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Promoting exercise behavior with monetary and social incentives: An empirical study based on an online fitness program

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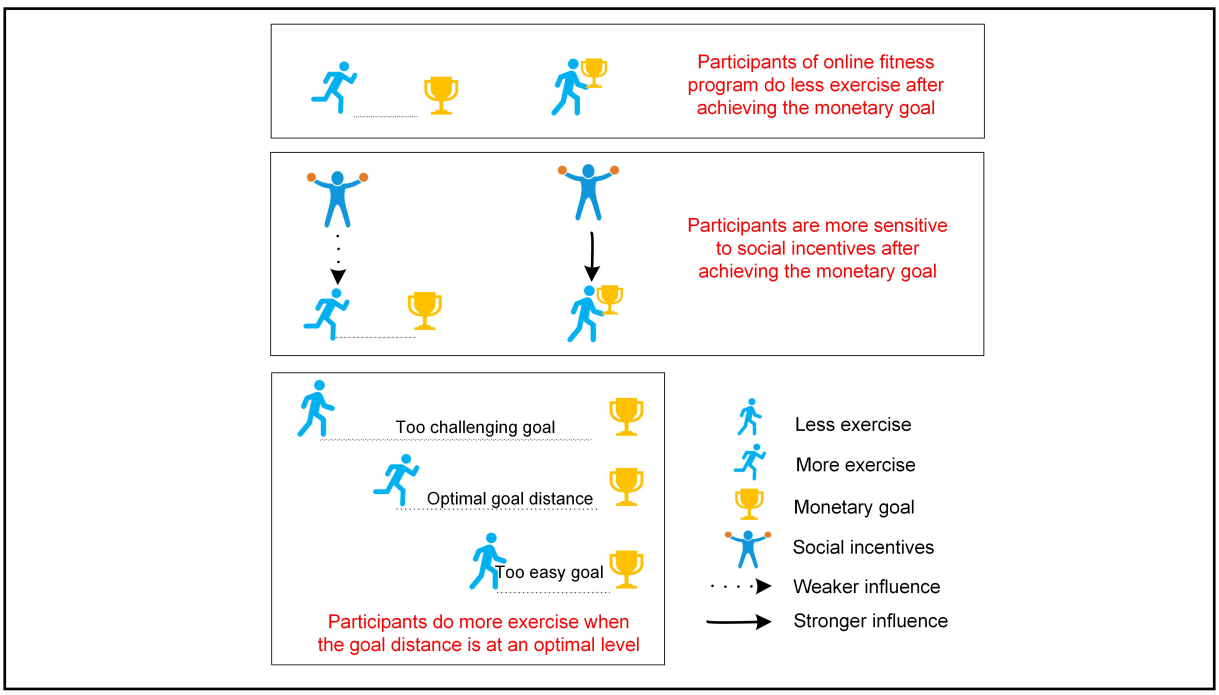
Graphical abstract



In online fitness programs, the exercise behavior of participants changes along with the dynamic goal distance and the goal-achieving status.

Public summary

- In online fitness programs, offering monetary incentives will motivate participants to do more exercise. However, participants' exercise behavior will dramatically drop after they achieve the monetary goal.
- When the dynamic goal is at an optimal level, participants' daily steps will be maximized.
- There is a crowd-out effect between the monetary and social incentives in motivating people to do more exercise. The influence of social incentives will become stronger after individuals achieve their monetary goals.

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Abstract: Due to the importance of employees' physical well-being, organizations have long been conducting wellness programs to motivate their employees to exercise. The wide use of wearable devices (e.g., smart bands and smartphones) and fitness applications (e.g., fitness mobile applications) enable organizations to shift from offline to online fitness programs where participants use physical activity records tracked by wearable devices to complete fitness tasks and challenges. To better motivate employees' exercise behavior, online fitness programs widely offer monetary or social incentives strategies. However, little is known about the interaction effects of the two types of incentives when they are jointly offered. Besides, organizers lack knowledge of how to set an optimal fitness challenge for the incentives in online fitness programs. In this study, we obtained a rich panel dataset from a university-wide online fitness program, which includes the daily exercise records of 2578 participants during a 100-day period, to empirically investigate the joint effects of monetary and social incentives on individuals' exercise behavior. Most interestingly, we found that there is a crowd-out effect between monetary and social incentives—the influences of social incentives (i.e., social support and social contagion) are relatively weaker when there exists an unachieved monetary goal; once the monetary goal has been achieved, the influences of social incentives become stronger. In addition, we found that participants' exercise behavior can be maximized when the dynamic goal is set at an optimal level. Our findings can help practitioners better design the online fitness programs and the associated fitness technologies.

Keywords: online fitness program; fitness technology; exercise behavior; monetary incentives; social support; social contagion; optimal goal setting

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1 Introduction

With the wide use of wearable devices (e.g., smart bands and smartphones) and fitness applications (e.g., fitness mobile applications), individuals' fitness records such as step counts and calories burned can be easily tracked, recorded, synchronized to the Internet, and shared in the online community. These fitness technologies enable organizations to shift their fitness programs from offline to online. Specifically, individuals are allowed to upload their fitness records tracked by their fitness devices, as their performance in online fitness competitions and challenges. During the COVID-19 pandemic, due to the various social distancing policies and restrictions on holding offline sports meetings, more and more organizations take advantage of such online fitness programs to encourage their employees to exercise[1]. Compared with traditional offline fitness programs, online fitness programs are less limited to time and space, and bring better fitness experiences to participants[2, 3].

For organizations that want to help their employees to develop a healthier lifestyle and do more exercise, they are curious to identify effective strategies that can be used in designing organizational online fitness programs[4, 5]. However, many organizations have been faced with the problem of employees' inactivity in online fitness programs[6]. The maintenance of fitness behavior can be very difficult[7], because doing physical activities regularly requires strong motivation and willpower[8]. It requires individuals' immediate task efforts but only brings long-term benefits (e.g., becoming healthier). Accordingly, previous studies have shown strong interest in identifying effective strategies and techniques to promote users' physical activities in the online fitness program, including offering monetary and social incentives[9].

The most commonly adopted strategy to motivate individuals to engage in the online fitness program is offering monetary incentives (e.g., cash and gifts)[10, 11]. For example, a worldwide fitness mobile application, *Evidation*, which has more

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than 4 million users, offers monetary incentives to promote users' exercise behavior. Users earn virtual points by walking more steps, and can exchange every 10000 points for $10①. Similarly, another fitness app *Achievement* also launched a "get paid for healthy actions" program in which participants can get paid for their walking and exercise. The previous studies demonstrate that offering monetary incentives could encourage individuals to engage in more exercise behavior[12, 13]. For instance, in the field experiment conducted by Adjerid et al.[14], offering monetary incentives could lead to a 10% increase in participants' daily exercise behavior.

In addition to monetary incentives, many online fitness programs or technologies also offer social incentives to foster individuals' exercise motivation. Social incentives refer to the benefits that derive from social interactions with others, which often include "being cool, gaining approval and respect, forming deeper friendships, building trust with parents, and being a good role model"[15]. Fitness technologies or online fitness programs provide social incentives by offering the opportunities and functional design elements for users or participants to interact with others online, so that users could get social support and social contagion as non-monetary benefits (or intangible benefits). For example, participants of online fitness community activities could give and receive Like and Comments from other participants which helps increase participants' engagement[16]. Previous studies indicated that exercise is socially contagious in a way that an increase in an individual's walking steps could lead to an increase in their friends' steps[17].

Despite the fact that in existing studies, both monetary and social incentives have already been found to be effective in fostering individuals' exercise behavior, we have identified a few research gaps as follows. First, prior studies have compared users' exercise behavior with and without monetary incentives. However, they did not investigate the longitudinal and continuous effect of offering monetary incentives, as well as the "sequela effect" of stopping offering more monetary incentives. Practically, it is almost impossible for organizations or platform owners to offer unlimited and continuous monetary incentives. It remains unknown whether the individuals' exercise behavior will return to the original level after they achieve a longitudinal monetary goal, or when the organization stops offering more monetary incentives for more exercise behavior. Hence, in this study, we attempt to compare the exercise behavior before and after the achievement of a monetary goal in an online fitness program.

Second, although setting a reasonable personal health goal is crucial in motivating users to improve or maintain exercise[18], prior studies have not demonstrated what is an optimal goal that can best motivate an individual's exercise behavior and how to set an optimal goal for offering monetary incentives. While some studies suggested that the existence of a challenging long-term goal has a positive effect on people's exercise behavior[19, 20], some other studies suggested that the long-term goal may cause users to give up during the fitness program[21]. Besides the contradictory findings, there is also a lack of thorough understanding of the effect of dynamic goal setting on exercise. Accordingly, the second research objective of this study is to understand the dynamics of individuals' goal setting in longitudinal online fitness programs, as well as the effects of individuals' dynamic goal setting on fitness behaviors. We aim to identify an optimal dynamic goal for individuals' daily steps. We argue that neither a too-easy-to-reach goal, not a too-hard-to-reach goal could motivate people; instead, when the dynamic goal is in an optimal level, individuals' fitness behavior can be maximized. Hence, in this study, we aim to reveal the inverted U-shape relationship between dynamic goal distances on users' exercise behavior, and thus contribute to the controversy in the goal-setting research.

Third, although both monetary and social incentives are found to be effective in promoting users' exercise behavior, they are investigated separately in previous studies. It remains unclear about the interaction effect between monetary and social incentives in motivating users' physical exercise[22]. For example, little is known about whether the two incentives would have a crowd-out effect or crowd-in effect when they are simultaneously offered in online fitness programs[23]. Therefore, another research objective of this study is to reveal how monetary and social incentives affect participants' physical exercise behavior. We argue that the influence of social incentives on exercise behavior will become stronger without the existence of a monetary goal (e.g., when the monetary goal has been achieved).

To fill the three above research gaps, this study obtained a rich panel dataset from a technology-enabled online fitness program held by the University of Science and Technology of China (USTC). In 2021, the university launched a technology-enabled fitness program called "the USTC Brisk Walking Program" (the USTC-BWP for short) to encourage its faculties to actively participate in walk-based physical activities such as walking and running. The USTC-BWP is technologically supported by a WeChat mini-program, which can track and display participants' daily exercise records. We obtained fitness records of 2578 faculties and their social interaction behaviors within the WeChat mini-program to test our proposed hypotheses.

To summarize, this study aims to deepen the current understanding of how monetary and social incentives could be jointly used to motivate users' exercise behavior in online fitness programs. We also aim to reveal the dynamics in individuals' longitudinal goal setting in perusing a monetary reward, as well as the effect of such dynamic goal setting on their exercise behavior.

2 method

2.1 Literature review

2.1.1 *Monetary incentives and exercise behavior*

Drawing on behavioral economics research, monetary incentives (e.g., rewarding individuals to walk more) were used by fitness technology producers to address the low level of user engagement problem[24]. Behavioral economics revealed that increasing the immediately rewarding aspects of exercise (e.g., by offering monetary incentives) may increase people's

① Details about the monetary incentives offered by *Evidation* can be found at https://my.evidation.com/.

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propensity to exercise[25].

In practice, to promote users' motivation and engagement, some fitness technology service providers provide users with monetary incentives including cash and physical gifts[4, 26]. A growing body of studies broadly supports the positive effects of monetary-incentive-based interventions on fitness behaviors. For example, a systematic literature review suggested that monetary incentives generally improve "lifestyle" health behaviors, including dietary behaviors, smoking cessation, and weight loss[27, 28]. However, recent research has provided some preliminary evidence that individuals generally revert to the baseline level of exercise soon after the monetary incentives are removed[28, 29]. Therefore, how monetary incentives impact fitness technology users' exercise behavior deserves further investigation.

2.1.2 Social incentives and exercise behavior

Social incentives including social support[30] and social contagion[17] are found to be crucial predictors of exercise behavior. As explained above, social incentives are the benefits that derive from one's social interactions with others in social activities. Social support, which broadly refers to the care and assistance from others, can be regarded as a typical form of social incentive[31]. Social support usually comes in the form of emotional support such as encouragement and instrumental support such as health-related help from their friends[32, 33]. In the context of fitness technology, users receive and give social support in the form of Like or Comments[34]. Social support from important others (e.g., friends and family) plays a necessary role in the adoption and maintenance of exercise[35, 36]. One stream of researchers has provided evidence for the direct effect of social support on exercise behavior[37, 38]. Other researchers paid attention to the psychological mechanisms of how social support positively impacts exercise behavior[39–41]. For example, McAuley et al.[39] demonstrated that self-efficacy plays the mediating role between social support and exercise.

Social contagion is usually defined as "the spread of affect, attitude, or behavior from one individual (the 'initiator') to another individual (the 'recipient')"[42]. Social contagion is also associated with social incentives, because individuals feel a sense of belongingness when they perceive that they behave consistently with the group norms. The contagion occurs either consciously or unconsciously[43]. Studies on social contagion theory found that people tend to emulate the behaviors or adopt the attitudes of their social network members[44]. For example, the food choices in one spouse can predict similar food choices in the other[45]. If one sibling is obese, the opportunities of the other becoming obese increase by 40%[46], which suggests that obesity can spread through social networks.

In the context of fitness technology, attitudes and behaviors could spread within the user group[47]. Moreover, the effect of social contagion depends on the position of an individual in the group in a way that a person in centrality might affect others' behaviors and attitudes to a greater extent than those on the edge of the group[48]. For instance, Fowler and Christakis[49] have found that an individual's happiness depends on the happiness of others they are connected. Their findings also suggested that individuals who are surrounded by a great number of happy people as well as who are central in the network are more tend to become happy in the future[49].

To summarize, through a comprehensive literature review in Sections 2.1.1 and 2.1.2, we found that although the effects of both monetary and social incentives have already been investigated in the extant literature, there lack research that comprehensively considers their interaction effect when monetary and social incentives are jointly implemented in online fitness programs.

2.2 The 2021 USTC Brisk Walking Program

We leverage data from a university-wide fitness program to answer the proposed research questions. In 2021, the USTC launched a fitness program USTC-BWP to encourage the faculties to develop a healthy lifestyle②. The USTC-BWP was supported by a WeChat mini-program operated by the USTC Trade Union, which can record participants' daily exercise steps, and display users' exercising records in a user-friendly dashboard, as shown in Fig. 1. The program lasts for 100 days in total, from March 23, 2021 to June 30, 2021. 2578 faculties of the USTC from 25 different colleges and departments registered and participated in this fitness program.

Notably, both monetary incentives and social interaction features are provided in the USTC-BWP. As for monetary incentive, participants could receive an award worth ¥150 once they have accumulated 710000 or more steps in total during the 100-day program (i.e., with a daily average step equal to or greater than 7100). To promote scientific daily exercise plans and avoid over-exercise, the program sets the upper limit for daily step count as 20000 suggested by the USTC Trade Union. For example, an amount of 23000 daily steps was displayed as "20000+ steps" in the dashboard.

Moreover, social interaction elements were also used to support user-to-user interactions. Fig. 1 shows the user interfaces of the WeChat mini-program for the USTC-BWP. First, users could see their daily walking steps data and the amount of Like received from other users. Second, users could see their ranking information as well as the daily steps of users from the same department. In such a leaderboard, all colleagues who walk more than 20000 steps on a certain day would have a record of "20000 +" steps and they could be seen by other colleagues as "role models". Based on this specific empirical setting, in the following sections, we propose several hypotheses about the effects of monetary goals, dynamic goal distance, and social interactions on participants' daily step count.

2.3 Hypothesis development

2.3.1 Monetary incentives and exercise behavior

Doing physical exercise is of great immediate cost but only long-term benefits. Individuals are facing a "present cost" such as spending time and energy and a "future benefit" such as increased health condition. Users tend to place excessive emphasis on the present "cost" of a health behavior while discounting the future "benefits" of that behavior[50]. According

② More details about the 2021 USTC Brisk Walking Program can be found at https://gonghui.ustc.edu.cn/_upload/article/files/c7/bd/2eea394340cb8c6feef6f6124c34/4b268e03-a0d9-4e40-9fdf-70437945fdd5.pdf.

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Fig. 1. User interfaces of the WeChat mini-program for the USTC-BWP.

to the existing studies in behavioral economics, providing immediate monetary incentives for delayed behavior (i.e., rewarding aspects of exercise) could increase individuals' tendency to exercise[25]. In other words, individuals will be motivated to engage in exercise when they hold a motivation to earn monetary rewards by doing exercise[13].

In the USTC-BWP, we argue that the motivation to obtain the monetary reward, which is worth ¥150, provides users with extra motivation to do exercise because such a monetary reward serves as an immediate benefit of doing exercise[27]. Compared with some intangible benefits such as becoming healthier, such a tangible benefit could be more easily perceived by participants. Hence, at the beginning of the program, with a motivation to get the monetary reward, participants will actively engage in doing walk-based exercises. However, such a reward will be ensured once the accumulated step reaches 710000 during the 100-day period. In other words, a goal to obtain monetary incentives disappears after 710000 steps, because participants will not receive any additional monetary incentives by doing more exercise. As a result, after participants achieve the monetary goal (i.e., 710000 steps), we expect to observe a significant decrease in their daily steps. Thus, we propose:

H1: An unachieved monetary goal is positively related to the exercise behavior of the participants. In other words, participants are more motivated to do exercise if there is an unachieved monetary goal, and less motivated to do exercise if the monetary goal has already been achieved.

2.3.2 Dynamic goals distance and exercise behavior

In this section, we extend H1 by revealing the dynamic goal-setting process in a longitudinal online fitness program.

Empirical research based on the goal-setting theory[51] has shown that difficult and specific goals could motivate individuals to perform better in a variety of contexts[52]. According to goal setting theory, goal difficulty is defined as the difference between the wished-for and the realistically expected performance[53]. Too easy and too difficult goals are supposed to be demotivating and reduce performance. Only a reasonable goal can motivate individuals the best and lead to an increase in performance[54].

According to the goal-setting theory, this study first defines dynamic goal distance as the remaining daily average steps to achieve the monetary goal. For example, the required step to obtain the reward is 710000. If an individual has accumulated 510000 steps in the first 50 days, in the remaining 50 days, he or she needs to walk 4000 steps per day on average to get the reward. In this example, the dynamic goal distance on the 51st day is 4000.

We propose that when the goal distance is at an optimal challenge level which is reasonable and moderately difficult, users will be better motivated to do exercise. A reasonable and moderately difficult goal distance could motivate users to put enough effort into the fitness program, at the same time not losing their commitment to the reward[21]. However, with a very high goal distance, participants will perceive that it is too difficult or almost impossible to achieve the monetary goal,

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and get discouraged by such a hard-to-reach goal. As a result, exercise behavior will decrease because people may lose their commitment to these difficult goals[21]. Similarly, with a low level of goal distance and an easy-to-reach goal (e.g., 500 steps per day), participants will feel less challenging and less motivated to do more exercise. We hypothesize:

H2: There is an inverted U-shape relationship between dynamic goal distance on exercise behavior. Specifically, when the dynamic goal is at an optimal level, the users' exercise behavior reaches its peak. When the dynamic goal distance is either above or below the optimal level, users' level of exercise will be relatively lower.

2.3.3 Social incentives and exercise behavior

In this section, we argue that social incentives including social support (i.e., amount of Like received from other participants) and social contagion (i.e., average steps of colleagues in the same department and the amount of role models in the department) positively influence an individual's daily step count in an online fitness program. First, social support from friends can help to consolidate intended behavior[55]. In the context of fitness technology, when users receive Like from other users, they can perceive others' encouragement and comfort[32]. This social support can motivate users and result in an increase in their exercise behavior by promoting self-regulate[32]. Past studies have confirmed our hypothesis. For example, Rackow et al.[55] found that receiving emotional social support can enhance exercise-related self-efficacy, and that self-efficacy in turn translates into exercising. Another study found that three types of social support (i.e., Like, Comments, and Share) have positive effects on exercise behavior. Therefore, we propose that:

H3a: There is a positive effect of social support on exercise behavior. In other words, when users receive more Like from other users, then their subsequent daily steps would increase.

Moreover, an individual's behavior is often influenced by the people they interact within the social network[56]. Exercise is socially contagious[17] in a way an increase in a user's steps often leads to an increase in others' steps. That is, social contagion within the network can motivate users and result in an increase in their exercise behavior. In this study, when users find that colleagues from the same department achieve more steps, they are more likely to spend more effort in doing exercise in the subsequent period. In addition, there exists an uneven distribution of interaction with others in the network[4]. Users who possess many information resources within the networks (e.g., role models listed on the leaderboard) have a stronger impact on the behavior of others[49]. In our study, when users found colleagues from the same department achieve more than "20000+" steps, they are more likely to increase their subsequent exercise. In conclusion, we proposed that:

H3b, c: In online fitness programs, there is a social contagion effect on the exercise behavior of an individual participant. In other words, (b) the average steps of colleagues in the same department, and (c) amount of role models listed on the leaderboard are positively related to one's subsequent daily steps.

2.3.4 The crowd-out effect between monetary and social incentives

This section depicts the crowd-out effect when the motivations aroused by monetary and social incentives coexist. Monetary incentives highlight a tangible monetary payoff motivation[57, 58], while social incentives are directed at a social preference motivation which refers to motivations that represent the relationship between the self and others[23]. Past studies suggested that monetary incentives arouse individuals' economic market thinking[59]. On the contrary, a preference for social incentives can invoke a social thinking pattern[59]. These two types of think patterns jointly determine participants' exercise behavior in online fitness programs.

In our study, before the long-term monetary incentives have been achieved, the exercise behavior of a participant is driven by both the monetary and social incentives, and the person will adopt both economic market thinking and social thinking pattern. Due to the existence of the monetary incentives and the economic market thinking pattern, users' social preference motivation would be less influential, because the social thinking pattern will be to some extent inhibited by the economic market thinking pattern. In other words, at the beginning of the USTC-BWP, the unachieved monetary goal will largely determine one's exercise motivation, and the participant will pay relatively less attention to the social interactions with other users. Thus, the effect of all social factors on exercise behavior would be weakened.

However, when the monetary incentives have been achieved, users will not get extra monetary incentives by doing more exercise. At this moment, the social thinking pattern will play a dominant role in determining individuals' exercise behavior due to the absence of additional monetary incentives. Without any additional monetary incentives, participants will be more sensitive to the social interactions in the WeChat mini-program of the USTC-BWP. As a result, the effect of social incentives on exercise behavior would be strengthened after a participant accumulate 710000 steps. Therefore, we hypothesize:

H4: When the monetary goal has been achieved, the effects of ① amount of Like from other users, ② average steps of colleagues in the same department, ③ amount of role models listed on the leaderboard, on users' exercise behavior will become stronger.

3 Results

3.1 Data description

In total, 2578 faculties of the USTC from 25 different colleges and departments registered and participated in the USTC-BWP. We obtained a rich panel dataset about the USTC-BWP, which include the daily steps of the 2578 participants during the 100-day period (i.e., 257800 daily step records), the daily Like received by each participant, and some other time-invariant information such as the department information of each participant. For privacy reasons, we did not obtain any identifiable demographic information from the participants, such as their age, gender, and job position. De-

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tailed descriptions of the variables can be found in Table 1.

Notably, in our dataset, $\text{Award\_achieved}_{it}$ and Dynamic_goal_{it} reflect the monetary goals: the difference is that $\text{Award\_achieved}_{it}$ is a dummy variable proxy of the remaining monetary goal, while Dynamic_goal_{it} is a continuous variable proxy of the remaining monetary goal. Meanwhile, Like_{it}, Dept_ave_{it}, and Role_model_{it} reflect the social incentives during the USTC-BWP. Participants perceive greater social support when they receive more Like from colleagues, and feel a greater sense of belongingness and achievement when they catch up with others colleagues. The summary statistics are shown in Table 2.

3.2 Data description

We applied fixed-effect panel data models with the lagged dependent variable as an instrument (FE-LDV models) to test our proposed research hypotheses. First, to test H1 and H3a–c, the regression equation can be specified as follows:

$$\text{Step}_{it} = \beta_0 + \beta_1 \cdot \text{Step}_{t-1} + \beta_2 \cdot \text{Award\_achieved}_{it} + \beta_3 \cdot \text{Like}_{it-1} + \beta_4 \cdot \text{Dept\_ave}_{it-1} + \beta_5 \cdot \text{Role\_model}_{it-1} + \alpha_t + \varepsilon_{it}. \quad (1)$$

As introduced above, Step_{it} is the daily step count of user i on day t. Step_{t-1} is the logged dependent variable. $\text{Award\_achieved}_{it}$ represents the effect of the existence of a monetary goal. Like_{it-1}, Dept_ave_{it-1}, and Role_model_{it-1} represent the social support and social contagion from other technology users. Notable, we used the first-order lagged form for all social-related factors. Finally, α_t is the date fixed effect, and ϵ_{it} is the error term. The estimation results were summarized in Table 3.

As shown in Table 3, $\text{Award\_achieved}_{it}$ is significantly negatively related to users' daily steps, suggesting that individuals' daily step count decreases significantly by 320 steps after the monetary goal is achieved. Hence, H1 is supported. In addition, users' daily step is positively associated with the amount of Like received on the previous day ($\beta = 32.78$, $p < 0.001$), the average step of department colleagues on the previous day ($\beta = 0.097$, $p < 0.001$), and the number of role models listed on the leaderboard in the previous day ($\beta = 9.253$, $p < 0.001$). We concluded that H3a–c are all supported by the empirical results.

Next, to test the non-linear effect of individual users' dynamic goal distance, we added Dynamic_goal_{it}, as well as its quadratic term to form Eq. (2):

$$\text{Step}_{it} = \beta_0 + \beta_1 \cdot \text{Step}_{t-1} + \beta_2 \cdot \text{Like}_{it-1} + \beta_3 \cdot \text{Dept\_ave}_{it-1} + \beta_4 \cdot \text{Role\_model}_{it-1} + \beta_5 \cdot \text{Dynamic\_goal}_{it} + \beta_6 \cdot \text{Dynamic\_goal}_{it}^2 + \alpha_t + \varepsilon_{it}. \quad (2)$$

As depicted in Table 3, the linear component of Dynamic_goal_{it} is positively associated with Step_{it}, while the coefficient of the quadratic term is significantly negative. In addition, we followed the standard approach in the existing literature to calculate the turning point of the observed relationship between the dynamic goal and daily steps[60]. According to the estimated coefficients of Eq. (2), the turning point is 6813 ($-\beta_5/(2\beta_6)$), with a 95% confidence interval of (5891, 8333). The 95% confidence interval of the turning point is fully located within the data range of the dynamic goals of participants, suggesting that the proposed reversed U-shape relationship in H2 was supported. Specifically, when the dynamic goal distance is below the optional level (i.e., 6813), with the increase of the dynamic goal distance, user's daily step significantly increases. However, as the dynamic goal reaches an optimal level and continuously increases, user's daily step reaches the peak and then gradually decreases. This supports our H2 that users' daily steps can be maximized when the dynamic goal distance stays around an optimal challenge level. Either an unchallenging goal (e.g., 2000 steps per day) or a hard-to-reach goal (e.g., 12000 steps per day) will demotivate users and lead to a decrease in their physical exercise.

Finally, to further test the interaction effects (the crowd-out effects) between the monetary and social incentives, we added several interaction terms accordingly, and the regression equation can be specified as follows:

$$\text{Step}_{it} = \beta_0 + \beta_1 \cdot \text{Step}_{t-1} + \beta_2 \cdot \text{Award\_achieved}_{it} + \beta_3 \cdot \text{Like}_{it-1} + \beta_4 \cdot \text{Dept\_ave}_{it-1} + \beta_5 \cdot \text{Role\_model}_{it-1} + \beta_6 \cdot \text{Award\_achieved}_{it} \cdot \text{Like}_{it-1} + \beta_7 \cdot \text{Award\_achieved}_{it} \cdot \text{Dept\_ave}_{it-1} + \beta_8 \cdot \text{Role\_model}_{it} \cdot \text{Like}_{it-1} + \alpha_t + \varepsilon_{it}. \quad (3)$$

As shown in Table 3, all the interaction terms between the achievement of the monetary goal and the three social factors are positively significant, suggesting that the effects of social support and social contagion are stronger after the monetary

Table 1. Definitions of key variables.

Variable	Description
Step_{it} [a]	The daily step walked by user i on day t [b].
$\text{Award\_achieved}_{it}$	A dummy variable whether the 710000-step ultimate monetary goal has been achieved by user i on day t.
Dynamic_goal_{it}	Dynamic goal distance: how many steps user i need to walk on average during the remaining period of the program to achieve the 710000-step goal [c]. If the ultimate award has already been achieved, then Dynamic_goal_{it} equals to 0.
Like_{it}	The number of Like received by user i on day t.
Dept_ave_{it}	The average daily step walked by colleagues in the same department with user i on day t.
Role_model_{it}	The amount of "role models" in the department of user i on day t. Role models are people with a daily exercise record of "20000+" steps as displayed on the leaderboard.

[a] Step_{it} is the actual step and is not restricted to the 20000 limit for step count (i.e., can be greater than 20000).

[b] The corner mark t ranges from 1 to 100.

[c] For example, user i has walked 310000 steps during the first 20 days, then on the 21st day, the dynamic_goal = (710000−310000)/(100−20) = 5000. Moreover, the rules about the 20000 limit for step count is applied in calculating Dynamic_goal_{it}.

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Table 2. Summary statistics.

	Mean	SD	1	2	3	4	5	6
1. $Step_{it}$	10206.1	5698.3	1					
2. $Award\_achieved_{it}$	0.226	0.418	0.226	1				
3. $Dynamic\_goal_{it}$	6343.7	7106.8	−0.125	−0.200	1			
4. $Like_{it}$	0.036	1.082	0.038	0.003	−0.005	1		
5. $Dept\_ave_{it}$	9927.4	1284.5	0.207	−0.016	−0.059	0.010	1	
6. $Role\_model_{it}$	10.30	9.74	0.170	0.056	−0.047	0.019	0.647	1

Table 3. Model estimation results.

DV: $Step_{it}$	Model 1 (fixed-effect estimator)	Model 2 (fixed-effect estimator)	Model 3 (fixed-effect estimator)	Model 1 (AB-LDV estimator)
$Award\_achieved_{it}$	−320.24*** (33.66)	–	−357.95*** (33.86)	−739.79*** (104.21)
$Dept\_ave_{it-1}$	0.087*** (0.018)	0.084*** (0.018)	0.052** (0.018)	0.067*** (0.009)
$Role\_model_{it-1}$	9.253*** (3.074)	8.862** (3.073)	9.119** (3.075)	6.527** (2.345)
$Like_{it-1}$	32.78*** (10.22)	40.90*** (10.14)	33.23*** (10.21)	1.272 (ns) (10.04)
$Dynamic\_goal_{it}$	–	0.0104*** (0.0012)	–	–/
$Dynamic\_goal_{it}^2$	–	−7.63E−7*** (1.27E−7)	/	–
$Award\_achieved_{it} \cdot Like_{it-1}$	–	–	119.23*** (17.98)	–
$Award\_achieved_{it} \cdot Dept\_ave_{it-1}$	–	–	0.094*** (0.022)	–
$Award\_achieved_{it} \cdot Role\_model_{it-1}$	–	–	21.140*** (3.039)	–
$Step_{it-1}$	0.288*** (0.002)	0.288*** (0.002)	0.287*** (0.002)	−0.433*** (0.002)
Date fixed effect	Yes	Yes	Yes	No
Constant	6213.98*** (196.53)	6169.15*** (196.80)	6579.34*** (199.38)	N/A
R-square	0.3797	0.3929	0.3888	0.1866

*: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$, ns: not significant, N/A: not applicable.

goal is achieved. In other words, before achieving the monetary goals, users are less influenced by the received Like and their colleagues' fitness performance. However, after the monetary goal is achieved, users will be more sensitive to the Like they received and their peers' fitness performance. We concluded that H4 are all supported.

3.3 Robustness check on endogeneity issues

Our estimation results suffer from several potential endogeneity issues. First, endogeneity can be caused by homophily in a social environment, as individuals tend to build social relationships with people who are similar to them[61]. In our context, users in the same department are more likely to have a similar lifestyle, hence their daily steps are somehow naturally correlated. The coefficients of social contagion variables (i.e., $Dept\_ave_{it-1}$ and $Role\_model_{it-1}$) in the above Models 1–3 can be overestimated due to the existence of this homophily bias. Second, there is probably a reversed causality between the amount of Like received by users and their daily step count. Users who do more exercise are more likely to receive more Like from peers.

To rule out the potential endogeneity induced by homophily and reversed causality, we further applied the AB-LDV model (lags of the outcome variable as instruments in a first-differencing model) to estimate Model 1[62]. First-differencing removes the group fixed effect, allowing us to estimate the social contagion effects that are not contaminated by homophily[63]. The results of the first-differencing estimators are generally consistent with the fixed-effect estimators, with one exception that the influence of social support (i.e., amount of received Like) becomes insignificant. We generally concluded that homophily seems not to be a serious concern in this study, because the social relationships in the same academic and admin departments are naturally formed. In universities, faculties with the same research areas get into the same department, and they do not necessarily have similar lifestyles in doing physical exercise. However, the effect of social support (i.e., $Like_{it-1}$) is somehow overestimated due to the potential reversed causality. People with better fitness performance are more likely to receive more Like and become a "star" in the USTC-BWP.

4 Conclusions

4.1 Summary of findings

In technology-enabled online fitness programs, both monetary

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and social incentives are widely adopted to promote fitness technology users' exercise behavior. This study systematically examined the monetary incentives, social incentives, and goal setting on users' exercise behavior, as well as the potential interaction effects among them. Using data collected from the USTC Brisk Walking Program, our proposed hypotheses are to a large extent supported.

First, the existence of an unachieved monetary goal has a positive effect on individuals' exercise behavior. The finding suggests that offering monetary incentives for exercise behavior would promote users' engagement. However, the motivation will be weakened once the monetary goal is removed. The effect of monetary incentives on exercise behavior is consistent with the studies on adults' physical activity[13].

Second, our findings reveal that dynamic goal distance is found to have a reversed U-shape effect on exercise behavior. To be specific, an optimal and reasonable goal would motivate users and lead to an increase in their exercise behavior. However, either an unchallenging goal or a hard-to-reach goal would demotivate users and result in a decrease in their exercise behavior.

Third, social support and social contagion are found to have a positive effect on fitness technology users' exercise behavior. While this finding is consistent with previous studies on the effect of social support on exercise behavior[30], this study provides a more detailed investigation of the influences of social incentives. To be specific, social support from others can encourage users to do more exercise. Moreover, the social contagion within the network, as well as the social influences from the network's core members (i.e., the role models in doing physical exercise), will motivate users to do more exercise behavior.

Finally, social incentives are found to serve as supplements for monetary goals in motivating exercise behavior. When both the monetary and social incentives coexist in an online program, there is a potential crowd-out effect, which weakens the influence of social incentives on participants' daily steps. After individuals have achieved all monetary goals, the influences of social incentives would become stronger.

4.2 Theoretical implications

This study has several theoretical implications. First, our study contributes to the extant literature on technology-enabled fitness behavior change by shedding light on how monetary and social incentives can be jointly implemented to facilitate users' exercise behavior. Previous studies have examined the separate effect of monetary and social incentives on exercise behavior. However, there is a limited understanding of the joint effects of monetary and social incentives on exercise behavior. This study is an early effort to reveal the crowd-out effect between monetary and social incentives. Our findings suggest that the effect of social incentives on exercise behavior will become stronger after the monetary goal is achieved. We argue that the existence of monetary goals invokes an economic market thinking, while incentives from social interactions arouse a social thinking. When monetary and social incentives coexist, the economic market thinking will to some extent crowds out the effect of social incentives on exercise behavior.

Second, we propose an inverted U-shape relationship between dynamic goal distance on exercise behavior, which enriches the existing understanding of individual's dynamic goal setting in longitudinal online fitness programs. We suggest that to maximize the influence of monetary incentives on users' exercise behavior, users' dynamic goal distance should be controlled in an optimal range.

4.3 Practical implications

Our findings also contribute to practice by helping organizations and fitness technology service providers to better design the reward mechanisms of longitudinal online fitness programs. First, we suggest that online fitness programs can take advantage of both monetary and social incentives to increase users' exercise motivation. The social interaction features serve as an important supplement when the monetary goal is absent. For those organizations that do not have enough budget to offer monetary incentives in their fitness programs, they should rely more on the social interaction features in fitness technologies, such as the "liking" feature and leaderboard.

Second, the goals for exercise should be set at a reasonable level, because an unchallenging goal or a hard-to-reach goal would demotivate users and result in a decrease in their exercise behavior. Only a reasonable goal with an optimal level of difficulty can effectively motivate users to do more exercise. Our findings reveal that the optimal goal for users' daily steps in the USTC-BWP is 6813, which is very close to the daily step requirement set by the university union (i.e., 7100 steps).

Finally, we suggest the hosts of online fitness program and designers to separate an overall longitudinal goal into several independent sub-goals. Participants quickly lose motivation after the overall goal is achieved or given up. Accordingly, we suggest the host of the USTC-BWP can separate the overall goal into about 15 weekly-based sub-goals. For each achieved weekly-based goal, participants can get a monetary reward of about ¥10.

4.4 Limitations and future research directions

Our study has several limitations. First, the data is obtained from a university-wide fitness online program, and the participants of the program are mainly researchers and admin staff in the university. Most of these faculties are highly educated and are of high income, as compared to the overall population. As a result, our findings may not be fully generalized to online fitness programs in other organizations. For example, the effect of monetary goals for high-income people will be relatively weaker. Second, in our study, the mechanism for offering monetary incentives is fixed. Future studies can consider comparing the different rewarding strategies using randomized controlled experiments. Third, the program was held during the COVID-19 pandemic. The exercise behavior of the participants may have been affected by the pandemic. Finally, there are several potential endogeneity issues in estimating the effect of social incentives. Our study passed the robustness test, but with one exception that the influence of social support (i.e., the amount of received Like) becomes insignificant in the AB-LDV estimation. Future research is

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suggested to use randomized controlled experiments to further validate the effects of social interactions on exercise behavior, which can fully eliminate the endogeneity concerns.

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Conflict of interest

The authors declare that they have no conflict of interest.

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