when the benefits of the desired behavior cannot be felt immediately. One approach to alleviate this challenge is creating apps that encourage the desired behavior with incentives or immediate positive feedback [5–7] or discouraging unwanted behavior with immediate negative feedback [8]. Doing so in a gameful way can be a promising approach to improving people's health behaviors [5–7,9–12]. Using game elements to improve people's behavior in the real world is known as gamification [13]. One of the most commonly used gamification methods is awarding people points for specific behaviors [14,15]. The awarded points are often used to provide feedback to the user, define levels, award badges, or create leaderboards.

Despite the widespread use of points, levels, badges, and leaderboards, there is currently no principled way to choose precisely how many points a person should be awarded when. This is a problem because making those decisions based on intuition can lead to point systems that inadvertently incentivize counterproductive behaviors or undermine the users' motivation [16–18]. For instance, a recent study found that the point system of the popular gamified habit formation app Habitica is actively harmful [17].

To help practitioners master the challenge of designing effective point systems that reliably foster positive behavior change, we introduce a mathematical principle for computing the number of points a person should receive for engaging in the desired behavior depending on their history of (not) engaging in this behavior and how many points they should lose when they fail to do so. We call this principle *optimized gamification of behavior change*. As a proof-of-concept, we apply optimized gamification to design a chatbot that helps people develop the healthy habit of drinking water before every meal [3,4]. Our chatbot awards points for the desired behavior and deducts points for its omission. Critically, the number of points the user gains or loses is computed by optimized gamification. Our chatbot combines optimized gamification with three established principles of behavior change. Concretely, it i) guides the user to set an implementation intention, ii) reminds them of their good intentions, and iii) supports self-monitoring.

We evaluated our chatbot in a longitudinal field experiment and found that optimized gamification can make digital behavior change interventions more effective. Our findings provide a proof of concept for a very general and principled approach to improving human behavior in the real world. In addition to this theoretical contribution, we also introduce a chatbot for helping people develop a specific healthy habit (water drinking): the Good Habit Bot. This chatbot can easily be adapted to other health behaviors, including more critical health behaviors, such as exercising, healthy eating, and other good habits people want to establish.

The plan for this article is as follows: We first introduce relevant background information about behavior change and gamification. We then present our theory of optimized gamification for behavior change. Next, we present the chatbot we designed as a proof of principle. After that, we present the methods and results of our field experiment and discuss its findings and implications.

Background

Behavior change goals versus automatic behavior

Human behavior is controlled by a combination of goal-directed decision-making (e.g., "I will buy a gym membership because I want to lose weight.") and more automatic reactions to certain stimuli (e.g., always stopping by the gym on the way home from work) [19]. Goal-directed decision-making derives choices from the outcomes people value (e.g., health or money) or want to avoid (e.g., pain) according to their mental models of how those outcomes can be obtained. By contrast, automatic reactions do not consider the behavior's likely consequences in the current situation.

Two obstacles to behavior change: automaticity and temporal discounting

Most of our behavior is not primarily controlled by goal-directed decision-making but determined by people's automatic reactions. Therefore, automatic behavioral responses can interfere with people's ability to act in accordance with their behavior change goals. This is the proverbial conflict between bad habits versus good intentions. People can inhibit and override their automatic behavioral responses ("bad habits"), but their capacity to do so is limited [20]. Therefore, the automaticity of human behavior is a crucial obstacle to intentional behavior change.

A second obstacle to successful behavior change is that the mechanisms of goal-directed decision-making are demonstrably biased in favor of immediate outcomes [21]. People give too much weight to their decision's immediate consequences and too little weight to their long-term consequences. This phenomenon is known as present bias [22]. It has been proposed that present bias occurs because the brain discounts delayed benefits as if they became less valuable the later they occurred [23]. This phenomenon, which is known as temporal discounting, is well-established in research on economic decisions and animal behavior.

Moreover, according to temporal motivation theory [24], temporal discounting is one of the main reasons people fail to enact good intentions. Such failures of self-regulation are a critical obstacle to health behavior change [25,26]. Consistent with this explanation, people who discount delayed outcomes more strongly are likelier to engage in unhealthy behaviors and suffer from poor health [26].

Reinforcement learning as a mechanism of behavior change

Because automatic responses are a powerful driver of human behavior, successful behavior change typically involves translating behavior change goals into automatic behavioral responses [27].

Automatic behavioral responses, including exercise habits, can be acquired through learning from experience. Model-free reinforcement learning is a well-established mechanism of learning automatic behavioral responses from experience [19]. This mechanism increases or decreases a person's propensity to engage in a specific behavior in a particular situation (e.g., going to the gym after work) according to whether they

experience the behavior's overall consequences as positive versus negative. The vast literature on operant conditioning in animals and humans underscores that learning from reward and punishment is a powerful mechanism of behavior change [28,29]. Another complementary learning mechanism is strengthening habits by mere repetition [30].

Supporting behavior change through incentives and reinforcement

The literature surveyed above demonstrates that goal-directed decision-making and automatic behavioral responses are responsive to rewards and punishments. Goal-directed decision-making is sensitive to anticipated future rewards, and automatic behavioral responses are shaped by the rewards or punishments those behaviors have generated in the past. These effects can be leveraged to support behavior change. To foster behavior change via goal-directed decision-making, behavior change interventions can create and announce incentives for engaging in the desired behavior. To foster behavior change via reinforcement learning, behavior change interventions can reinforce the desired behavior with rewards or positive feedback.

One highly effective behavior change intervention that leverages both effects is contingency management [31]. Contingent management incentivizes a desired behavior change and rewards people when they enact it. Voucher-based reinforcement therapy for treating addiction is a highly successful example of contingent management [32]. This behavior change intervention awards the patient a voucher every time they submit a negative drug test. More recently, it has also been applied to foster other types of behavior change, including physical exercise [7,33] and treatment attendance [34]. Contingency management appears to be more effective when the desired behavior is reinforced more promptly, more frequently, and with rewards that are larger or increase throughout the intervention [35–37].

Digital behavior change interventions

Developing digital behavior change interventions is a young and booming field [38]. Mobile apps have shown potential for fostering positive behavior change in domains such as physical exercise and healthy eating [38,39]. However, the average effect size of such interventions is still relatively small [40,41]. Most behavior change interventions are not derived from any theory, model, or framework [38]. We, therefore, suspect that there is still room for improvement and that at least some of this potential can be realized by adopting a more theory-driven approach.

Goal-setting and self-monitoring are the most commonly used behavior change techniques [38]. A meta-analysis of studies on digital intervention for promoting physical exercise found that those two interventions are also the most effective ingredients of current digital behavior change interventions [41]. Goal-setting entails guiding people to articulate their intent to perform certain behaviors in certain situations (e.g., drinking a glass of water before every meal). Supporting self-monitoring often takes the form of helping people check or record whether they enacted those intentions or track related outcomes (e.g., their weight). Goal-setting is especially effective when people formulate simple plans that specify the intended behavior and the situation in which they want to perform it as concretely as possible [42,43]. This approach is known as *implementation intentions*. Moreover, reminding people of their intentions via text messages [44] and presenting them with positive reinforcement when they enact their intentions [5,7,33] have been found to be highly effective at promoting physical exercise.

Gamification

A recent meta-analysis found that about one in five digital behavioral change interventions are designed within the gamification framework [38]. Gamification is applying principles from game design and game elements, such as storytelling and rules for earning points and winning the game, to address real-world problems [13]. The basic idea is to motivate people to do things that benefit them or others, such as exercising and studying, in a gameful way. Previous research has found that gamification can improve people's behavior, achieve desired outcomes, and improve people's subjective experience [45].

Gamification is already widely used in designing digital behavior change interventions [5], and previous studies suggest that it can improve people's health behaviors [7,9–12,33]. One gamification strategy that is effective in digital behavior change interventions is awarding the user points as positive feedback for desired behavior [5,7,33]. Such extrinsic incentives can increase the frequency of the targeted behaviors without affecting people's intrinsic motivation [46,47].

However, when gamification is not correctly designed, it can backfire and have adverse effects [16,17,48]. This has also been observed in the behavior change literature [12,49] and for gamified habit formation apps [17]. Getting the incentives exactly right can be crucial because points, levels, badges, and leaderboards do not foster the user's intrinsic motivation [46,47] and might sometimes even undermine it when they are not embedded in a compelling narrative [18]. Motivated by these problems, many authors have called for a more theory-driven approach to gamification in general [50] and gamifying digital behavior change interventions in particular [12].

Optimized gamification

Previous work has investigated how many points should be awarded for which behavior to maximally benefit the user in the context of to-do list apps that help the user achieve their own goals [51,52]. Building on temporal motivation theory [24], this work assumed that people's motivation is insufficiently sensitive to long-term benefits, such as good health in old age, and overly sensitive to immediate costs (e.g., the effort of exercising) and short-term pleasure (e.g., from receiving immediate positive feedback). To help people overcome the resulting motivational problems (e.g., procrastination) [53], Lieder et al. [51] developed a mathematical theory for designing point systems that provide immediate positive feedback for activities that are beneficial in the long run and immediate negative feedback for activities that are not. The basic idea is to align each action's immediate and long-term consequences. The action that is best in the long run should be made most appealing in the short run, and actions with undesirable long-term consequences should be made unappealing in the short run.

Optimized gamification, therefore, strives to incentivize each of the available actions by a number of points proportional to how much that action increases or decreases the sum total of future happiness. This idea is implemented by modeling the activities to be incentivized as steps that lead towards a valuable goal or away from it. Actions that lead toward the goal increase the time the person will spend in the more valuable state in which the goal has been achieved. In contrast, actions that lead away from the goal decrease it and increase the effort required to achieve it afterward. Based on this mathematical model, dynamic programming and reinforcement learning methods can estimate how much a given action improves or worsens the person's situation. Those estimates are then translated into incentives that encourage good choices and discourage bad ones. The resulting point values are optimal in that they would enable even a purely myopic decision-maker who only cares about immediate outcomes to choose those actions that are best for them in the long

run [51].

Although optimized gamification construes points as incentives and uses mathematical and computational methods from the field of reinforcement learning, using optimized gamification does not constitute a commitment to behaviorism and is fully compatible with cognitive theories of motivation [54].

Optimized gamification has been used to encourage users to tackle the tasks on their to-do lists [32] and to encourage students to select the most valuable learning activities [55,56]. Optimized gamification has also been applied to give people feedback on how they think about what to do [57] and on whether they succeeded in staying focused on a chosen task or got distracted [58]. However, up until now, this approach has never been applied to support habit formation.

Objectives

The first goal of this article is to introduce a principled method for computing feedback on the enactment or omission of the desired behavior and experimentally test whether it can be used to enhance digital behavior change interventions. The second goal of this article is to introduce a chatbot that uses this method to help people develop healthy water-drinking habits and evaluate it in a longitudinal field experiment.

Methods

Optimized gamification of behavior change

We conceptualize behavior change as a special case of repeatedly choosing and learning when to do what. As reviewed in the Background section, optimized gamification can encourage desired behaviors and accelerate learning [57]. To apply this method to promote the desired behavior and accelerate the formation of healthy habits, we first have to model habit formation as a Markov Decision Process (MDP) [59].

Modeling habit formation

An MDP is a scenario where an agent faces a series of choices. Each choice (a) has two effects. First, it yields an immediate reward (r) that may be positive, negative, or zero.

Second, it may change the state (s) the agent finds itself in. In an MDP, the agent's goal is to maximize the sum of the rewards it accumulates from its first decision to its last one.

We model behavior change problems as a straightforward MDP where a person repeatedly chooses between two possible actions when they find themselves in a particular situation: enacting the desired behavior ($a = 1$) or not enacting it ($a = 0$). Our model assumes that a

given behavior change intervention aims to turn the desired behavior into a habit. Therefore, we define the state as the strength of the person's healthy habit, measured by a single number, s_{habit} , which can range between 0 and 1. Following standard habit formation

models [30], we assume that enacting the habit increases its strength from s_{habit} to $s_{\text{habit}} + \alpha \cdot (1 - s_{\text{habit}})$, where α is a free parameter that describes how quickly habits form.

Conversely, our model assumes that failure to enact the desired behavior decreases the strength of the habit to $s_{\text{habit}} \cdot (1 - \alpha)$. We assume that the habit has been cultivated when

its strength exceeds some threshold θ (e.g., $\theta = 0.9$) and model the health benefits conferred by achieving this goal as a reward (r_{goal}) that is attained when the habit strength crosses this threshold. Enacting the desired behavior is assumed to incur a cost that decreases with the strength of the habit ($f(s_{\text{habit}}, 1) = -(1 - s_{\text{habit}})$) whereas not performing the behavior is assumed to be effortless ($f(s_{\text{habit}}, 0) = 0$).

Computing optimal feedback.

The basic idea of optimized gamification is to reward each action by a number of points that is proportional to its long-term benefits. Those long-term benefits are measured by the decrease in future costs and the increase in future rewards brought about by transitioning into a state where the habit is stronger. In situations where the benefits of developing the good habit outweigh its costs, the value of having a habit of strength s_{habit} and then following through with the process of building the habit is

$$V^*(s_{\text{habit}}) = r_{\text{goal}} - (1 - s_{\text{habit}}) \cdot \sum_{i=1}^{n(s_{\text{habit}}; \theta)} (1 - \alpha)^{i-1},$$

where the number $n(s_{\text{habit}}; \theta)$ specifies how often the behavior must be enacted until the habit strength reaches its target value θ . Therefore, for someone who will follow through with building the habit, the long-term benefits of enacting the habit one more time when its current strength is s_{habit} are

$$f(s_{\text{habit}}, 1) = V^*(s_{\text{habit}} + \alpha \cdot (1 - s_{\text{habit}})) - V^*(s_{\text{habit}}) = 1 - s_{\text{habit}}.$$

Conversely, the long-term costs of failing to enact the desired behavior in the situation where it is supposed to become a habit are

$$f(s_{\text{habit}}, 0) = V^*(s_{\text{habit}} \cdot (1 - \alpha)) - V^*(s_{\text{habit}}).$$

Please note that even though we are talking about a situation where it is rational for people to build the habit, this does not mean we assume people to be rational. For our method, it doesn't matter why people follow through with building the habit. In fact, we assume that some people will follow through with building the habit only because they are (irrationally strongly) motivated by the immediate rewards conferred by feedback.

The lowest possible negative value of f is $f(\theta, 0)$, and the largest possible positive value is $f(0, 1)$. While the exact values depend on the model parameters, they are typically around -1 and 1 , respectively. To transform those values into points, it is therefore desirable to scale them by the desired maximum point value (M) the application should award to the user and then round the scaled values to the nearest integer. This yields the following equation for the number of points that the application should award when a user reports that they have enacted their intention ($a = 1$) or have not enacted their intention ($a = 0$):

$$\text{points}(s_{\text{habit}}, a) = \text{round}(M \cdot f(s_{\text{habit}}, a)). \quad (1)$$

Figure 1 illustrates the point values as a function of the user's habit strength in an example application with a learning rate of $\alpha = 0.1$, a target habit strength of $\theta = 0.9$, and a maximal

point value of $M = 13$. For more details on our mathematical model and the resulting optimal point system, please see Appendix 1.

As illustrated in Figure 1, the number of points for enacting the desired behavior is largest when the habit is weakest and gradually decreases towards zero as the habit strengthens. This is intuitive because performing the desired behavior becomes easier the more often one has already performed it. Conversely, the number of points that should be deducted when the user fails to enact the habit is smallest when the strength of the habit is zero and then increases as the habit becomes stronger. This is an intuitive consequence of our model's assumption that failing to enact the desired behavior in the specified situation weakens the habit strength by about 10%. The stronger the habit, the more is lost when its strength is reduced by 10%. The number of points awarded for enacting the desired behavior is a monotonically decreasing function of the habit strength. By contrast, the point value for failing to enact the desired behavior changes more erratically. This is because the number of steps required to reach the desired habit strengths changes abruptly with the current habit strength. For instance, failing to enact the behavior at a habit strength of 0.09 increases the number of times the behavior needs to be enacted to achieve the desired habit strength from 21 to 22 times. However, if the habit strength were 0.08 or 0.10, the number of times the desired behavior has to be enacted remains 22 and 21 times, respectively. Individual users rarely experience such irregular changes because the change in their habit strength typically skips across those small areas where the point value changes non-monotonically. Moreover, our simulations suggest that the penalty for failing to enact the desired behavior can be approximated by a linear function with the same slope as the number of points for performing the desired behavior.

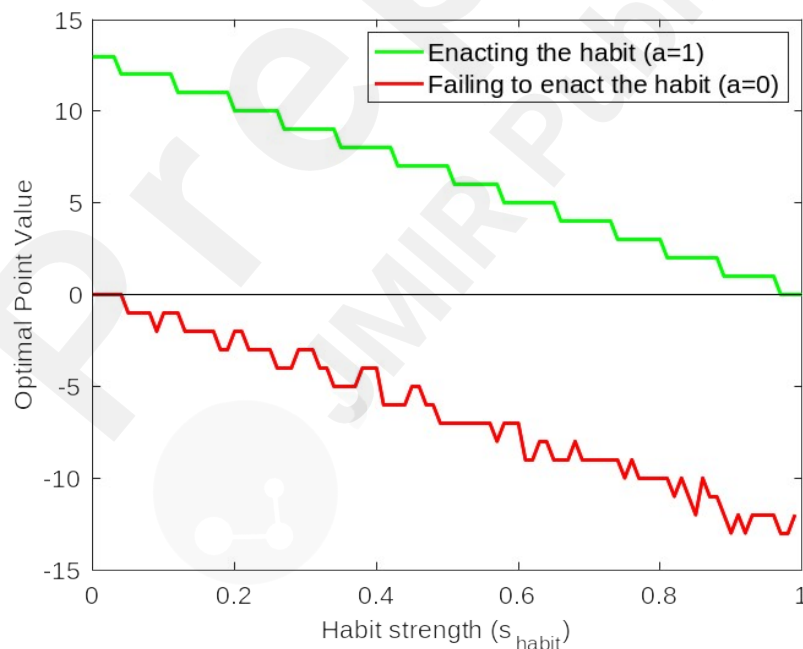


Figure 1. Point values for enacting versus failing to enact the habit at different habit strengths for a learning rate of $\alpha = 0.1$ and a threshold of $\theta = 0.9$.

Application to supporting positive behavior change

The optimized gamification method described above can be applied to help people form good habits. The equations for computing the number of points are easy to implement inside digital behavioral change interventions such as chatbots and habit trackers. All that is

needed is to ask the user which habit they want to develop and estimate its initial strength, set the learning rate parameter and the habit's target strength to reasonable values (e.g., $\alpha = 0.1$ and $\theta = 0.9$), and record when the user did versus did not act in accordance with the desired habit. To define the desired habit, the user has to specify the desired behavior and the situation in which they want to perform it. The user's initial habit strength can be estimated by the desired behavior's relative frequency in that situation in the previous week(s) (e.g., at 2 of the past 7 lunches). The habit strength can then be initialized with that proportion. Alternatively, when it makes sense to assume that the user wants to build an entirely new habit, the strength can be initialized as zero. Then, whenever the user reports (not) having enacted their intention, the optimized gamification equation can be applied to compute how many points the user should gain or lose. Whenever the user reports having performed the desired behavior, the estimate of the habit strength should be increased to $s_{\text{habit}} + \alpha \cdot (1 - s_{\text{habit}})$, and whenever the user reports having missed an opportunity to enact their intention, the estimate of their habit strength is decreased to $s_{\text{habit}} \cdot (1 - \alpha)$. Then, the same procedure repeats when the user reports on their next opportunity to enact the behavior.

This approach can be used to support many different kinds of positive behavior change. It can help people build good habits in areas such as exercise, sleep, taking medication, nutrition, work, chores, and leisure activities. It can be used in interventions focusing on specific habits and in general habit formation tools that let users choose any habit they want to develop. Another possible application is helping people overcome bad habits (e.g., smoking cessation) [60]. It can support applications that run on virtually any device, from smartwatches and wristbands to mobile phones, desktop applications, web applications, and smart glasses.

Proof of concept: a chatbot for building a healthy water-drinking habit

As a proof-of-concept for the application of optimized gamification to support behavior change, we implemented idea as a Telegram chatbot called the *Good Habit Bot*. chatbot helps the user develop a healthy water-drinking by combining four behavior change techniques: goal-setting, reminders, support for self-monitoring, and feedback. Concretely, the Good Habit Bot guides the user formulate an implementation intention that links a specific desired behavior to a concrete daily event, reminds the user of their intention on a daily basis, checks in with them on whether or not they followed through on their intention every day, and then gives them positive or negative feedback depending on whether they did or did not follow through on their intention.

When the user starts their first conversation with the Good Habit Bot, the chatbot introduces itself and says its purpose is to help the user form a healthy water-drinking habit. The Good Habit Bot then asks the user to choose at which of eight concrete, recurring moments in their day they want to use as the trigger for their water-drinking habit (e.g., "when my wake-up alarm rings" or "when I have the first bite of my lunch"; for the complete list, see Appendix 2). Next, the Good Habit Bot asks the user how much water they want to drink in that situation (e.g., 1 glass or 0.5 glasses) and how often they did so in the previous seven



Figure 2. Screenshot of the feedback method to with point values

days. The chatbot then uses the number of days $\bar{n}$ of the previous week on which the user acted in accordance with the habit (e.g., $\bar{n} = 2$) to initialize their habit strength by $\bar{s}_{\text{habit}} = \frac{2}{7}$ (e.g., $\bar{s}_{\text{habit}} = \frac{2}{7}$). Then, in the evening of the first day (i.e., at 9 pm), the chatbot reminds the user of their intention to drink a specific amount of water at a particular moment of the following day (e.g., "Remember your intention 'When I have the first bite of my lunch, I will drink 1.5 glasses of water.'"). Then, sometime after the user wanted to enact their intention, the chatbot asks them whether they did so (i.e., "Did you accomplish your goal today to drink 1.5 glasses of water."). If the user affirms that they followed through on their intention, the chatbot gives them positive feedback (see Error: Reference source not found). This feedback comprises a congratulatory message (e.g., "That's wonderful!") whose text alternates between five possible phrases (see Appendix 2) and a second message that awards the user the number of points computed by our optimized gamification method (e.g., "I am glad to grant you 5 points for keeping a good habit! Your total score is 49 points."). By contrast, if the user responds that they missed their chance to enact their water-drinking intention, the Good Habit Bot tells them, "Okay. Keep going tomorrow!" and informs them how many points they lost and how many they have left (see Appendix 2). Afterward, the chatbot updates the user's habit strength. Later that day, the Good Habit Bot reminds the user of their intention for the next day, and then the cycle repeats.

Critically, the chatbot computes how many points to award or take away from the user according to the optimized gamification method described above (see Equation 1). You can read off the number of points the chatbot we used in our experiment awarded in different situations from Figure 1 because it used the same set of parameters (i.e., $\alpha = 0.1, \theta = 0.9, M = 13$). For instance, if a user who had reported having performed the desired behavior twice in the previous week enacted their intention on the first day, they earned 9 points, and their habit strength increased from $\frac{2}{7} \approx 0.29$ to $\frac{2}{7} + 0.1 \cdot \left(1 - \frac{2}{7}\right) \approx 0.36$. Conversely, if they failed to enact their intention, they would lose 4 points, and their habit strength would decrease to $0.9 \cdot \frac{2}{7} \approx 0.26$. The Good Habit Bot is freely available on the Telegram messenger app, where it can be found by searching for its alias @learn_good_habits_bot.

Table 1. Experimental conditions.

	Implementation Intentions	Support for Self-Monitoring	Reminders	Feedback
Optimized gamification condition	yes	yes	yes	optimized gamification & positive vs. negative text
Control condition with reminders & feedback	yes	yes	yes	positive vs. negative text
Baseline	yes	yes	no	none

condition				
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Study design

To evaluate the effectiveness of our intervention and assess the relative contributions of reminders versus optimized gamification, we ran a longitudinal between-subjects experiment with one experimental condition with optimized gamification (*optimized gamification condition*), one *baseline condition*, and one *control condition with reminders and feedback* (see Table 1). In the *optimized gamification condition*, the chatbot delivered all four interventions described above, including feedback messages based on optimized gamification (see Error: Reference source not found). Participants in the other two conditions could not gain or lose any points (no optimized gamification). They differed in whether or not they received feedback messages for enacting versus failing to enact the intended behavior. In the *control condition with reminders and feedback*, participants received a positive feedback message when they reported having enacted their intention (e.g., "That's wonderful!") and a more neutral message when they reported not having done so (e.g., "Okay. Keep going tomorrow! :)"). To create the *baseline condition*, we replaced the first control group's positive/negative feedback message with a neutral message ("OK.") and removed the daily reminders. Participants completed the self-report measures of habit strength described below before the intervention (pre-test), immediately after the intervention (post-test), and approximately three weeks later (follow-up). Moreover, participants reported how often they often engaged in the desired behavior the week before the intervention (pre-test) and the week after the intervention (post-test). Finally, participants also completed daily reports of whether or not they had enacted their intention on each day of the intervention.

Ethical Approval

This experiment was conducted according to study protocol number 401/2020BO2 [approved by the Independent Ethics Commission at the Medical Faculty of the University of Tübingen](#).

Recruitment and reimbursement

We recruited 132 participants ($N_{\text{Baseline}} = 41$, $N_{\text{Optimized gamification}} = 43$, $N_{\text{Control}} = 48$; 93 female) on the online research platform Prolific. The requirements for participation were being a native speaker of English, not having interacted with our chatbot before, and previously having completed at least 10 HITs with an approval rate of at least 95%. Moreover, participants had to be at least 18 years old. The average age of our participants was 31.5 years ($SD = 9.9$ years, range: 19 years – 79 years).

The study description informed participants about the study's duration, activities, time commitment, and pay. Participants were paid £1.95 for completing the onboarding survey. We informed them that the base pay for completing the remainder of the 40-day study would be £7.80 and that they could earn an additional bonus of £8. The description strongly recommended that only people who are already using Telegram on their smartphones should participate. Moreover, the study description informed potential participants about the potential health benefits of regular water drinking. Participants were then shown the consent form. Upon giving informed consent, participants who already had the Telegram app clicked on a link that started a conversation with the Telegram chatbot for their respective condition of the experiment. Participants who had not installed the Telegram app yet were directed to download the Telegram app first.

At the end of the 40-day study, the chatbot directed participants to a second Prolific HIT,

where they received the announced payments contingent on their sustained active participation. All participants who completed the pre-test, post-test, and follow-up measures and continued to report on their daily intention enactment after the tenth day received a second payment of £15.80. Participants who did not meet those criteria did not receive the second payment.

Outcome Measures and Procedure

Outcome Measures

We measured the following outcome variables as described below:

Dropout. We measured whether a participant dropped out of our study by a binary variable indicating whether the participant stopped responding to all daily reports at least three days before the end of the study.

Engagement. We measured each participant's *engagement* with our digital intervention by the number of days on which they interacted with the Good Habit Bot.

SRHI. The Self-Report Habit Index [61] is a 12-item, 7-point Likert scale self-report measure of habit strength. It comprises three subscales measuring the behavior's *history of repetition*, its *automaticity*, and the extent to which it is part of the person's *identity*. In this study, we administered the first two subscales. The SRHI has been found to be a one-dimensional construct. We, therefore, averaged the scores of all items. The SRHI has been found to have high validity and very high reliability (Cronbach's $\alpha \approx 0.90$; test-retest reliability: $r = 0.91$).

Daily Intention Enactment. To measure how often each participant enacted their water-drinking intention during the intervention, we asked them the question, "Did you accomplish your goal to drink 1 glass of water?" on each day of the intervention period. The question was asked between 30 minutes and 2.5 hours after the time at which the participant had intended to drink water. Participants responded by selecting between the responses "Yes, I did!" and "No, I didn't." After the study, we calculated each participant's *Daily Intention Enactment* score by counting on how many of the 21 days of the intervention period they enacted their intention. The Daily Intention Enactment score could therefore range from 0 to 21.

Retrospective Intention Enactment. To measure how regularly participants engaged in the intended behavior (e.g., drinking a glass of water before lunch) in the weeks before and after the intervention, we asked them to answer the question, "On how many days of the previous week did you keep the habit of drinking water?" by selecting one of the answer choices 0, 1, 2, 3, 4, 5, or 6 days. We refer to the resulting number of days as the *Retroactive Intention Enactment* score.

Procedure

We created three separate Prolific HITs for each of the three conditions of the experiment (see Table 1), and each person was allowed to participate in at most one of those HITs. As illustrated in Table 2, the experiment was divided into three phases: the pre-intervention period (Day 0), the intervention period (Days 1-21), and the post-intervention period (Days 22-40). In the pre-intervention period, participants gave informed consent, completed the onboarding process, and completed the pre-test. During the onboarding, participants were directed to start the first conversation with the Good Habit Bot in the Telegram app on their mobile phones. In this initial conversation, the chatbot asked the participant to select a concrete daily situation in which they want to drink water and how much water they want to

drink, as described above. The pre-test comprised two self-report measures: the *SRHI* and the *Retrospective Intention Enactment* measure for the week before the study.



Table 2: Experimental procedure.

		Optimized gamification condition	Control condition with reminders & feedback	Baseline condition
Pre-Intervention	Day 0	Onboarding Retrospective Intention Enactment SRHI		
Intervention	Day 1-21	Reminder, Report, Feedback (optimal points + text) Daily Intention Enactment	Reminder, Report, Feedback (text only) Daily Intention Enactment	Daily Intention Enactment
	Day 21	SRHI		
Post-Intervention	Day 22-27	No reports		
	Day 28	Retrospective Intention Enactment		
	Day 29-34	No reports		
	Day 35	Retrospective Intention Enactment		
	Day 36-39	No reports		
	Day 40	SRHI		

During the intervention period, each participant interacted with one of the three versions of our chatbot according to the condition they were in (see Table 1). On each day of the intervention period, all three groups reported on whether or not they successfully enacted their intention to drink water in the specific situation they had selected (*Daily Intention Enactment*). At the very end of the intervention period, all three groups completed the *SRHI* for the second time (post-test).

The post-intervention period started with a one-week break during which the chatbot did not communicate with the participants. Then, on Day 28 (follow-up 1) and Day 35 (follow-up 2), the chatbot asked participants from all three groups to report on how many days of the previous week (i.e., the first and the second week of the post-intervention period, respectively) they had acted in accordance with the desired habit (*Retroactive Intention Enactment*). Finally, on Day 40, the chatbot asked all participants to complete the *SRHI* questionnaire for the third time (follow-up). Participants received three email reminders to resume interacting with the chatbot on the day of the first follow-up survey (Day 28), the day of the second follow-up survey (Day 35), and the day of the final follow-up survey (Day 40), respectively.

Data analysis

The hypotheses and statistical analysis plan were pre-registered at <https://osf.io/h7jn8>. Participants who completed zero daily water consumption reports were excluded from all analyses, aside from the dropout analysis. We used Poisson regression analyses for binary outcome variables. For continuous outcome variables, we used linear multilevel modeling.

Results

There was no indication of failure of random assignment for initial habit strength, automaticity, or history of repetition, all pairwise $p > .140$.

Dropout. As an initial step, we examined whether there was differential dropout between the three conditions with a chi-square test of independence. There was no effect of condition on dropout, $\chi^2(2) = 0.66$, Cramer's $V = 0.07$, $p = 0.72$.

Engagement. The *Engagement* variable was entered into a Poisson regression model with two dummy variables for the effects of optimized gamification and feedback and reminders, respectively. The *Automaticity* and *History of Repetition* scores from the *SRHI* prior to the intervention, and the pre-intervention *Retrospective Intention Enactment* score were entered as control variables. As displayed in Table 3, optimized gamification did not increase engagement compared to the *baseline condition*. However, it appears that being in the control condition with reminders and feedback without optimal points reduced *Engagement*, compared to the *optimized gamification* condition (see Table 3) and the *baseline* condition, $I.R. = 0.84$, 95% C.I., [0.75; 0.94], $p = .002$.

Daily Intention Enactment. The outcome variable measuring participants' daily enactment of the desired behavior (i.e., water drinking) was submitted to a Poisson regression model with the same set of predictors as for *Engagement*. Critically, we found that participants in the optimized gamification condition enacted the daily intention to drink water more often ($M=14.71$ times, $SD=6.57$ times) than either the participants in the baseline condition ($M=11.64$ times, $SD=5.43$ times) or the participants in the control

condition with reminders and feedback (M=11.64 times, SD=6.38 times), see Table 4. Furthermore, reminders and feedback without points did not produce more water drinking than the *baseline condition*, *I.R.* = 1.03, 95% C.I. [0.90; 1.17], $p = .701$.

Table 3. Predicting the number of days participants engaged with the app (*Engagement*) from their condition and Time 1 habit-related control variables.

Predictors	Incidence Rate		p
	Ratios	95% CI	
(Intercept)	18.88	16.61 – 21.43	<.001
Baseline vs. optimized gamification	1.02	0.91 – 1.14	.717
Reminders & feedback vs. optimized gamification	0.86	0.76 – 0.96	.008
Pre-intervention habit strength	1.03	1.00 – 1.07	.069
History of repetition	0.85	0.79 – 0.92	<.001
Automaticity	1.08	1.01 – 1.16	.033

Note. $N = 126$. R^2 Nagelkerke = .33. Treatment group with optimal points is the reference group.

Table 4. Predicting the number of days participants drank water (*Daily Intention Enactment*) from their condition and pre-intervention measurements of habit-related control variables.

Predictors	Incidence Rate		p
	Ratios	95% CI	
(Intercept)	16.02	13.93 – 18.41	<.001
Baseline vs. optimized gamification	0.78	0.69 – 0.89	.001
Reminders and feedback vs. optimized gamification	0.80	0.71 – 0.91	<.001
Pre-intervention retrospective intention enactment	1.01	0.97 – 1.05	.643
History of repetition	0.91	0.84 – 0.99	.021
Automaticity	1.07	0.99 – 1.15	.099

Note. $N = 118$. R^2 Nagelkerke = .21. Treatment group with optimal points is the reference group.

Self-reported habit strength. To test whether optimized gamification promoted habit formation, we compared the change in the SRHI self-report measures of *Automaticity* and *History of Repetition* from pre-test to post-test to follow-up between the three experimental conditions (see Figure 3 in Appendix 3) using a multilevel model with fixed effect predictors for time point, two dummy codes for the experimental condition with the *optimized gamification condition* as the reference, and all pairwise *Time x Condition* interactions (see Table 6 and Table 7 in Appendix 3). We found that, compared to the pre-test, both measures of habit strength were significantly higher right after the intervention (all $p < .001$) and at follow-up (all $p < .001$). However, these effects were no

larger in the *optimized gamification condition* than in the baseline condition (all $p \geq .199$) or the control condition with reminders and feedback (all $p \geq .115$).

Behavior after the intervention. As a further test of whether the behavior change we observed during the intervention was maintained, we analyzed the number of times participants reported having enacted their intention in the week before the intervention versus the first week after the intervention and the second week after the intervention (*Retrospective Intention Enactment*; see Figure 4 in Appendix 3) using a multilevel model with fixed effect predictors for time point, two dummy codes for the experimental condition with the *optimized gamification condition* as the reference, and all pairwise *time x Condition* interactions (see Table 5 in Appendix 3). We found that compared to the week prior to the intervention (1.8 ± 2.1 times), participants enacted the desired behavior significantly more often after the intervention (1-week follow-up: 5.2 ± 1.9 times, $t(299) = 15.21, p < .001$; 2-week follow-up: 5.1 ± 2.1 times, $t(299) = 14.86, p < .001$). However, these effects were no larger in the optimized gamification condition than they were in the baseline condition (all $p \geq 0.18$) or the control condition with reminders and feedback (all $p \geq 0.321$).

Discussion

Principal Results

In this article, we derived a mathematical principle for designing the point systems of gamified behavior change interventions. Our proof-of-concept study suggests that this principled approach to gamifying behavior change can be beneficial. We found that our gamified behavior change chatbot fostered positive behavior change during the intervention. This is consistent with previous findings that goal-setting, reinforcement, reminders, and self-monitoring are effective interventions for promoting behavior change [7,33,41,44,62].

Moreover, we found that the behavior change that occurred during the intervention was maintained in all three conditions. The elements that the behavior change interventions of all three groups shared were goal-setting and self-monitoring. Therefore, goal-setting and self-monitoring might be sufficient for sustained behavior change. Adding reinforcement to goal-setting and self-monitoring was beneficial during the intervention. But the additional benefits of reinforcement ceased to be statistically significant in the week following the intervention. However, because our study had a small sample size, this apparent discrepancy could be an artifact of us having used different methods to measure behavior change during versus after the intervention. During the intervention, we measured behavior by daily self-reports. After the intervention, we asked participants to retrospectively report on their behavior in the previous week, which is less accurate due to participants' fallible memory, and self-report measures of perceived habit strength, which are less objective than reports on behavior. Consistent with the interpretation that our study had insufficient statistical power for detecting retention effects, the measures we used to assess the maintenance of behavior change

consistently showed a non-significant trend in favor of optimized gamification (see Figure 3 and Figure 4 in Appendix 3). Moreover, previous studies found that gamification-induced behavior change can persist over extended periods [63].

Limitations

From a theoretical perspective, the main limitation of our study is that it did not compare the effectiveness of the points computed by our optimized gamification method to alternative point schemes. Previous work found optimized gamification to be more effective than several heuristic methods for designing point systems in contexts where people choose between several activities [51]. However, the decisions people face in behavior change applications appear to be simpler. It, therefore, remains unclear how much of the beneficial effects of optimized gamification on behavior change are specific to optimized gamification. Relatedly, it remains unclear which property of the points generated by optimized gamification is responsible for their effects on behavior change. Future work could address these questions by comparing optimized gamification of behavior change against simpler, alternative feedback mechanisms, such as always awarding the same number of points or a streak-based point system.

We did, however, evaluate optimized gamification against rewarding each enactment of the desired behavior with the same positive feedback message and punishing each failure to enact the desired behavior with the same negative feedback message (Control Condition with reminders and feedback). From a reinforcement learning perspective, this condition is equivalent to always awarding the same number of points when the behavior is enacted and always deducting the same number of points when the user fails to enact the behavior. We found that optimized gamification is more effective than this alternative feedback mechanism. This suggests that optimized gamification might be more effective than awarding the same number of points for each instance of the desired behavior. But whether this interpretation is correct remains to be tested.

We illustrated the application of the general framework of optimized gamification to behavior change with a simple model of habit formation, which assumes that the user will indefinitely maintain the good habit once it has been established. This assumption is highly simplistic. In reality, maintenance is far from automatic. On the contrary, people may experience backsliding, and the strength of the habit may continue to wax and wane [64]. This could be captured by letting the process of deciding whether to perform the behavior continue indefinitely until the user dies. In that way, lapses could occur at any time and weaken the habit no matter how strong it is. In such a model, the health benefits of the behavior could be modeled explicitly in terms of its effects on a state variable that models the user's health status. Refining our method's model in this way would reduce the reinforcement for engaging in the behavior when the habit is weak and increase it when the habit is strong. This might make our method even more effective.

From an empirical perspective, the main limitation of the work presented in this article is the relatively low sample size of our field experiment. Given that we collected less than 30 complete data sets per condition, the power of some of the statistical tests is relatively low. The absence of significant differences in self-reported habit strength and retroactive intention enactment after the intervention, therefore, does not provide strong evidence against the maintenance of the benefits of optimized gamification. Moreover, given that habit formation can take a very long time, our intervention might have been

too short to fully capture the effect of the three different interventions on habit formation. One flaw of our experiment was that some of the chatbot's messages were not worded in perfect, idiomatic English (see Appendix 2). We think it is unlikely that our participants misunderstood any of the messages. However, it is possible that participants would have taken the messages more seriously if all of them had been written in perfect, idiomatic English. Another minor limitation of our chatbot was that its users started with a score of zero. Thus, if they failed to enact the desired behavior, their score fell into the negative realm, which might be demotivating. Future versions of our chatbot will therefore award users some number of points (e.g., 20) for setting the intention to build a good habit.

Finally, another weakness of our study design was that our intervention sought to strengthen water drinking in healthy people. We, therefore, cannot draw conclusions about the potential utility of our chatbot for clinical populations for whom developing a healthy water-drinking habit might be crucial [3,4]. Moreover, it remains unclear whether our findings can be generalized to other habits that are more vital to people's health. Moreover, our study was not specifically about water drinking as a weight-loss strategy because only some participants tied water drinking to their meals. However, we have introduced a general method that can be used to improve digital interventions for many critical behavior change applications.

Comparison with Prior Work

This article builds on previous work on optimized gamification [51]. Optimized gamification has been previously applied to helping people decide what to work on [51], and which goals to set [52,55,56,65]. Moreover, optimized gamification has also been applied to help people stay focused on their work [58]. However, the work presented in this article is the first application of optimized gamification to support habit formation. Moreover, it is one of the first real-world applications of optimized gamification because most previous work on optimized gamification was confined to controlled laboratory experiments.

Because our chatbot combined four established behavior change techniques (i.e., goal-setting, reminders, support for self-monitoring, and reinforcement), its design and effectiveness are therefore consistent with several extant theories of behavior change [66]. In particular, our optimized gamification method is consistent with behavior change methods that acknowledge the importance of giving positive feedback on improvements in behavior [28,66–69].

The most similar gamified digital intervention for behavior change we are aware of is the text-message-based WalkIT intervention for promoting physical exercise [7,33,70]. Participants of the WalkIT trial received text messages with daily physical exercise goals. Physical exercise (walking) was measured via the accelerometers of their smartphones and reported to a server. Participants received feedback on whether or not they met the exercise goal via a text message that included points that were converted into money. Depending on the stage of the experiment, the number of points for awarding a goal was either constant or determined at random. The number of points awarded for failing to achieve a goal was zero. By contrast, our optimized gamification method provides a principled way for choosing the exact number of points that a person should be awarded for meeting their daily goal or lose for failing to meet that goal. Our

method could therefore be used to enhance the WalkIT intervention with a more principled method for choosing the number of points depending on the user's history of (un)successful goal achievement. Conversely, WalkIT has many sophisticated features that go beyond the chatbot we introduced here. This includes an algorithm for adaptive goal-setting, automatically delivered financial incentives, and an evidence-based sequence of different reward schedules that differ in the probability that goal achievement will be rewarded and whether the magnitude of the reward will be fixed or random. Consistent with our finding that the more performance-contingent feedback of the optimized gamification condition was more effective than less informative feedback or no feedback, the WalkIT studies found that immediate, behavior-contingent reinforcement was more effective at promoting behavior change than delayed, behavior-independent reinforcement.

Another gamified digital intervention for supporting behavior change is Habitica. Habitica embeds working through one's to-do list into a role-playing game in which the user's character can earn points by completing their daily to-dos. The points serve as an in-game currency the player can use to buy weapons and armor for their avatar. Conversely, when the user does not complete a daily to-do, they lose points. As far as we can tell, the developers of Habitica chose the number of points the user gains for completing a to-do and the number of points they lose for failing to complete a daily, somewhat arbitrarily based on their intuitions. A recent study found that only 49% of Habitica's users rate its rewards as (rather) appropriate and that most experience counterproductive effects of Habitica's approach to gamification [17]. Given that optimized gamification was effective in our study and previous studies, it is possible that redesigning Habitica's point system according to optimized gamification could alleviate some of the counterproductive effects of their users' experience.

The method introduced in this article mitigates the adverse effects of temporal discounting on people's health behavior [26]. Its approach is to add immediate rewards that are aligned with the behavior's long-term consequences for the user's health. That is, optimized gamification redesigns the decision environment so that people's short-sighted biases lead to decisions that are good for them in the long run [51]. Recent work on this topic introduced a computational model of inter-temporal choice and applied it to compute personalized incentives for helping people to more patiently work towards obtaining a larger reward later instead of abandoning the project in favor of a smaller immediate reward [71,72]. Like optimized gamification, their approach uses a Markov-Decision-Process framework. However, their problem formulation and solution are different. The main difference lies in the application area. Sukumar et al. [71] focused on canonical delay-of-gratification tasks, whereas we modeled habit formation. They tested their approach in online experiments where participants played a "queue waiting game" and found that personalized incentives can increase people's patience while waiting in a simulated queue. By contrast, we conducted a field experiment on behavior change where the incentives motivated people to act more farsightedly in the real world. Despite this critical difference, investigating whether modeling and measuring individual differences can be used to make optimized gamification more effective is an exciting direction for future work. Moreover, a computational model like the one proposed by Sukumar et al. [71] could be used to simulate the effects of alternative incentive schemes.

Previous work found that drinking water before meals is an effective weight-loss strategy for adults with obesity [3,4]. In the randomized controlled trial by Parretti et al. [4], participants were instructed to use the water-drinking strategy in a face-to-face weight loss consultation. They did not receive any additional support in implementing this strategy. The chatbot we developed could be used to augment those weight loss consultations with a digital tool that helps people follow through on their resolutions. Alternatively, an appropriately adapted version of our chatbot could be used as a highly-scalable low-cost alternative to face-to-face weight loss consultations.

Conclusions

In conclusion, optimized gamification is a practically helpful theoretical principle for designing the point systems of (digital) behavior change tools and interventions. It can be implemented in just a few lines of code, and the point values can be computed instantaneously. It can be applied to improve or augment many existing (digital) behavior change interventions and can also be used to create new ones. Optimized gamification can thus help tackle many challenging behavior change problems with scalable digital interventions. Testing whether, when, and how optimized gamification can make a positive difference in critical practical applications is an exciting direction for future research. A crucial next step will be to test our point system against simpler, heuristic point systems for supporting behavior change. Moreover, our chatbot can be extended to support various health behaviors and other forms of positive behavior change.

Acknowledgments

FL conceived and designed the research, developed the optimized gamification method, and wrote the article. PZC designed and implemented the Good Habit Bot and co-designed and ran the field experiment. MP conducted the data analysis. VA supported PZC in designing and running the field experiment and in the design of the Good Habit Bot. MT contributed to the implementation of the Good Habit Bot. No generative AI was used in the writing of this article.

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Data Availability

The data generated in this study, the R scripts used to analyze the data, and the Matlab implementation of the optimized gamification method are available in the project's OSF repository [73].

Conflicts of Interest

None declared.

Abbreviations

MDP: Markov Decision Process

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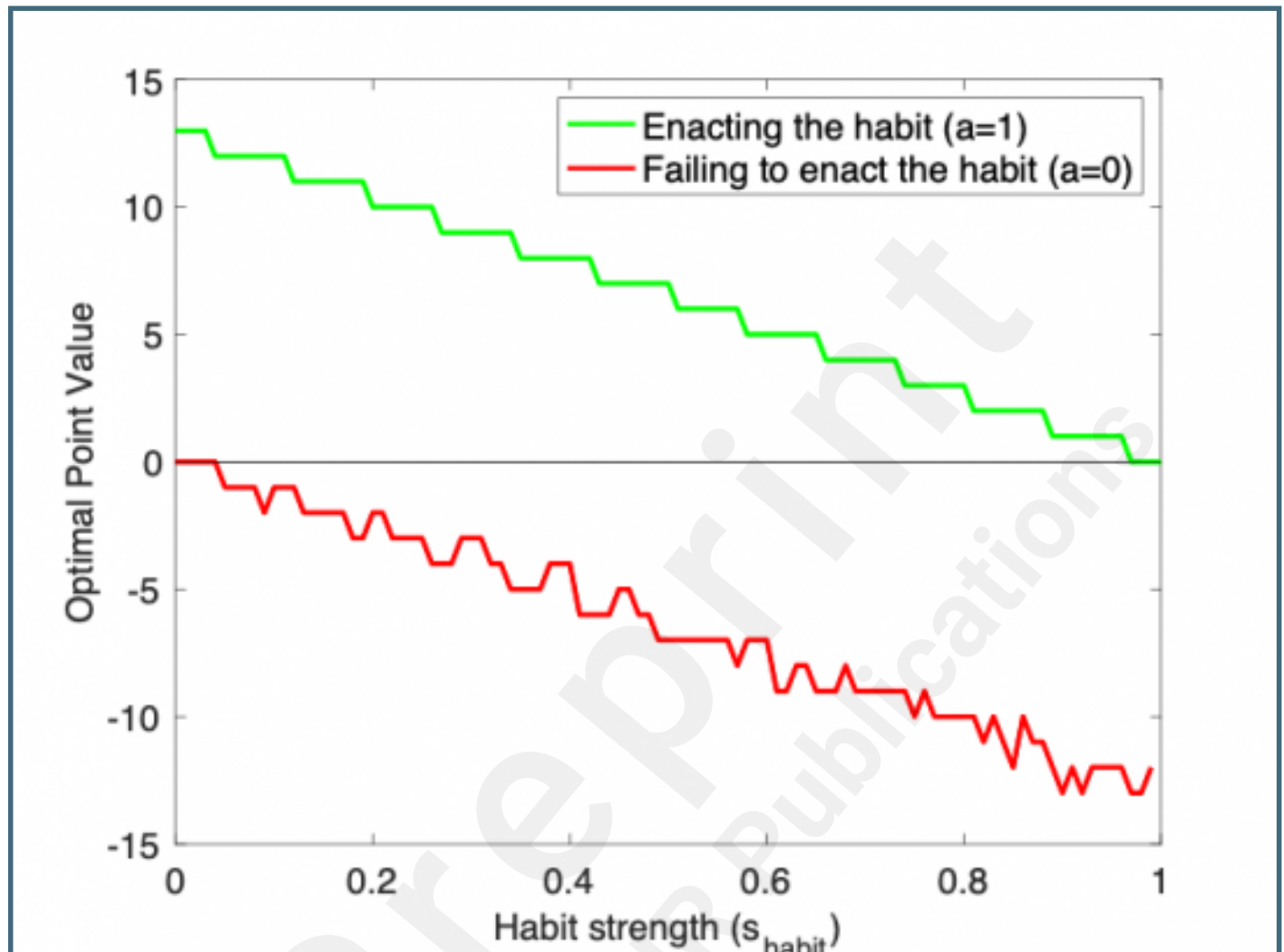
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Supplementary Files

Figures

Point values for enacting versus failing to enact the habit at different habit strengths for a learning rate of 0.1 and a threshold of 0.9.



Screenshot of the feedback method with point values computed by our optimal gamification method.



Multimedia Appendixes

An Optimal feedback method for accelerating positive behavior change.

URL: <http://asset.jmir.pub/assets/64e783eccdb3f6d97a346ba4ac877ba2.docx>

Details about the Good Habit Bot.

URL: <http://asset.jmir.pub/assets/ffaae6ee59241f9e1d7b1717335fdb81.docx>

Supplementary figures and tables.

URL: <http://asset.jmir.pub/assets/ed4224819961519c1839b4aba47680f2.docx>

