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Health management gamification: Understanding the effects of goal difficulty, achievement incentives, and social networks on performance

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ABSTRACT

Motivating users to change their health management behaviors and improve their behavioral performance is a challenge for designers of health management platforms. Gamification has the potential to motivate individuals to manage their health. To better understand the role of gamification in health management, this study investigates the role of goal difficulty and achievement incentives in health management performance as well as the moderating effects of social network exposure and active interaction. We collected data from an online weight management platform in China to test our research hypotheses. The results show that a U-shaped relationship exists between goal difficulty and weight management performance. Moreover, achievement incentives have a positive effect on performance and partially moderate the effect of goal difficulty. In addition, social network exposure strengthens the U-shaped relationship between goal difficulty and performance, while active interaction in social networks positively moderates the relationship between achievement incentives and performance. These findings facilitate the understanding of the role of social networks in health management gamification and contribute to goal-setting theory by providing new insights and suggestions for users and designers of health management platforms.

1. Introduction

Obesity has become a serious problem in countries around the world. The United States has the highest rates of obesity worldwide, with adult and child obesity being 36.5% and 17%, respectively (Yan 2018). China is rapidly becoming the second most obese country in the world (Yang et al. 2019b), with the number of obese people in China reaching more than 250 million in 2019.[1] Obesity increases the risk of hypertension, diabetes, heart disease, and other chronic diseases and can affect health and quality of life. Problems related to obesity have become an important issue for health industries and organizations. In recent years, online health platforms and mobile applications have become vital channels for helping individuals manage their weight and health conditions (Yang et al. 2019a). Although these digital platforms have made it easier for individuals to create exercise and dietary plans and change their health-related behaviors, their weight management performance (i.e., degree of weight loss or change in body mass index [BMI]) may be reduced by a lack of motivation and interest (Tortorella et al. 2020; Yang et al. 2019b). Hence, the issue of how to motivate a change in users' health management behaviors and improve weight management performance remains a significant challenge for designers of health management platforms.

Designers of health management platforms have developed gamification functions to encourage users to engage in health self-management (Alahäivälä and Oinas-Kukkonen 2016). Gamification is the use of game design features in nongame contexts to motivate user behaviors (Deterding et al. 2011). For example, users can complete certain tasks to change their health-related behaviors and enhance their weight management performance (Yang et al. 2019b). Health management platforms enable users to set their weight loss goals, obtain rewards for achievements (e.g., badges and points), and engage in social networks. They can also play "games" to increase their interest and motivation (Johnson et al. 2016; Sardi et al. 2017). Therefore, the use of gamification in health management platforms has the potential to motivate users' health management behaviors.

Despite the prevalence of gamification in health management, its efficacy is unclear. Therefore, understanding the effects of gamification can improve the efficacy of online health management platforms. This

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in-depth study on goal difficulty, achievement incentives, and social networks was motivated by the following. First, in gamification design, achievement incentives are considered external motivators of behavioral change (Koivisto and Hamari 2019; Seaborn and Fels 2015) through the use of reward and ranking systems such as scores, badges, and leaderboards (Fried and Slowik 2004; Locke and Latham 2002). However, given that health management is an important intrinsic human need, relying only on external incentives is not sufficient to effectively motivate individual effort and behavioral change. Thus, goal setting is another key component of gamification design that can convert users' needs into motivations and shift behaviors toward a predetermined direction (Landers et al. 2017). Designers of online weight management platforms and mobile apps often develop goal-setting systems to guide users in a predetermined direction. For example, users of the Keep and Bohe apps must set precise weight loss goals (e.g., the amount of weight they want to lose) before they can use the gamification function. Unlike external achievement incentives, setting personal goals reflects individuals' internal health-related needs and desires, thus may motivate behavioral change and improve weight management performance. To better understand the role of gamification in health management, the combined effect of goal setting and achievement incentives should be investigated.

Second, goal setting is a key component of gamification design (Groening and Binnewies 2019). Individuals should set realistic goals when participating in weight management platforms. However, the results of empirical research on the effects of goal difficulty have been mixed. Previous studies have shown a positive linear relationship between goal difficulty and performance levels because people adjust their efforts according to different goals (Groening and Binnewies 2019). That is, difficult goals direct individuals toward goal-related behaviors, enabling them to enjoy the attainment of goals and increasing their behavioral persistence (Locke 1968). In contrast, other studies have found that easier goals are more likely to be achieved, positively affecting behavioral performance (Lewis et al. 1992; Locke and Latham 2002). When an individual achieves or exceeds an easy goal, they obtain additional satisfaction, which further motivates behavioral change. The relationship between goal difficulty and level of performance remains particularly unclear in the domain of health management. Unlike previous studies (Groening and Binnewies 2019; Locke and Latham 2002), we consider that there is a U-shaped relationship between goal difficulty and weight management performance. That is, as goal difficulty increases, weight management performance initially decreases before increasing again.

Third, the coexistence of external (achievement incentives) and internal (goal setting) mechanisms may also improve weight management performance. However, few gamification studies have investigated the potential relationship between goal difficulty and achievement incentives. Goal-setting theory posits that a combination of goal setting and external incentives can affect behavioral performance (Locke 1968; Locke and Latham 2002). However, individuals may have little motivation to set goals if they consider it tedious (Yang et al. 2019a; Yang et al. 2019b). Therefore, individuals need external motivators to stimulate the process of goal setting. Achievement incentives are common motivational strategies in gamification and may moderate the U-shaped relationship between goal difficulty and performance.

Fourth, although previous studies have explored the direct effect of social networks in the gamification domain (Du et al. 2020; Hamari and Koivisto 2015), few have investigated the moderating effect of social networks. Social networks improve individuals' participation in gamification. According to goal-setting theory (Locke and Latham 2002), when individuals publicly announce that they have set a goal, their commitment to their goals and self-efficacy are strengthened, positively affecting the execution of the goal. Hence, a social network may moderate the relationship between goal setting, achievement incentives, and performance. This research explores the effect of the social network in relation to two characteristics: the degree of social network exposure and the frequency of active interactions within the social network. Network exposure indicates how much attention individuals receive in their social networks (Hsieh et al. 2008). Active interaction refers to an individual's active interactions with other members of the social network (Maier et al. 2015; Yang et al. 2019b). These two factors reflect the role of the social network from active (active interaction) and passive (network exposure) perspectives.

To fill these research gaps, the present study investigates the role of goal difficulty and achievement incentives in weight management performance as well as the moderating effect of network exposure and active interaction. The study aims to answer the following research questions:

(1) How do goal difficulty and achievement incentives affect weight management performance?
(2) What is the interaction relationship between goal difficulty and achievement incentives?
(3) Do exposure and active interaction in social networks moderate the relationship between goal difficulty, achievement incentives, and weight management performance?

Goal-setting theory is used to explain how goal setting can motivate individuals' behaviors and performance. We use goal-setting theory as the basis for our empirical research model to examine the influence of gamification on weight management performance. In this paper, weight management performance refers to the degree of weight loss and change in BMI. To test the research hypotheses, we collected data from 1,554 users of an online weight management platform in China. The results of the empirical model demonstrate that a U-shaped relationship exists between goal difficulty and weight management performance; in other words, individuals who set easy or difficult goals perform better than those who set moderate goals. Moreover, achievement incentives have a positive effect on health management performance and positively moderate the relationship between goal difficulty and performance. In addition, the results demonstrate that high network exposure positively moderates the U-shaped relationship between goal difficulty and performance, and frequent active interactions positively moderate the relationship between achievement incentives and performance.

This paper contributes to the existing literature in the following ways. First, this study combines internal (goal difficulty) and external (achievement incentives) mechanisms to investigate the role of gamification in health management. Second, the findings enrich the literature on goal-setting theory and health management behavioral change by providing an understanding of the U-shaped relationship between goal difficulty and performance. Third, the study contributes to the gamification literature by exploring the interaction between goal difficulty and achievement incentives. Fourth, the study extends the literature on gamification health management by investigating the moderating effects of social network exposure and active interaction. These findings help us to understand the role of gamification and social networks in health management as well as providing several practical strategies for users and practitioners.

2. Literature review

2.1. Gamification and health management

In recent years, gamification has become an important topic in a range of research disciplines (Almarshedi et al. 2015; Aparicio et al. 2019; Liu et al. 2013; Santhanam et al. 2016). Gamification refers to the use of game design elements in nongame contexts to influence individuals' behaviors (Deterding et al. 2011) and attitudes, cultivate interest, and improve behavioral performance in entertainment systems (Huotari and Hamari 2017; Su and Cheng 2015; Suh et al. 2017). Unlike traditional extrinsic motivators, gamification design elements aim to arouse individuals' intrinsic motivations and improve their behavioral performance (Hamari 2017; Kuo and Chuang 2016; Mekler et al. 2017; Xi and Hamari 2019). An increasing number of industries are adopting gamification methods to influence and improve individuals' behaviors and performance (Baptista and Oliveira 2019), including education (Aparicio et al. 2019; González et al. 2016; Landers and Armstrong 2017), health management (Alahäivälä and Oinas-Kukkonen 2016; Groening and Binnewies 2019), e-commerce (Baptista and Oliveira 2017; Hamari 2015; Rocha Seixas et al. 2016; Yang et al. 2017), environmental conservation (Du et al. 2020), and crowdsourcing (Feng et al. 2018).

Goal setting is a key component of gamification design (Groening and Binnewies 2019). Thus, many scholars have defined gamification as the science of converting individuals' behaviors into games to help them achieve their goals (Landers et al. 2017). Goal setting can stimulate the conversion of individuals' needs into motivations and shift their behaviors in a certain direction (Locke and Latham 2002). When a goal is set, individuals can decide whether to accomplish the goal (Landers et al. 2017). Gamification can increase individuals' behavioral motivations to achieve their set goals (Sailer et al. 2017). Previous studies have noted that achievements attained through gamification can serve as a proxy for external goal setting and facilitate individuals' motivation and performance (Groening and Binnewies 2019). In the gamified environment, achievement is reflected through three principal mechanisms: scores, badges, and leaderboards (Hamari and Koivisto 2014; Landers et al. 2017; Sailer et al. 2014; Seaborn and Fels 2015).

In general, achievement incentives have two functions affecting individuals' behaviors. First, they serve as a reward system (Sailer et al. 2014). Rewards are conferred when tasks are successfully completed, demonstrating users' improvement and performance levels. Individuals can improve their executive motivation by earning rewards for achievement. Second, achievement incentives can serve as a feedback system. Individuals can complete tasks to obtain subgoal feedback, which is a common motivational strategy and behavioral modification method (Groening and Binnewies 2019).

Health care practitioners have sought effective ways to change individuals' health management behaviors and improve health management performance (Johnson et al. 2016; Sardi et al. 2017). Health management gamification has rapidly grown, and many studies have explored its effectiveness (Allam et al. 2015; Michie et al. 2011; Wouters et al. 2013). Gamification is used in the health care domain as an information technology solution to motivate behavioral change in patients (Pereira et al. 2014; Sola et al. 2015). An important reason for the use of gamification in health care is to promote individuals' enjoyment of and engagement in their own health management (Park and Bae 2014; Sardi et al. 2017). Gamification technologies can satisfy users' basic inner needs and be a useful way of intrinsically motivating behavioral change and performance (Feng et al. 2018; Xi and Hamari 2019). Table 1 outlines the literature on the role of gamification in the health management domain. The research results present the positive influences of gamification on individuals, including improvements in performance levels and healthy behaviors and the willingness to continue using health management apps.

Although previous studies have investigated the influence of gamification on individuals' health management behaviors, they lack in several important aspects. First, previous studies have generally focused on the effect of achievement incentives rather than the effect of personal goal setting. Second, although studies have found a positive linear relationship between goal difficulty and level of performance, few have investigated the nonlinear relationship. Third, few studies on gamification have explored the potential interaction relationship between goal difficulty and achievement incentives. To fill these research gaps, this paper investigates the role of personal goal setting and achievement incentives in weight management gamification and explores the U-shaped relationship between goal difficulty and weight management performance.

Table 1
Literature on the role of gamification in health domain

Study	Category	Variables	Research content
Bock et al. (2019)	Physical activity	Use of video games	Effect of exercise video games on level of exercise and physical activity
Mo et al. (2019)	Physical activity	Points and social incentives	Use of gamification and social incentives may significantly enhance physical activity levels
Harris (2019)	Physical activity	Competition and points	Effect of community-wide gamification interventions on physical activity
Cechetti et al. (2019)	Chronic disease	Gamification system design	Develops a method for individuals to promote their engagement in hypertension monitoring
Cheng et al. (2019)	Mental health	Gamification incentives	Literature review to analyze the role of gamification in improving mental health
Patel et al. (2017)	Physical activity	Points	Role of achievement in individuals' performance
Lee (2019)	Intention to use mHealth	Enjoyment	Effect of gamification on intention to use mHealth and perceived usefulness
Chung et al. (2017)	Weight management	Social interaction	Effect of social gamification on BMI
Almarshedi et al. (2016)	Chronic disease	Socializing, badges, points, and challenges	Designs a gamification mechanism for individuals to perform self-management of chronic illnesses
Lee and Cho (2017)	Weight management	Entertainment, networkability	Factors motivating users' engagement in diet and fitness
Allam et al. (2015)	Chronic disease	Badges and medals	Effect of internet-based intervention using gamification on patients with rheumatoid arthritis
Hamari and Koivisto (2015)	Physical activity	Rewards and social interaction	Compares effects of gamification and non-gamification mobile app on users' physical activity level
Maher et al. (2015)	Health management behavior change	Rewards, leaderboard, and social interaction	Effects of gamification and non-gamification app on users' health management behaviors
Koivisto and Hamari (2014)	Physical activity	Gender, age, and social influence	Moderating effects of age and gender on relationship between perceived benefits of gamification and exercise engagement
Riva et al. (2014)	Chronic disease	Points	Influence of internet-based health management of patients with chronic back pain
Elias et al. (2013)	Chronic disease	Gamification incentives and monitoring	Whether gamification incentives improve the frequency of monitoring in asthma
Cafazzo et al. (2012)	Chronic disease	Rewards and points	Impact of mHealth gamification app on diabetes patients

2.2. Online health communities and social networks

Online health communities have become an important means by which to motivate individuals to effectively manage their health conditions (Chen et al. 2020a; Yang et al. 2020). Online health communities can be used to access health care services and relevant health care information conveniently and rapidly and enable users to engage in online interactions and exchange health-related experiences (Yan and Tan 2014; Yang et al. 2015). Users can manage their health conditions based on information and knowledge obtained from online communities (Yan 2018). Thus, online health communities offer users a health self-management tool. Most of the relevant literature on online health communities has explored the factors influencing users' health self-management and the management mechanisms used to improve health management performance (Ba and Wang 2013; Yang et al. 2019a; Yang et al. 2019b).

Online health management communities offer a safe and convenient health management platform for users (Li et al. 2019), but knowing how to motivate users and improve their health management performance through engagement in such communities remains an important challenge for designers (Tortorella et al. 2020). Hence, understanding users' motivation for engaging in online health communities is an important research issue. Previous research has noted that social support (including informational support, emotional support, esteem support, and companionship) (Chen et al. 2019; Chen et al. 2020b; Maier et al. 2015) is the main antecedent influencing individuals' psychology (belongingness and health attitudes) (Hamari and Koivisto 2013; Liu et al. 2020) and behaviors (value co-creation, engagement behaviors, and knowledge sharing) (Liu et al. 2020; Zhou et al. 2020). Social support generally refers to interactions between different individuals through sharing information and emotions (Yan 2018; Yan and Tan 2014). This support from members of online health communities can satisfy users' inner needs, improve their motivation to cope with negative events, motivate behavioral change, and enhance behavioral performance (Yang et al. 2019a; Yang et al. 2019b).

Social network characteristics are the antecedents of social support, meaning that they can significantly influence users' behavioral change and performance (Davlembayeva et al. 2020; Islam et al. 2020; Maier et al. 2015; Yang et al. 2019b). Generally, social network characteristics can be divided into active and passive characteristics. Active characteristics refer to individuals' active interactions with other members of the social network (Yang et al. 2019b). A higher frequency of active interactions may help individuals share information as well as their perspectives and emotions about their conditions with other social network members. Passive characteristics refer to the size of the social network and level of members' activities (Maier et al. 2015). These factors may reflect actual connections between individuals and improve a users' degree of exposure in their social network.

Social networks play an important role in gamification (Hamari and Koivisto 2013; Hamari and Koivisto 2015; Simões et al. 2013). They expose users to the opinions and attitudes of others, potentially influencing their behaviors. A user's social network exposure is likely to affect the number of tasks and activities in which they engage (Chang and Wang 2008). Social networks represent a social connection between individuals and provide users with more opportunities to interact with others (Kallinikos and Tempini 2014; Maier et al. 2015). Social network members can obtain social support by interacting with others (Yan 2018; Yan and Tan 2014). Providing informational and emotional support can help individuals cope with stressful events and positively influence their behaviors (Maier et al. 2015). Prior studies have demonstrated that there is a positive relationship between social support and health management performance (Yang et al. 2019a; Yang et al. 2019b). Further, social networks can promote individuals' social influence. Social networks invoke a sense of competition in terms of obtaining a higher number of achievements and rewards, in turn affecting satisfaction, self-esteem, and pride (Hamari and Koivisto 2015). Therefore, social networks in gamification technologies help individuals to engage in and maintain positive behaviors (Hamari and Koivisto 2015).

Although previous studies on gamification has explored the direct influence of social networks on individuals' behaviors (Du et al. 2020; Hamari and Koivisto 2015), few have investigated their indirect and moderating effects. In addition, comprehensive research on the moderating effects of the active and passive characteristics of social networks is lacking. To fill this gap, this paper examines the moderating effect of social network exposure and active interactions on the relationship between gamification and behavioral performance in health management.

3. Research hypotheses

3.1. Goal-setting theory

Developed by Lock (1968), goal-setting theory holds that individuals' behaviors and performance can be motivated to help them achieve their goals. Goals provide individuals with a standard against which to measure their own performance (Groening and Binnewies 2019). Different goals have different influences on individuals' performance. Self-regulation enables individuals to adjust their behaviors by identifying differences between their goals and their performance (Fried and Slowik 2004). Therefore, goal setting is an effective motivational intervention (Landers et al. 2017) that can influence individuals' performance through four means (Locke and Latham 2002). First, goal setting has a directive function, meaning that it can effectively direct individuals' efforts toward goal-related behaviors and activities. Second, goal setting has an incentive function, meaning that internal and external mechanisms can incentivize individuals to achieve their goals. Third, goal setting has a persistence function. Fourth, goal setting has an indirect function by affecting individuals' behavior through acquiring knowledge and information related to the goal.

3.2. Development of research hypotheses

In the weight management context, individuals must set realistic goals to motivate their weight management performance. Lack of motivation is a major reason for the failure of health management (Ba and Wang 2013). Specific goals can shift behaviors toward a certain direction, enhancing behavioral performance. Goal-setting theory posits that there is a strong relationship between goal difficulty and performance (Hamari 2015). Difficult goals give individuals the satisfaction of challenging themselves, leading to a higher level of performance. Goal setting is a cause rather than a result of performance and can reflect individuals' aspirations for task success (Fried and Slowik 2004). The expectancy, probability, and valence of task success can be high if performance goals are difficult and challenging. Goal-setting theory predicts that when goal difficulty increases, an individual's performance will improve (Landers et al. 2017). Goals can help individuals direct their activities toward goal-related behaviors, enable them to adjust their efforts according to goal difficulty, and lead to persistence of behaviors (Locke and Latham 2002). In relation to weight and health management, the goals set by individuals reflect their inner health-related needs, which are the foundation of personal health and quality of life. Difficult goals may indicate that an individual has poor health or excess weight and that they have a strong motivation to achieve their personal goals. Hence, difficult goals will positively influence an individual's weight management performance.

In contrast, many studies have found that easy goals can also motivate behavioral change and improve performance (Lewis et al. 1992). There are two possible reasons for this phenomenon. First, easy goals are easier to achieve than difficult goals. That is, people can become impatient when attempting to achieve difficult goals and may give up (Locke and Latham 2002). Second, achieving or exceeding goals leads to greater individual satisfaction, motivating individuals to continue to pursue the goal (Fried and Slowik 2004). When actual performance exceeds the goal, the individual's satisfaction in performing the task is significantly increased because their performance exceeds their expectation. The easier the task, the more likely the individual is to succeed, thus leading to the individual experiencing a satisfaction that comes with success. When goals are difficult, success is less likely, and individuals can experience less satisfaction. Thus, compared with difficult goals, easy goals can produce more satisfaction and lead to a higher level of performance.

Moderate goals are likely to produce a lower level of performance compared with easy and difficult goals. There are two principal reasons for this. First, moderate goals are more difficult to achieve than easy goals, making it more difficult for people to attain the satisfaction of reaching and exceeding them. Second, a moderate goal is less challenging than a difficult goal, thus does not effectively motivate the individual's desire for success. Therefore, this paper examines whether there is a U-shaped relationship between goal difficulty and level of performance. That is, easy goals are associated with improved behavioral performance; however, as goal difficulty increases, performance level decreases. Once performance level reaches the bottom of the nonlinear curve, it then begins to increase as goal difficulty further increases. Thus, the study presents the following hypothesis:

H1: There is a U-shaped relationship between goal difficulty and weight management performance such that individuals who set easy or difficult goals perform better than those who set moderate goals.

Achievement incentives are systems of reward and reputation aimed at satisfying individuals' inner needs, motivating them to complete tasks, regulating their behaviors, and influencing their behavioral performance (Sailer et al. 2014). Achievement incentives in gamification are based on the completion of specific actions and tasks (Groening and Binnewies 2019; Hamari 2013; Hamari 2017) and provide clear behavioral instructions to individuals with the purpose of providing them with rewards or enhancing their reputation (Landers et al. 2017). For example, in weight management gamification, a specific task may be to engage in more exercise or eat less throughout the day. When the level of achievement increases, behavioral motivation and performance levels will also increase (Groening and Binnewies 2019). Therefore, achievement incentives will positively affect the weight management performance. Thus, the study presents the following hypothesis:

H2: Achievement incentives have a positive effect on performance in weight management gamification.

Achievement incentives may also moderate the relationship between goal difficulty and performance. Goal-setting theory holds that external incentives (e.g., rewards) can enhance the effect of goal setting on behavioral performance. Hence, external rewards for goal setters should be used as a tool to achieve improved behavioral performance. Achievement incentives in terms of rewards and reputation can facilitate individuals' behavioral motivations and improve the positive effect of goal difficulty on performance. Moreover, achievement incentives can serve as feedback (Hamari 2017) between goal setting and individuals' response to performance (Locke and Latham 2002). Goals are the criteria by which individuals evaluate their own performance (Locke 1968). Feedback provides information to individuals about how well these criteria have been satisfied, what has been done well, and what needs to be improved. As a result of feedback, individuals can relate the reward they receive to their level of performance (Fried and Slowik 2004). Goal setters view feedback as an evaluation of their worth and level of competence and a way to make progress, correct mistakes, and solve problems (Locke and Latham 2002). When individuals set an easy goal, achievement incentives in the form of rewards and reputation can enhance their satisfaction of goal attainment. When individuals set a difficult goal, achievement incentives can serve as behavioral feedback that facilitates their adherence to a challenging goal. Therefore, achievement incentives may positively moderate the relationship between goal difficulty and performance. Thus, the study presents the following hypothesis:

H3: Achievement incentives enhance the U-shaped relationship between goal difficulty and level of performance in weight management gamification.

Goal-setting theory posits that goal commitment can moderate the relationship between goal difficulty and performance level (Locke 1968; Locke and Latham 2002). Goal commitment refers to individuals' determination to reach the goal and the degree to which the individual is attracted to the goal, believes the goal is important, and perseveres with reaching the goal (Locke 1968). Individuals who have high motivation to solve problems are better able to commit to their goals and solve problems. An individual's commitment to a goal is strengthened if they believe that the goal is achievable and significant. When individuals are publicly committed to reaching a goal and have a strong need for success, their level of commitment to the goal may be higher (Locke and Latham 2002). For example, if individuals tell one or two close friends about their goal, it will help them keep their commitment. Social networks provide a channel through which individuals can announce their goals. Network exposure reflects how much attention an individual receives in their social network (Hsieh et al. 2008). When an individual in a high-exposure social network announces a difficult goal, their commitment to achieving the goal is strengthened, enhancing the relationship between goal difficulty and performance. In contrast, when individuals are in a low-exposure social network, their goal commitment is weakened, thus diminishing the relationship between goal difficulty and performance.

Moreover, network exposure may increase both the positive and negative effects of goal difficulty on performance level. For example, if individuals post a difficult goal in a high-exposure social network, their goal commitment will increase, in turn motivating them to overcome the difficulty of the related task and achieve the goal. Therefore, network exposure can enhance the upward curve in the U-shaped relationship between goal difficulty and performance level. However, if individuals publish an easy goal on a high-exposure social network, their level of performance will decrease. Individuals can easily achieve easy goals; thus, the role of goal commitment is weakened. In addition, posting easy goals on a high-exposure social network decreases satisfaction in achieving or exceeding the goal because easy goals are less likely to attract attention in a public context. This can lead to individuals' behavioral performance being negatively affected. Thus, a high degree of network exposure strengthens the U-shaped relationship between goal difficulty and performance. Thus, the study presents the following hypothesis:

H4: High network exposure strengthens the U-shaped relationship between goal difficulty and level of performance in weight management gamification.

Self-efficacy refers to an individual's ability to engage in certain behaviors in specific situations to achieve the desired results (Locke 1968). Self-efficacy also refers to individuals' confidence or belief in their ability to achieve a specific goal (Sun et al. 2012). High self-efficacy can help individuals persevere in an activity for a long period, particularly when the activity requires overcoming difficulties and obstacles. An individual's self-judgment of how well they can deal with a problem is based on their assessment of their own resources (e.g., their ability to achieve). Active interaction refers to users' active behaviors in a social network (Yang et al. 2019b). If individuals are actively interacting with other members of the social network, they will share their achievements with those members, which can dramatically increase their self-efficacy and promote behavioral performance. Thus,

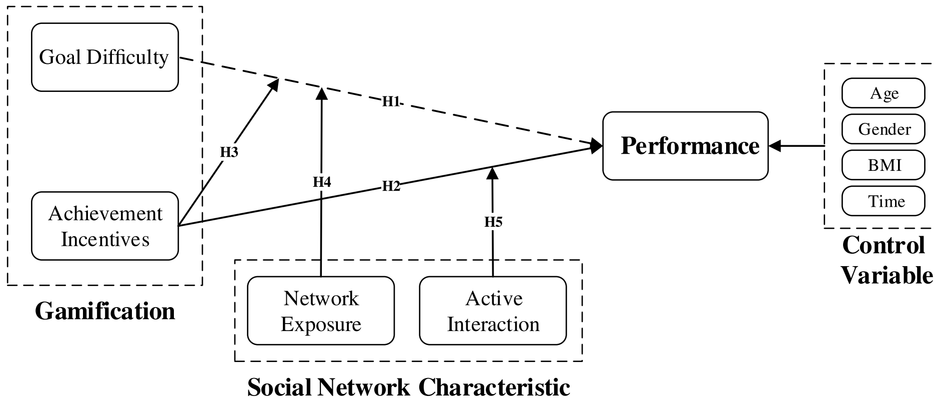

Fig. 1. Research model

active interactions can moderate the relationship between achievement incentives and performance level in weight management gamification. Thus, the study presents the following hypothesis:

H5: Frequent active interaction positively moderates the relationship between achievement incentives and performance in weight management gamification.

Fig. 1 presents the research model.

4. Methodology

4.1. Data collection and variable measurement

Data for this study were collected from Bohe (www.boohee.com), the most popular online weight management platform in China. Bohe was officially established in 2007 and provides a number of professional health services, including weight management. It has more than 80 million registered users and is the most successful gamification weight management platform in China. Users create their own home page and set their own weight management goals, and relevant health tasks are assigned according to these goals. By completing health tasks, users can obtain points and badges and share their achievements with other users. In addition, the platform has comprehensive social functions. Users can interact and compete with other users through the platform's social network. Based on the discussion above, this platform was suitable for our empirical study because it could provide data on user health and gamification. Many other studies have used Bohe to explore the effects of online platforms on health management (Yang et al. 2019a; Yang et al. 2019b). An example of the platform is presented in the appendix.

According to the website's terms and conditions,[2] its information and content may be used for non-commercial purposes such as research. The collected data were voluntarily disclosed by users, thus do not breach privacy regulations or reveal sensitive personal information (e.g., real names or ID numbers). This method of data collection has been widely adopted in medical and management research (Chen et al. 2020b; Zhang et al. 2019). The collected data included users' ages, genders, height, initial body weight, badges, achievements, weight loss goals, and current body weight. Data were collected from September 2019 to October 2019 using a Java-based program. Following data collection, data were cleaned, and invalid data—primarily those from users with incomplete health information, those who did not participate in gamification (i.e., goal setting or achievement mechanisms), and those who had never updated their information—were deleted, leaving data from 1,554 users.

In addition, in line with methods used in previous research (Yang et al. 2019a; Yang et al. 2019b), we used BMI (a measure of obesity) to reflect individuals' health conditions. The World Health Organization defines a BMI of 18.5–24.9 as healthy, higher than 24.9 as overweight, and higher than 29.9 as obese. Thus, BMI is a useful measure of users' health conditions. Specifically, BMI is calculated as follows:

$$BMI = \frac{Weight(kg)}{Height^2(m)}$$

The dependent variable in our research model was users' weight management performance. We used the change in BMI as a proxy for individual's weight management performance. In line with previous studies (Yang et al. 2019a; Yang et al. 2019b), BMI change was calculated as initial BMI minus current BMI. This variable was then normalized by subtracting the means and dividing the standard errors. Thus, weight management performance was calculated as follows:

$$Performance = STD(Initial\ BMI - Current\ BMI)$$

$$STD(x) = \frac{(x - \overline{x})}{\delta_x}$$

The first independent variable, goal difficulty, was measured as users' initial body weight minus their goal body weight (in kilograms). The following was the method used to calculate goal difficulty:

$$Goal\ Difficulty = Initial\ Weight - Goal\ Weight$$

The second independent variable, achievement, was measured using the gamification achievement incentives provided by the weight management platform (i.e., badge ranking). Badges are awarded to users who have accomplished health tasks. The higher the ranking of the badge, the higher the level of achievement. Thus, badge ranking was used as a proxy for users' levels of achievement.

The moderating variables in our research model were social network exposure and active interaction. Social network exposure refers to the number of the members and degree of member activities in a gamification system (Hsieh et al. 2008). Thus, this study used the number of visits made to a user's homepage by other network members as a proxy for degree of network exposure. Active interaction refers to the active interactions with other members in the social network (Yang et al. 2019b). Thus, this study used the number of posts shared by the user as a proxy for the frequency of active interactions.

Users' demographic information (i.e., age and gender), usage time, and health conditions were used as control variables in the research model. A dummy variable was used to measure gender (i.e., male = 1, female = 0). The number of days since the user joined the weight management platform was used to measure usage time. Table 2 presents the description of the variables. Tables 3 and 4 present the descriptive statistics and correlations between variables in our research model, respectively.

[2] http://www.boohee.com/boohee/declare

Table 2
Variable descriptions

Variable type	Variable name	Symbol	Measurement
Dependent	Performance of health management	Performance	Initial body mass index (BMI) minus current BMI
Independent	Goal difficulty	Goal	Initial body weight minus goal body weight (kg)
	Achievement incentives	Achievement	Badge ranking
Moderating	Network exposure	Exposure	Number of visits to a user's homepage
	Active interaction	Interaction	Number of posts shared
Control	Age	Age	Users' age (years)
	Gender	Gender	Male = 1, Female = 0
	Usage time	Time	Number of days since users joined gamification
	Health condition	BMI	BMI

Table 3
Descriptive statistics

Variable	Min.	Max.	Mean	SD
Age	18.000	35.000	28.320	2.480
Gender	0.000	1.000	0.455	0.499
Time	3.000	372.000	104.960	17.474
Body mass index	15.74	48.440	25.915	5.056
Goal	1.000	114.000	59.442	12.114
Achievement	1.000	14.00	4.726	1.767
Exposure	0.000	261.000	7.605	11.382
Interaction	0.000	246.000	2.930	10.717
Performance	−1.515	10.032	0.000	1.000

4.2. Model estimation

Based on prior research (Aiken et al. 1991; Hatak et al. 2016), this study used a log-nonlinear regression model to test our research hypotheses. We created the following regression model:

$$Performance_i = a_0 + a_1 Age_i + a_2 Gender_i + a_3 log(Day_i) + a_4 log(BMI_i) + a_5 log(Exposure_i) + a_6 log(Interaction_i) + a_7 log(Achievement_i) + a_8 log(Goal_i) + a_9 log(Goal_i)^2 + a_{10} log(Goal_i) * log(Achievement_i) + a_{11} log(Goal_i)^2 * log(Achievement_i) + a_{12} log(Goal_i) * log(Exposure_i) + a_{13} log(Goal_i)^2 * log(Exposure_i) + a_{14} log(Achievement_i) * log(Interaction_i) + \varepsilon_i$$

Let i = 1 … N index the user. In the model, a_0 to a_{12} were the parameters estimated in the research model. The terms log($Goal_i$) and log ($Goal_i$)^2 were used to test the U-shaped relationship between goal difficulty and performance. The interaction terms log($Goal_i$)*log ($Achievement_i$), log($Goal_i$)^2*log($Achievement_i$), log($Goal_i$)*log($Exposure_i$), log($Goal_i$)^2*log($Exposure_i$), and log($Achievement_i$)*log($Interaction_i$) were used to test the moderating effect. The term ε_i is an error term associated with observation i.

4.3. Empirical analysis and results

Table 5 presents the equation estimates and displays the empirical models hierarchically. We show the model with the control variables only in Column 1 and add the independent variables and interaction terms in Columns 2, 3, 4, 5, 6, and 7, respectively. In the regression equation, the adjusted R-squared and F-test values were reasonable and statistically significant. The mean variance inflation factor statistics for the variables were less than 2.0, indicating that there was no significant multicollinearity among the independent variables.

H1 predicted that a U-shaped relationship exists between goal difficulty and weight management performance. According to the empirical results of Columns 3 shown in Table 5, the coefficient of the nonlinear term of goal difficulty was positive and statistically significant ($a_9 = 0.191$, $t = 5.749$, $p < 0.01$), and the coefficient of the linear term was negative and statistically significant ($a_8 = -0.689$, $t = -4.339$, $p < 0.01$). This result supports H1, showing that there is a U-shaped relationship between goal difficulty and performance such that individuals who set easy or difficult goals perform better than those who set moderate goals. In other words, as goal difficulty increases, performance level initially decreases. Once the performance level reaches the bottom of the curve, it begins to increase as goal difficulty increases. Fig. 2 presents the U-shaped relationship between goal difficulty and performance.

H2 posits that achievement incentives positively affect weight management performance. Column 2 of Table 5 shows that the coefficient of the interaction term for the achievement incentive was positive and statistically significant ($a_7 = 0.255$, $t = 2.592$, $0.01 < p < 0.05$). This result supports H2, indicating that increasing achievement incentives improves weight management performance.

H3 posits that achievement incentives enhance the U-shaped relationship between goal difficulty and weight management performance. Column 4 of Table 5 shows that the coefficient of the interaction term *log (Goal$_i$)*log(Achievement$_i$)* was not statistically significant ($a_{10} = -0.718$, $t = -1.297$, $p > 0.1$), but the coefficient of the interaction term *log (Goal$_i$)^2*log(Achievement$_i$)* was positive and statistically significant (a_{11}

Table 4
Correlations between variables

Variable		1	2	3	4	5	6	7	8	9
1	Age	1								
2	Gender	−0.042	1							
3	Time	−0.006	0.186**	1						
4	BMI	0.170**	0.238**	−0.008	1					
5	Goal	0.052*	0.506**	0.095**	0.629**	1				
6	Achievement	0.249**	−0.433**	0.110**	−0.108**	−0.259**	1			
7	Exposure	0.105**	−0.171**	−0.025	−0.059*	−0.107**	0.182**	1		
8	Interaction	0.007**	−0.029	0.041	−0.100	−0.042	0.074**	0.118**	1	
9	Performance	0.128**	−0.093**	0.068**	0.412**	0.088**	0.030**	0.042	−0.034	1

Note: * and ** means correlation (two-tailed) is significant at the 0.01 and 0.05 levels, respectively.

Table 5
Results of research model (N = 1,554)

Independent variable	1	2	3	4	5	6	7
Constant	−9.146***	−8.075***	−5.982***	−6.395***	−6.595***	−5.605***	−5.254***
	(−18.092)	(−13.069)	(−8.404)	(−4.668)	(−6.992)	(−7.765)	(−3.766)
Age	0.022**	0.009	0.009	0.009	0.009	0.007	0.006
	(2.344)	(1.184)	(0.927)	(0.907)	(0.979)	(0.698)	(0.652)
Gender	−0.477***	−0.309***	−0.296***	−0.308***	−0.299***	−0.272***	−0.279***
	(−9.593)	(−5.311)	(−5.126)	(−5.357)	(−5.200)	(−4.688)	(−4.837)
Log(Day)	0.180***	0.165***	0.154***	0.155***	0.152***	0.166***	0.169***
	(5.477)	(4.900)	(4.619)	(4.675)	(4.586)	(4.961)	(5.081)
Log(BMI)	2.365***	1.833***	1.490***	1.477***	1.474***	1.536***	1.519***
	(18.112)	(9.415)	(7.387)	(7.335)	(7.309)	(7.610)	(7.556)
Log(Exposure)		0.097**	0.101**	0.104**	0.457	0.098**	0.662*
		(2.248)	(2.363)	(2.438)	(1.392)	(2.301)	(1.639)
Log(Interaction)		−0.086**	−0.092**	−0.083**	−0.089**	−0.724***	−0.900***
		(−2.182)	(−2.347)	(−2.115)	(−2.277)	(−3.283)	(−4.020)
Log(Achievement)		0.255**	0.228**	0.489	0.237**	−0.088	−0.868
		(2.592)	(2.344)	(0.730)	(2.438)	(−0.602)	(−1.020)
Log(Goal)		0.176***	−0.689***	0.533	0.182	−0.657***	0.333
		(3.424)	(−4.339)	(0.555)	(0.357)	(−4.141)	(0.347)
$Log(Goal)^2$			0.191***	−0.200	−0.036	0.183***	−0.208
			(5.749)	(−1.013)	(−0.354)	(5.510)	(−1.055)
Log(Goal)*log (Achievement)				−0.718			0.029
				(−1.297)			(0.043)
$Log(Goal)^2$*log (Achievement)				0.229**			0.092*
				(2.021)			(1.692)
Log(Goal)*log (Exposure)					−0.471*		−0.563*
					(−1.787)		(−1.764)
$Log(Goal)^2$*log (Exposure)					0.122**		0.126**
					(2.318)		(2.034)
Log(Achievement)*log (Interaction)						0.346***	0.450***
						(2.913)	(3.711)
Adjusted R^2	0.199	0.213	0.229	0.235	0.233	0.233	0.243
F-test	97.491***	53.656***	52.356***	44.415***	44.008***	48.198***	36.612***

Note: t statistics are given in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

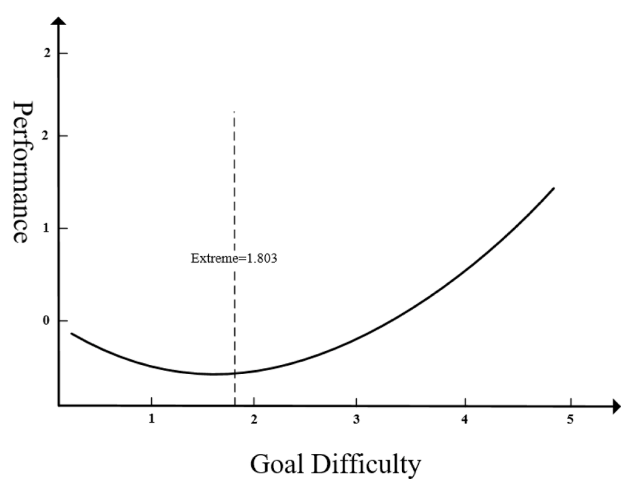

Fig. 2. U-shaped relationship between goal difficulty and performance (H1).

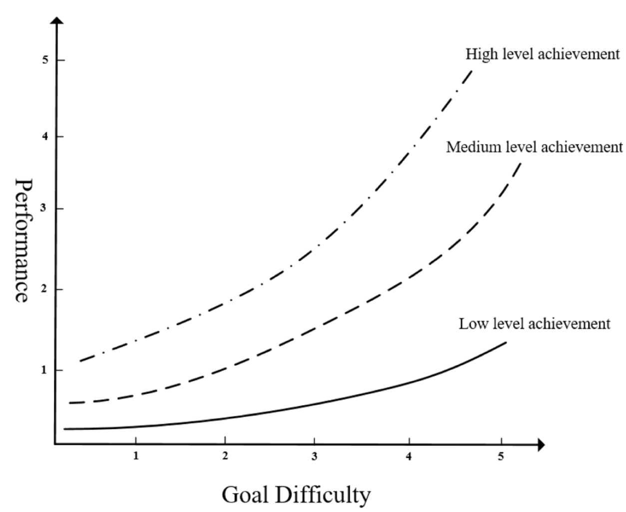

Fig. 3. Moderating effect of achievement incentives (H3).

= 0.229, t = 2.021, 0.01 < p < 0.05). This result partially supports H3, indicating that there is a positive interaction relationship between goal difficulty and level of achievement. The results demonstrate that achievement incentives mainly moderate the increasing side of the U-shaped curve rather than the decreasing side of the U-shaped curve. Thus, achievement incentives are more effective for those who set difficult goals than for those who set easy goals. Fig. 3 presents the moderating effect of achievement incentives.

H4 predicts that a high degree of network exposure strengthens the U-shaped relationship between goal difficulty and weight management performance. Column 5 of Table 5 shows that the coefficient of the interaction term *log(Goal$_i$)*log(Exposure$_i$)* was negative and statistically significant (a_{12} = −0.471, t = −1.787, 0.05 < p < 0.1), while the coefficient of the interaction term *log(Goal$_i$)^2*log(Exposure$_i$)* was positive and statistically significant (a_{13} = 0.122, t = 2.318, 0.01 < p < 0.05). A high degree of network exposure strengthens both the positive and the negative effects of goal difficulty on performance, thus strengthening the U-shaped relationship. Hence, this result supports H4, indicating that a high degree of network exposure strengthens the relationship between goal difficulty and weight management performance. Fig. 4 presents the moderating effect of the degree of network exposure.

H5 predicts that frequent active interactions in social networks positively moderates the relationship between achievement incentives and weight management performance. Column 6 of Table 5 shows that

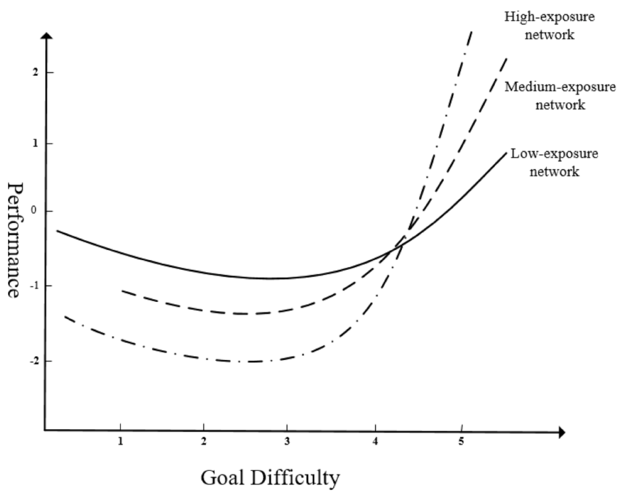

Fig. 4. Moderating effect of network exposure (H4).

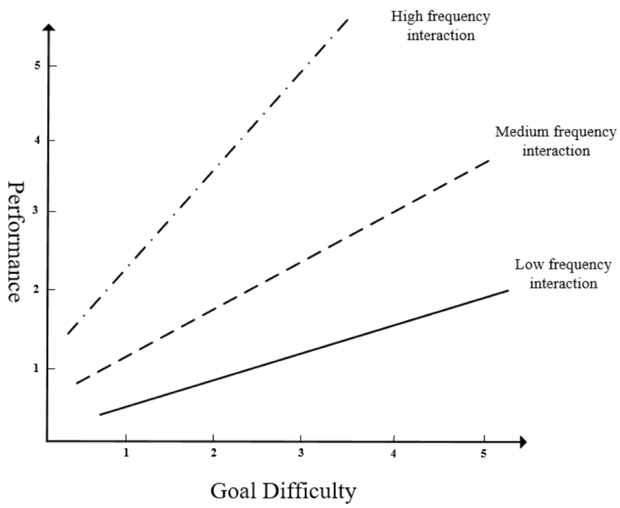

Fig. 5. Moderating effect of active interaction (H5).

the coefficient of the interaction term $log(Achievement_i)*log(Interaction_i)$ was positive and statistically significant ($a_{14} = 0.346$, $t = 2.913$, $0.01 < p < 0.05$). This result supports H5, indicating that active interactions positively moderate the relationship between achievement incentives and weight management performance. Fig. 5 presents the moderating effect of active interaction.

4.4. Robustness check

To check the robustness of the results, in line with previous methods, we ran the model using replacements for the independent variables. The main model used the difference between initial body weight and goal body weight to measure goal difficulty. For the robustness check, we used the difference between BMI based on initial body weight and BMI based on goal body weight as a proxy (goal BMI) for performance level. Moreover, the main model used the gamification score as a proxy for achievement difficulty. For the robustness check, we used the points obtained by users to measure achievement difficulty. The results of the robustness check are presented in Table 6 and are consistent with the results of the previous model.

4.5. Post-hoc analysis

The results of ordinary least squares regression support all hypotheses. However, there may be reciprocal causation between the level of achievement and the level of performance, which may lead to endogeneity in the research model. To reduce this problem, we employed a quasi-experimental research approach using a combination of propensity score matching (PSM) and difference-in-differences (D-in-D) analysis to test the research questions.

First, the use of PSM based on the collected data enabled us to design a randomized experiment to establish a causal link between the independent and dependent variables. Users with matching characteristics prior to engaging in the online weight management platform were chosen, allowing for statistical equivalence and balance between the treatment and control groups. In contrast with ordinary least squares, which uses a continuous variable, PSM uses a dummy variable to measure level of achievement. In the former, a value of less than 5 indicates that the level of achievement is low, while a value greater than 5 indicates that the level of achievement is high. In PSM, low and high levels of achievement were expressed as 0 and 1, respectively. Four characteristics could be used to calculate users' propensity score: age, gender, usage time, and BMI. To test the role of achievement incentives, we performed PSM twice to identify differences between the treatment and control groups. We build a logit regression model to calculate the propensity scores, which were then used to locate matched pairs. The regression model is as follows:

$$Logit(Achievement_i) = b_0 + b_1 * Age_i + b_2 * Gender_i + b_3 * log(Day_i) + b_4 * log(BMI_i) + \theta_i$$

Let i = 1 ... N index the users. In this regression, b represents the parameters to be estimated in the logit regression. The term Achievement is a dummy variable. Table 7 presents the results of the logit regression models.

The treatment and control groups were matched based on the estimated propensity scores. We used optimal pair matching to treat every matched pair, including the treatment and control groups, separately. Further, we used a match tolerance of 0.02 to match the treatment and control groups. This means that the treatment and control groups performed matched pairs based on propensity scores of ± 0.02. Table 8 presents the results of the matched pairs.

Second, D-in-D was based on the matched data, allowing us to test our research results, obtain unbiased estimates, and reduce the endogeneity of the research model. The D-in-D model tested the effect of goal difficulty and achievement ranking. For every matched pair, including the treatment and control groups, the regression model was as follows:

$$\begin{aligned} Performance_{ij} = {} & b_0 + b_1 Age_i + b_2 Gender_i + b_3 log(Day_i) + b_4 log(BMI_i) \\ & + b_5 log(Exposure_i) + b_6 log(Interaction_i) + b_7 log(Goal_i) + b_8 log(Goal_i)^2 + b_9 Time_{ij} \\ & + b_{10} Treated_{ij} + b_{11} Treated_{ij} * Time_{ij} + b_{12} Treated_{ij} * Time_{ij} * log(Goal_i) \\ & + b_{13} Treated_{ij} * Time_{ij} * log(Goal_i)^2 + b_{14} Treated_{ij} * Time_{ij} * log(Interaction_i) + \varepsilon_i \end{aligned}$$

Table 6
Results of robustness check (N = 1,554)

Independent variable	1	2	3	4	5	6	7
Constant	−9.146***	−7.420***	−5.755***	−5.371***	−6.022***	−5.493***	−4.759***
	(−18.092)	(−11.610)	(−8.446)	(−5.395)	(−7.330)	(−7.986)	(−4.677)
Age	0.022**	0.011	0.011	0.011	0.012	0.009	0.006
	(2.344)	(1.088)	(1.125)	(1.131)	(1.202)	(0.962)	(0.988)
Gender	−0.477***	−0.296***	−0.281***	−0.292***	−0.284***	−0.264***	−0.270***
	(−9.593)	(−5.088)	(−4.892)	(−5.065)	(−4.943)	(−4.567)	(−4.680)
Log(Day)	0.180***	0.169***	0.162***	0.163***	0.160***	0.172***	0.174***
	(5.477)	(5.042)	(4.891)	(4.934)	(4.851)	(5.166)	(5.243)
Log(BMI)	2.365***	1.640***	1.374***	1.371***	1.357***	1.409***	1.402***
	(18.112)	(8.199)	(6.809)	(6.797)	(6.729)	(6.982)	(6.959)
Log(Exposure)		0.100**	0.105**	0.109**	0.268	0.106**	0.478*
		(2.302)	(2.464)	(2.564)	(1.087)	(2.478)	(1.650)
Log(Interaction)		−0.084**	−0.091**	−0.085**	−0.087**	−0.546***	−0.699***
		(−2.131)	(−2.327)	(−2.163)	(−2.230)	(−3.010)	(−3.680)
Log(Score)		0.050**	0.042*	−0.028	0.045*	−0.026	−0.276*
		(2.001)	(1.708)	(−0.224)	(1.829)	(−0.713)	(−1.778)
Log(GoalBMI)		0.288***	−0.763***	−0.676	−0.017	−0.739***	−0.609
		(4.525)	(−4.376)	(−0.751)	(−0.031)	(−4.241)	(0.672)
Log(GoalBMI)^2			0.333***	0.155	0.026	0.074***	0.050
			(6.462)	(0.572)	(0.157)	(6.281)	(0.181)
Log(GoalBMI)* log(Score)				−0.014			0.172
				(−0.089)			(0.953)
Log(GoalBMI)^2* log(Score)				0.031*			0.018*
				(1.764)			(1.639)
Log(GoalBMI)* log(Exposure)					−0.402*		−0.589*
					(−1.668)		(−1.724)
Log(GoalBMI)^2* log(Exposure)					0.164*		0.199**
					(1.928)		(2.056)
Log(Score)* log(Interaction)						0.074**	0.100***
						(2.569)	(3.313)
Adjusted R^2	0.199	0.216	0.237	0.239	0.240	0.239	0.246
F-test	97.491***	54.632***	54.483***	45.247***	45.539***	49.873***	37.099***

Note: t statistics are given in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7
Results of logit regression model (N = 1,554)

Independent Variable	Logit(Achievement)	Wald Statistic
Constant	−6.700***	63.236
Age	0.255***	102.836
Gender	−1.961***	220.206
Log(Day)	0.281***	12.483
Log(BMI)	−0.011	0.873
Log likelihood	1750.785	

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 8
Results of matched pairs

Match type	Matched pair
Perfect match	0
Fuzzy match	456
Total counter	456

This model tested the effect of achievement incentives on health management performance. The symbol i denotes a matched pair of users, j represents users in a treatment or control group, and t represents the status of users in the initial or current period. The terms treated and time are dummy variables. The interaction term $treated_{ij}*time_{ij}$ was used to measure the effect of D-in-D in the research model. The three-way interaction terms $treated_{ij}*time_{ij}*log(Goal_i)$, $treated_{ij}*time_{ij}*log(Goal_i)^2$, and $treated_{ij}*time_{ij}*log(Interaction_i)$ were used to examine the moderating effect. Table 9 represents, hierarchically, the estimated results of the D-in-D analysis. It presents a model with control variables only and then presents the independent variables and interaction terms, respectively.

Table 9
Results of difference-in-differences analysis (N = 912)

Independent variable	1	2	3	4
Constant	−7.068**	−9.297***	−8.930***	−10.997***
	(−2.026)	(−2.937)	(−2.831)	(−3.639)
Age	0.031	0.030	0.030	0.049
	(0.638)	(0.678)	(0.678)	(1.192)
Gender	−0.374	−0.406	−0.406	−0.698***
	(−1.336)	(−1.598)	(−1.604)	(−2.912)
Log(Day)	0.422***	0.165***	0.413***	0.470***
	(3.005)	(3.243)	(3.254)	(3.912)
Log(BMI)	2.037**	2.152**	2.152***	2.108**
	(1.997)	(2.324)	(2.333)	(2.418)
Log(Exposure)	0.435**	0.346**	0.346**	0.362**
	(2.520)	(2.117)	(2.124)	(2.353)
Log(Interaction)	−0.297*	−0.256*	−0.256*	−0.335**
	(−1.778)	(−1.672)	(−1.678)	(−1.973)
Log(Goal)	−3.512***	−3.501***	−3.501***	−0.873
	(−4.669)	(−5.140)	(−5.159)	(−1.195)
Log(Goal)^2	1.078***	1.070***	1.070***	0.313
	(6.705)	(7.341)	(7.368)	(2.000)
Time		3.867***	3.134***	3.134
		(19.907)	(11.448)	(12.136)
Treat		0.380*	−0.354	−0.262
		(1.852)	(1.258)	(−0.986)
Time*Treat			1.467***	5.767***
			(3.790)	(2.968)
Time*Treat *Log(Goal)				−9.016
				(−1.486)
Time*Treat *Log(Goal)^2				2.634***
				(8.794)
Time*Treat* Log (Interaction)				0.375**
				(2.271)
Adjusted R^2	0.125	0.282	0.288	0.366
F-test	33.566***	72.710***	67.893***	76.178***

Note: t statistics are given in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Column 3 of Table 9 shows that achievement incentives positively and significantly affected performance level ($treated_{ij}*time_{ij}$) ($b_{11} = 1.467$, $t = 3.790$, $p < 0.01$). Column 4 of Table 9 shows that the coefficient of the interaction term $treated_{ij}*time_{ij}*\log(Goal_i)$ was not statistically significant ($b_{12} = -9.016$, $t = -1.486$, $p > 0.1$), while the coefficient of the interaction term $treated_{ij}*time_{ij}*\log(Goal_i)^2$ was positive and statistically significant ($b_{13} = 2.634$, $t = 8.794$, $p < 0.01$). Column 4 also shows that the moderating effect of active interaction ($treated_{ij}*time_{ij}*\log(Interaction_i)$) was positive and statistically significant ($b_{14} = 0.375$, $t = 2.2713$, $0.01 < p < 0.05$). The results of the D-in-D analysis are consistent with the results of the main model. This method reduces concerns about self-selection and endogeneity in the research model.

5. Discussion and implications

This study developed research hypotheses based on goal-setting theory to investigate the effect of goal difficulty and achievement incentives on health management performance as well as the moderating effects of network exposure and active interaction. The research provides several key findings as well as theoretical contributions and implications for practice.

5.1. Key findings

This research presents four significant key findings. First, a U-shaped relationship exists between goal difficulty and weight management performance. Individuals who set easy or difficult goals have better weight management performance. As goal difficulty increases, performance levels decrease to a certain point before they begin to increase again. This result is inconsistent with prior literature on goal setting (Groening and Binnewies 2019; Hamari 2017), which has found a positive linear relationship between goal difficulty and performance levels. There are two possible explanations for the U-shaped relationship found in this study. First, easy goals are easier for individuals to achieve and exceed, leading to greater satisfaction. Second, difficult goals can direct individuals' activities toward goal-related behaviors and positively affect the persistence of behaviors. Hence, individuals who set easy or difficult goals perform better than those who set moderate goals.

Second, we found that achievement incentives positively moderate the increasing side of the U-shaped curve but not the decreasing side. This result indicates that achievement incentives are more effective for those who set difficult goals than for those who set easy goals. Achievement incentives offer a type of feedback about how effectively the goal criteria have been satisfied, what has been done well, and what needs to be improved. Hence, more difficult goals require higher levels of achievement to improve individuals' performance.

Third, a high degree of network exposure strengthens the U-shaped relationship between goal difficulty and weight management performance. According to goal-setting theory, goal commitment can strengthen an individual's determination to achieve goals. Social networks provide a channel through which individuals can announce their goal commitments. When individuals are publicly committed to reaching a difficult goal in a high-exposure social network, their commitment is strengthened, improving their performance. In contrast, when individuals post easy goals in a high-exposure social network, their satisfaction from completing goals is reduced, which can worsen their performance. Thus, network exposure strengthens the U-shaped relationship between goal difficulty and level of performance.

Fourth, the study finds that active interaction in social networks positively moderates the relationship between achievement incentives and performance. If individuals are actively interacting with users in the social network, their achievements will be communicated. This can dramatically increase self-efficacy, in turn strengthening the relationship between achievement incentives and behavioral performance.

5.2. Implications for theory

This study makes the following theoretical contributions to the literature on health management gamification. First, the study contributes to the literature on gamification in health management behavioral change by incorporating goal setting and achievement incentives in the context of weight management gamification. Previous studies have considered achievement incentives in gamification as external goals provided by designers to motivate behavioral change and improve performance (Hamari and Koivisto 2015; Landers et al. 2017). Unlike externally provided incentives, personal goal setting may reflect individuals' internal health-related needs and better motivate their behaviors. However, few studies on gamification have investigated the combined effect of personal goal setting and achievement incentives on performance level. To fill this gap, this study investigated the effect of goal difficulty and achievement incentives on weight management performance. Our research findings contribute to the existing literature by providing a better understanding of goal setting in the context of weight management performance through gamification.

Second, our research extends the literature on goal-setting theory in the health context by identifying a U-shaped relationship between goal difficulty and health management performance. Previous studies based on goal-setting theory have found a positive linear relationship between goal difficulty and performance (Hamari 2017; Hamari and Koivisto 2015). However, this paper hypothesized a U-shaped relationship between goal difficulty and health management performance. Our empirical results support this hypothesis. Individuals who set easy or difficult goals perform better than those who set moderate goals. This finding provides a greater understanding of the relationship between goal difficulty and level of performance in the context of health management, thus making an important contribution to the literature on goal-setting theory.

Third, this study enriches the literature on health management gamification by providing an understanding of the potential relationship between goal difficulty and achievement incentives. Despite the prevalent use of achievement incentives in gamification (Hamari 2017; Hanus and Fox 2015; Harris 2019; Xi and Hamari 2020), it was unclear whether they interacted with goal difficulty. This paper hypothesized that achievement incentives enhance the U-shaped relationship between goal difficulty and performance. The empirical results demonstrate that achievement incentives positively moderate the increasing side of the U-shaped curve but not the decreasing side. This finding contributes to the existing literature by providing a better understanding of the relationship between goal difficulty, achievement incentives, and level of performance in health management gamification.

Fourth, this study contributes to the literature on health management gamification and social media by identifying the moderating effects of network exposure and active interaction (Allam et al. 2015; Hamari and Koivisto 2013; Hamari and Koivisto 2015). Although previous studies have investigated the direct effect of social network characteristics in gamification, few have examined the moderating effect of social network characteristics. To fill this research gap, this study examined the active (active interactions) and passive (network exposure) features of social networks to investigate their moderating effects on the relationships between goal difficulty, achievement incentives, and performance levels. The empirical results support the moderating effects of these characteristics. This finding provides a greater understanding of the role of social networks in health management gamification.

5.3. Implications for practice

The results of our study provide new insights into health management and gamification design and highlight several practical strategies for users and practitioners. First, gamification designers should develop specific goal-setting functions. Many gamification applications use achievement incentives as a proxy for goal setting. Designers of health management gamification should separate goal-setting functions from achievement incentives. Personal goal setting reflects users' inner health-related needs and motivates their behaviors, effectively influencing their level of performance.

Second, there should be a balance between individuals' abilities and the difficulty of their goals. The relationship between individuals' abilities and goal difficulty may affect their flow experience, in turn affecting their behavioral performance. Individuals with high ability but who set easy goals may experience poor flow and boredom, while those with low ability but who set difficult goals may experience poor flow and anxiety. When ability and goal difficulty are appropriately aligned, an optimal flow experience and positive emotions will be generated. Therefore, individual abilities (or skills) and goal difficulty should be aligned. Users of weight management gamification should set realistic goals based on their skills and abilities. When users engage in health management gamification, they should be guided toward setting appropriate goals. We recommend that users set different goals at different stages. In the early stages of using health management platforms, users should set easy goals to increase their satisfaction and motivation levels. After completing these primary goals, users should then set more difficult goals to motivate their behavioral performance in the long term.

Third, according to our empirical results, achievement incentives are more effective for those who set difficult goals than for those who set easy goals. Therefore, weight management gamification designers should develop different achievement incentives according to goal difficulty. Users with difficult goals should be given specific achievement incentives to motivate them to achieve their goals, while users with easy goals should be provided with more general incentives because the moderating effect of achievement incentives is weak.

Fourth, designers should pay attention to the role of social networks in health management gamification. Our research shows that network exposure and active interaction positively moderate the relationships between goal difficulty, achievement incentives, and performance level. Designers should develop social media functions to increase the size of users' social networks and stimulate user activities. An increase in network exposure and active interactions strengthens users' goal commitments and self-efficacy, improving their performance. Designers should ensure that users who set difficult goals communicate their goals as much as possible via the social network. Designers should also encourage users with high levels of achievement to interact in the social network as much as possible. These practical strategies will not only promote the development of health management gamification but also enhance users' behavioral performance.

5.4. Limitations and future research

Although the empirical results verify and support our hypotheses, this study has several limitations that must be acknowledged. First, we focused on the moderating effect of network exposure on the relationship between goal difficulty and performance. However, goal setting may be moderated by other characteristics of social networks. For example, network structure, scale, and stability may also moderate the effect of goal difficulty. Thus, in future research, we will examine other social network characteristics to explore the moderating effect of social networks.

Second, although we collected data from a real online health platform to establish a research model, the implications of our research may not be generalizable to other areas of health management. For example, the motivation to exercise may be different from the motivation to manage chronic illness. Thus, in future research, we will collect data from different online health platforms (such as those focused on chronic illness, diet, exercise, and weight loss) to test our research results.

Third, this study used cross-sectional data to test all research hypotheses. Although we used many control variables and the PSM method to address heterogeneity and endogeneity in the empirical model, data on the influence of goal setting and achievement incentives on performance levels were lacking. Future research could collect panel data that track differences in variables to investigate the dynamic influence of goal and achievement incentives.

6. Conclusions

Improving users' weight management performance is a challenge for designers and managers of health management platforms. Gamification has the potential to encourage individuals to engage in health self-management and improve their behavioral performance. Despite the prevalent use of gamification in health management, related empirical studies are lacking in several important areas. Few studies have investigated the combined effect of personal goal difficulty and external achievement incentives on weight management performance or the moderating effects of social network exposure and active interaction on this relationship. To address these research gaps, this study used goal-setting theory to develop research hypotheses and establish an empirical model to test the hypotheses. The results of the model show that goal difficulty has a U-shaped effect on weight management performance, while achievement incentives have a positive linear moderating effect on the increasing side of the U-shaped relationship between goal difficulty and weight management performance. In addition, the results demonstrate that higher social network exposure enhances the relationship between goal difficulty and performance, while more frequent social network interactions positively moderate the relationship between achievement incentives and performance. From a theoretical perspective, we combined goal-setting theory and social network characteristics in a research model to improve the understanding of the role of gamification in health management, making a significant contribution to the literature on health management. From a practical perspective, this paper provides new insights into health management and highlights several practical strategies for users and practitioners of health management platforms with gamification features.

Author Statement

All authors concur with the content of this paper, and agree to submit it to Technological Forecasting and Social Change. There is no conflict of interest exist.

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Appendix

An example of the research context

An example of a user homepage

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