Compete with Me? The Impact of Online Gamified Competition on Exercise Behavior

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Abstract

Online gamified competition utilizes competition as a core gamification design element with affordances from wearables and mobile applications to track competitive activities and visualize information in an integrated way to shape users' exercise behaviors. However, a clear understanding of how online gamified competition cultivates exercise behaviors in different types of individuals is still lacking. We take into account the individual differences in exercise behaviors and categorize exercisers into three groups (active, moderate, and inactive) based on an adapted Recency, Frequency, and Monetary Value framework using key exercise behavior metrics. Theorizing online gamified competition as a means for social and temporal self-comparison, we examine the effect of performance feedback from two distinct modes of comparison (performance ranking and performance gap), and participants' relationships with their social comparison referents (i.e., rivalry intensity), on different exerciser groups' exercise behaviors. Our results reveal that online gamified competition has differential effects on exercise behaviors across different exerciser groups. Specifically, we find that positive performance improvements are more motivational for active and moderate exercisers, while performance deterioration relative to historical exercise performance level is more discouraging for inactive exercisers. Performance ranking exhibits a more salient effect for moderate and inactive exercisers, and rivalry intensity has a stronger positive effect on active exercisers' exercise behavior. The strengthening effect of awareness affordances in mobile fitness apps is more notable with regard to the impact of rivalry intensity on moderate and inactive exercisers. We derive the theoretical and practical implications of gamified information systems that use competition as a core design element on shaping the exercise behavior of individuals in different exerciser groups.

Keywords: Gamified information systems; online gamified competition; fitness activity trackers; social comparison; temporal self-comparison; exercise behavior

1. Introduction

Gamified information systems have increasingly been emerging as one of the main types of information systems for engaging and steering individuals toward desired behaviors (Liu et al., 2017). Online gamified competition, one such gamified information systems, utilizes competition as a core gamification design element with affordances from wearables and mobile applications (apps) to track competitive activities, connect participants and present information in an integrated, visual way to shape users' exercise behaviors. Competition can engender a sense of challenge and excitement, and is thus deemed to be fun, engaging, and able to motivate contestants to expend greater effort toward achieving the targeted behavior (Tjosvold et al., 2006).[1] As such, it has been used frequently in the healthcare domain as an intervention to motivate obese individuals to lose weight and to encourage healthy eating in schoolchildren (Raju et al., 2010; Stunkard et al., 1989). Although competitions are popularly used as gamified interventions to promote positive health behavior both in offline interventions and on online health- or fitness-related platforms (e.g., Strava and Stridekick), it remains unclear how online gamified competition as a gamified information system could shape individuals' exercise behaviors. Specifically, we were motivated to investigate this phenomenon based on the four key research gaps in the related literature.

First, research on the effects of competition on motivation and performance has yielded divergent findings (Murayama & Elliot, 2012). Some scholars have found that competition is associated with improved motivation and performance (e.g., Tauer & Harackiewicz, 2004), while others argue that competition can be experienced as an external contingency that crowds out the intrinsic value of performing the targeted activity, even for winners (Deci et al., 1981). Competition may cause the losing party to become demoralized and discontinue the target behavior change (Buser, 2016). The mixed findings can be attributed to various factors, among

[1] Competition was defined as a contest situation in which two or more parties strive to maximize perceived rewards and superiority (Liu et al., 2013).

which individual heterogeneity is suggested to be an important factor that may help resolve the conflicting findings (Kilduff, 2014). Specifically, individuals differ in terms of their level of exercise activity (e.g., exercise frequency, distance, and duration) performed within a certain period (Duncan et al., 2010), and they could respond differently to the impact of online gamified competition. Thus, it is important to take such heterogeneity into account when evaluating the impact of online gamified competition on individuals' exercise behaviors.

Second, past literature has tended to view competition as a monolithic construct, in which competition is usually considered as an event occurring among individuals to evaluate themselves based on their capacity for a particular task (Deutsch, 2011). However, competition can also happen with oneself, such that individuals evaluate their current performance in relation to their own prior performance. Both competition with peers and competition with oneself constitute critical behavioral feedback for self-evaluation (Zell & Alicke, 2009). Thus, we go beyond the monolithic construct of competition and posit that competition can be viewed as a process occurring within oneself and between oneself and peers. Competing with peers serves as a social component of behavioral feedback to inform people on where they stand relative to others. However, competing with oneself captures the temporal aspect of behavioral feedback and reflects whether behavioral outcomes are improving or declining over time. To have a comprehensive understanding of how online gamified competition impacts on individuals' exercise behaviors, it is critical to consider performance feedback from both forms of competition (i.e., performance gap from competing with oneself and performance ranking from competing with peers).

Third, another important factor that has been overlooked thus far is participants' relationship with competitors. Research suggests that the relationship between competitors and their interaction patterns have a powerful effect on how they behave in a competition (Tjosvold et al., 2006). Many prior studies have shed light on the effects of competition, but they have examined competitions by primarily focusing on one-shot offline competitions to induce behavioral change (e.g., Beersma et al., 2003; Tauer & Harackiewicz, 2004). This may overlook the fact that a participant in real-world competitions may know and establish relationships with opponents. The history of prior competitive interactions is a featured aspect of real-world competitions and it can give rise to intense rivalry that may shape participants' competitive behavior (Lubbers et al., 2009). Taking into account the historical competitive interactions afforded by online gamified competitions, we deviate from past competition literature to examine the effect of rivalry intensity with competitors on individuals' exercise behavior.

Fourth, target system technology has been proposed as a facilitator or enabler of gamification design elements in gamified information systems (Liu et al., 2017).[2] As a target system technology in online gamified competitions, fitness activity trackers allow users to self-track or monitor their physical activity, and at the same time, visualize competitive interactions.[3] We consider the fitness activity trackers as an awareness and visualization systems that provides automatic, sensor-derived cues of other people's situations to facilitate social interactions (Oulasvirta et al., 2007). As such, online gamified competition allows participants to be apprised of competitors' exercise activities, online statuses, performance rankings, historical competitions, etc., via awareness cues afforded by fitness activity trackers. However, as a target system technology in online gamified competitions, little is known about the role of fitness activity trackers in shaping exercise behavior beyond tracking health parameters, and how they interact with gamification design elements (e.g., competition) to jointly affect individuals' exercise behavior (Leonardi, 2015; Stawarz et al., 2015).

[2] Gamification is defined as incorporating game design elements into a non-game target system while keeping the instrumental functions of the target system (Liu et al., 2017). In the context of our study, the fitness activity trackers are the technology used as the target system, and the competition is the game design elements employed.

[3] Here, fitness activity trackers refer to the devices or applications that enable users to track daily physical activities, together with other fitness-related metrics such as distance walked or run, calorie burned, and heart rate, etc. Examples of these include both hardware and software such as smart wristbands, pedometers, and fitness apps.

Our review suggests that how online gamified competitions can shape exercise behavior for different individuals in a repeated gaming scenario remains unclear.[4] Therefore, we have developed a nuanced theoretical model to answer the following research question: *How do online gamified competitions in the form of competing with oneself and competing with peers, relationships with peer competitors, and visualization functions afforded by fitness activity trackers jointly affect exercise behavior in different groups of individuals?* To this end, we draw on temporal self-comparison theory (Albert, 1977) and social comparison theory (Festinger, 1954) to conceptualize online gamified competition as a process of temporal self-comparison with past oneself and social comparison with peers, and the literature on visibility in ICT systems, to understand the impact of the role of fitness trackers as a visualization system in online gamified competitions (Leonardi, 2015; Oulasvirta et al., 2007).

Our research model and hypotheses were tested using competition-related exercise data from a popular online fitness platform, and were found to be largely supported. Our results reveal that online gamified competition has differential effects on exercise behavior in terms of exercise distance across different exerciser groups (i.e., active, moderate, and inactive exercisers). Specifically, we found that the positive performance improvements are more motivational for active and moderate exercisers' exercise behaviors, but performance deterioration relative to historical exercise performance level is more discouraging for inactive exercisers' exercise behaviors. Performance ranking exhibits a stronger positive effect on moderate and inactive exercisers' behavior in terms of distance run relative to that of active exercisers. Rivalry intensity has a stronger positive effect on active exercisers' behavior relative to that of inactive exercisers. Our findings reveal that, beyond self-tracking, the awareness cues in mobile fitness apps have a more salient strengthening effect on the impact of rivalry intensity for moderate and inactive exercisers.

[4] We have reviewed the literature on gamification in health behavior promotion as well as competition-based health promotion programs. The literature review is summarized in Table A1 in the appendix.

This study contributes to the emerging area of gamified information systems by developing a theoretical model to examine the role of gamified information systems with competition as a core design element in shaping exercise behavior across different groups of individuals. First, we contribute to the understanding of the personalization design principle of gamified information systems by accounting for the heterogeneity among exercisers. In doing so, we are able to provide useful insights and managerial implications to health IT proponents on developing segment-specific interventions to better target and engage users, and shape their exercise behaviors. Second, drawing on temporal self-comparison theory and social comparison theory, we go beyond the monolithic concept of competition in past literature and deconstruct competition into two different nuanced dimensions, i.e., temporal comparison with past oneself and social comparison with peers. Third, this study contributes to the competition literature by accounting for the relationship with competitors through their rivalry intensity in a repeated competition scenario. Finally, our study contributes to the understanding of how target system technology interacts with gamification design elements in a gamified information system to jointly steer individuals toward desired behaviors.

2. Theory and Hypotheses

Individuals exhibit different patterns in their exercise behavior. Building on prior literature on physical activity (e.g., Briki, 2020; Jung & Brawley, 2010), we theorize that there are different groups of exercisers and the extent to which these groups are affected by the online gamified competition may vary. Drawing on the temporal self-comparison theory and social comparison theory, we conceptualize online gamified competition as involving temporal self-comparison and social comparison processes and explicate how different groups of exercisers respond differently to these mechanisms of online gamified competition. Further, based on the literature on the visibility in ICT systems (Leonardi, 2015; Stawarz et al., 2015), we account for how the fitness activity trackers as the target system technology interact with gamification design elements (e.g., competition) to jointly affect exercise behavior.

2.1 Heterogeneity in Exercisers

Customer segmentation has been a critical strategy for better understanding and satisfying different customers' needs in business (e.g., Floh et al., 2014). In marketing, researchers categorize consumers into different segments (e.g., heavy, moderate, and light) based on their spending level, and have investigated the impact of loyalty programs on different consumer segments' purchase behaviors (e.g., Liu, 2007). In a similar fashion, it is paramount for researchers and health IT providers to have a better understanding of different exercisers and provide more personalized and suitable interventions to stimulate the desired exercise behavior and accrue the benefits of physical activity. In line with this trend, prior studies have attempted to categorize exercisers into high-frequency and low-frequency exercisers (Gammage et al., 2004; Jung & Brawley, 2010), high-active and low-active exercisers (Briki, 2020), and active and moderately active exercisers (Rodgers & Gauvin, 1998), based on the frequency of exercise activities in a certain period, such as a week. Based on previous literature, we posit that there are heterogeneous exerciser groups with different behavior characteristics.

Prior literature has primarily used the frequency of exercise in a particular period as a criterion to classify exercisers (e.g., Briki, 2020; Gammage et al., 2004; Jung & Brawley, 2010). However, in addition to frequency, exercise volume and duration are also suggested to be important indices of exercise behavior, and provide basic measures of individuals' exercise behaviors (Duncan et al., 2010). In this study, we expand on the categorization proposed in prior literature and categorize exercisers based on key exercise behavior metrics using the Recency, Frequency, and Monetary Value (RFM) framework. The RFM approach is an effective and commonly used framework for segmenting consumers based on three key attributes (i.e., recency, frequency, and monetary value of purchases) in marketing (Hughes, 1994). To accurately capture exercisers' behavior in our context, we have adapted the three RFM attributes to account for various critical exercise behavior metrics. In particular, *recency*, in the context of this study refers to the time interval between the last and current focal exercise activities. *Frequency* refers to the number of exercise activities an individual performs in a particular period (e.g., a week). In the RFM framework, *monetary value* refers to the average amount of money consumers spend in a specific period (Cheng & Chen, 2009). In our context, this metric is adapted to be the average magnitude of exercise activity that an individual performs in a certain period, as captured by the mean exercise duration and/or mean exercise distance. Based on the adapted RFM framework and previous related literature, we classify exercisers into three groups with different exercise levels, i.e., active, moderate, and inactive.

We expect that the three groups of exercisers (i.e., active, moderate, and inactive) classified based on the adapted RFM framework would exhibit different behavior characteristics and motivations toward exercise. The three exerciser groups differ in terms of the recency, frequency, and magnitude of exercise activities performed. Active exercisers are those with the shortest exercise recency, highest exercise frequency, and largest magnitude of exercise activities performed. Inactive exercisers have the longest exercise recency, lowest exercise frequency, and smallest magnitude, while the exercise level of those in the moderate group falls in between these two groups. Research has suggested that exercise level is positively related to exercisers' motivation which varies according to the amount of exercise an individual undertakes (Duncan et al., 2010; Mullan & Markland, 1997). According to the self-determination theory, individuals may exhibit different motivations toward exercise, and the motivation continuum incorporates various forms of behavioral regulations, from more autonomous regulation to more controlling regulation (James et al., 2019; Ryan & Deci, 2000). Exercise behavioral metrics such as frequency and duration were found to be more highly correlated with autonomous regulation than controlling regulation (Duncan et al., 2012). Prior study found that students from the high-frequency exercisers group exhibited a higher level of intrinsic motivation and autonomous regulation in comparison with those from the low-frequency exercisers group (Li, 1999). Among the three segments in this study, active exercisers are those with the highest exercise level (i.e., shortest recency, highest frequency, and largest magnitude of exercise activities), and thus are expected to be more affected by autonomous regulation and more self-determined compared to the other two exerciser groups (Briki, 2020). Moderate exercisers, with a relatively low level of exercise compared to active exercisers, are expected to be more affected by controlling regulation, and thus tend to exercise due to external pressure and attainment of separate outcomes (e.g., rewards) (Ryan & Deci, 2000). Inactive exercisers, with the lowest level of exercise compared to the other two segments, are usually insufficiently motivated (Teixeira et al., 2012).

Further, the difference in exercise behavior characteristics across the three exerciser groups may differentiate them in terms of exercise capability and perceived competence. Performance accomplishments, which reflect personal mastery experience of tasks or activities, have been suggested to be a critical information source affecting personal efficacy (Bandura, 1977). The level of exercise activity provides information about what exercisers have accomplished and serves as an important information source for exercisers to evaluate their competence (e.g., how well they perform) (James et al., 2019). Research has also shown that more active and adherent exercisers have relatively higher levels of self-efficacy and personal competence (McAuley, 1994). Compared to inactive exercisers, active and moderate exercisers, with more exercise activity accomplishments, tend to perceive comparatively higher exercise competence in themselves. Considering the differences among the three exerciser groups mentioned above, we expect that the different exerciser segments may exhibit diverse sensitivities toward the different focal factors of online gamified competition that we elaborate on below.

2.2 Competition as a Temporal Self-Comparison and Social Comparison Process

Individuals compete with themselves and use personal standards as a benchmark for self-evaluation (Wayment & Taylor, 1995). Temporal self-comparison addresses this point by emphasizing a process of ongoing comparison that happens within a single individual (Albert, 1977). The historical development of the self can be regarded as an index of one's ability and progress toward a personal goal (Redersdorff & Guimond, 2006). Historical performance information is accessible and pertinent and can serve as a benchmark against which the most recent past or last performance is evaluated. We thus conceptualize temporal self- comparison information feedback as the discrepancy between the latest and earlier historical self in terms of exercise performance, indicating performance improvement and/or deterioration over time. In online gamified competitions, individuals' exercise records at various points in time can be viewed as a continual process, allowing the evaluation of the latest exercise performance on the basis of historical exercise performance level.

We posit that the extent to which an individual's latest exercise performance relative to their historical exercise performance level affects the three exerciser groups' exercise behaviors may vary. Compared to inactive exercisers, active and moderate exercisers with higher exercise levels are more inclined to rely on motivational support that promotes personal competence and helps gauge progressive performance improvements (Ryan & Deci, 2000; Taylor & Brown, 1988). Such a need for personal competence and self-improvement guides active and moderate exercisers to rely more on the evidence from past performance information to corroborate their growth and progress (Albert, 1977). Fulfilling the psychological needs of competence is important to facilitate individuals' motivation to exercise (James et al., 2019). When the latest exercise performance is better than the historical exercise performance level, the positive performance discrepancy that serves as an effectance-promoting feedback supports active and moderate exercisers' need for personal competence (Ryan & Deci, 2000). Further, the positive performance discrepancy meets active and moderate exercisers' self-improvement needs by convincing them that they are on the right track and maintaining their image of personal competence, thereby encouraging them to exercise more by fostering a desire to keep up the performance momentum. The positive performance discrepancy could also boost inactive exercisers' perceived self-efficacy and serve as a positive reinforcement to affect their subsequent exercise behavior. However, such an effect is expected to be smaller for inactive exercisers, as sporadic super-normal performances are less stimulating to those who have little intention to be physically active or to gain a sense of competence at exercise (Teixeira et al., 2012). When the latest exercise performance is below the historical exercise performance level, the negative performance gap–a proxy of declining ability–may undermine inactive exercisers' perceived competence and sense of self, and thus demoralize their motivation to exercise. In contrast, active and moderate exercisers who are more assured of their exercise capabilities are likely to be less dissuaded by occasional unfavorable performance feedback. Consequently, we posit:

> **HYPOTHESIS 1a:** *The positive performance gap (when an individual's latest exercise performance is above the historical exercise performance level) in online gamified competitions has a stronger positive effect on active and moderate exercisers' exercise behavior compared to that of inactive exercisers.*

> **HYPOTHESIS 1b:** *The negative performance gap (when an individual's latest exercise performance is below the historical exercise performance level) in online gamified competitions has a stronger negative effect on inactive exercisers' exercise behavior compared to that of active and moderate exercisers.*

Individuals exhibit a natural tendency to make comparisons with others in many social contexts, and competition can intensify their comparison desire by providing a comparative environment with various comparison targets (e.g., Leahey & Rosen, 2014; Raju et al., 2010). Researchers have proposed the linkage between competition and social comparison (Festinger, 1954). Social comparison theory holds the view that a comparison process can drive people to improve their performance and reduce discrepancy with others through "unidirectional drive upward" pressure, which in turn can generate competitive behavior to defend one's superiority (Festinger, 1954). In other words, social comparison serves as a significant source of competitive behavior by fueling the motivation to compete, whereas competition is a manifestation of the social comparison process (Garcia et al., 2006). The social comparison process enables individuals to compare their performance with that of others, informs where an individual stands relative to others, and serves as a fundamental information feedback for evaluating one's ability and performance.

Ranking, as a key manifestation of competition, thus provides a meaningful reference point that enables people to make comparisons with peers and pinpoints their relative standing (Garcia et al., 2006). The value of a certain ranking is either determined by the natural characteristic of the ranking (i.e., intrinsic value), or by the additional outcomes associated with the ranking (i.e., extrinsic value) (Vriend et al., 2016). Individuals are motivated not only by the inherent preference for ranking, but also the tangible benefits the ranking brings (Tran & Zeckhauser, 2012). As an important source of external evaluation and feedback, performance ranking can be regarded as an indicator of personal competence (Pittman et al., 1980). For instance, a top ranking signifies the highest performance relative to others and brings about intrinsic value in terms of boosting an individual's sense of internal control and self-efficacy, and their enjoyment of the activity (Hagger et al., 2015). As for the extrinsic value of a ranking, higher rankings are often associated with positive consequences such as social status and rewards, whereas lower or bottom rankings are often associated with negative outcomes such as punishment and relegation.

Competition serves as a source of challenge that affects individuals' behaviors (Santhanam et al., 2016), though individual heterogeneity may arise as exercisers with different exercise behavior characteristics tend to react in different ways. In competitions, heterogeneous participants need to exert different amounts of effort to achieve a high ranking. Among the three exerciser groups, active exercisers exhibit the highest level of exercise in terms of recency, frequency, and magnitude. Such active engagement in exercise activity contributes to the growth of personal competence and perception of self-efficacy (Bandura, 1981). Perceived personal efficacy helps individuals determine how much effort will be expended in coping with given situations (Bandura, 1977). Thus, active exercisers tend to perceive their effort expenditure as lower relative to the effort expenditure required of moderate and inactive exercisers to achieve a high ranking. In other words, active exercisers perceive an effort advantage that allows them to achieve the same outcome with less effort compared to the moderate and inactive exercisers. Although achieving a high ranking supports active exercisers' needs for competence, expending less effort may not bring them an optimally challenging experience, and thus they are less likely to experience high levels of enjoyment (Liu et al., 2013). In contrast, moderate and inactive exercisers with a relatively low level of exercise activity tend to exhibit unfavorable efficacy appraisal of exercise capability. They may need to put in more effort to achieve a high ranking compared to active exercisers. For moderate and inactive exercisers, achievement of a high ranking, that is a positive relative performance feedback, tends to bring more joy and is more appreciated for boosting their self-efficacy beliefs in terms of exercise, thereby affecting their subsequent exercise behaviors. Further, compared to active exercisers, moderate and inactive exercisers with a lower level of exercise are more likely to be motivated by controlling forms of regulation or be insufficiently motivated (Briki, 2020; Teixeira et al., 2012). The extrinsic value of high rankings would be more stimulating for their engagement in subsequent exercise behaviors.

> **HYPOTHESIS 2:** *Performance ranking in online gamified competitions has a stronger positive effect on moderate and inactive exercisers' exercise behavior compared to that of active exercisers.*

2.3 Rivalry Intensity with Social Comparison Referents

Relationships with social comparison referents can affect how individuals perceive others' performance and their self-evaluation (Tesser & Campbell, 1982). Specifically, competitive relationships have been shown to affect individuals' motivation to win and their effort-based performance (Tjosvold et al., 2006). Thus, we consider the impact of competitive relationships with social comparison referents on exercise behavior across different exerciser groups. The competitive relationship between exercisers and their competitors can be depicted by rivalry, which captures the growth of competitive tensions through conflicting interests (e.g., one's winning results in the other's loss). Competing against opponents who share a history of rivalry may elicit greater need of social comparison (Kilduff, 2014).

Rivalry is conceptualized as a competitive relationship between competitors, in which an individual experiences increased psychological involvement and stakes, independent of the objective characteristics of the situation (Kilduff, 2014). The heightened psychological stakes associated with rivalry influence individuals' motivation to win and their competitive behavior (Brickman et al., 1972). In our context, the rivalry intensity reflects the extent of the competitive relationship between the focal individual and the target competitor. A competitive relationship is maintained or heightened through the competitive residue from past repeated competitions (Brickman et al., 1972; Kilduff et al., 2010). Competitive residue refers to the remaining sense of challenge or competitiveness from previous competition experiences even after the contest has ended (Kilduff et al., 2010). The competitiveness of prior competitive interactions (i.e., the extent to which the opponents have been evenly matched), which is critical to rivalry, has been found to be an important factor in influencing competitors' behaviors (Kilduff, 2014). Two teams that are evenly matched exhibit stronger rivalry and this is associated with increased performance (Kilduff et al., 2010). In one study, trainees who believed they were matched with equally skilled competitors reported a higher level of engagement in technology-mediated training programs (Santhanam et al., 2016).

We posit that rivalry is intensified during repeated gamified competitions, and will affect exercisers' ensuing competitiveness and competitive behaviors in a differentiated manner. For active exercisers with a relatively high perception of personal competence, a strong rivalry with accumulated competitive residue may heighten perceived competitiveness and boost their desire to win. Competitiveness has been shown to increase individuals' physical motivation, and the extent and adherence levels of physical activity or exercise (Frederick-Recascino & Schuster-Smith, 2003). In contrast, moderate and inactive exercisers with an unfavorable efficacy appraisal of exercise capability may feel less confident in their ability to outperform others. Therefore, competing against opponents with intense rivalry during exercise activities may not result in a similar level of enjoyment and arousal as it does for active exercisers, leading to a lower extent of influence on exercise behaviors for the moderate and inactive exercisers. Thus, we hypothesize:

> **HYPOTHESIS 3:** *Rivalry intensity in online gamified competitions has a stronger positive effect on active exercisers' exercise behavior compared to that of moderate and inactive exercisers.*

2.4 The Moderating Role of Activity Trackers

Fitness activity trackers can be considered as an awareness and visualization system that provides automatic, sensor-derived cues of other individuals' situational updates to facilitate social interactions (Oulasvirta et al., 2007). In the context of technology-mediated communications, awareness cues refer to computer-mediated real-time indicators of remote others' activities, online statuses, social relations, performance rankings, etc. (Oulasvirta et al. 2007). Research suggests that social networking technologies enable communication visibility by making message exchanges between individuals evident and their connections transparent in work settings (Leonardi, 2015). Past literature has also suggested that contextual cues (e.g., location, preceding actions, and reminders) enabled by health and fitness apps have great potential to support the formation of positive health behavior (Stawarz et al., 2015).

Individuals have to possess critical information as they enter a competition, especially information about their competitors (Epstein & Harackiewicz, 1992). Differing from offline competitions, participants in an online gamified competition are not usually co-located and it is difficult to access competitors' information directly. Therefore, the awareness cues provided by fitness activity trackers become crucial to bridging the information gap for individuals in online gamified competitions. During interaction with remote others, individuals have to rely on these cues to perceive one another, obtain a feeling of propinquity, and reduce ambiguity in technology-mediated interactions. As such, online gamified competition allows participants to be apprised of competitors' exercise activities, online statuses, performance rankings, etc., via awareness cues afforded by fitness activity trackers. For instance, digital leaderboards display the exercise performance and relative standings of all the contestants.

Online gamified competitions typically include a leaderboard, where participants' exercise performance or scores earned are displayed for all individuals to see (Liu et al., 2011). Awareness cues afforded by a digital leaderboard offer information on each participant's performance, relative position among competitors, and provide a sense of how well an individual performs among peers. The leaderboard and metaphorical visualization of mobile fitness apps present ranking and exercise performance (e.g., running distance) information in a notable manner rather than as mere numbers (Campbell et al., 2008). For instance, an individual's leaderboard position in the Runkeeper app is presented by a number and color spectrum, and individuals with top rankings obtain a ribbon icon next to their profile photos. For moderate and inactive exercisers who need to put in more individual effort to achieve a high ranking, such visualization is likely to amplify both the extrinsic and psychological rewards associated with achieving a high rank, which may further enhance their perceived personal competence and serve as an effectance-promoting feedback, stimulating their motivation to exercise more (Vriend et al., 2016). This is especially true for inactive exercisers who tend to feel a sense of incompetence at exercising (Teixeira et al., 2012). In contrast, active exercisers with a relatively high exercise level may be more assured of their exercise capabilities and tend to exhibit a higher personal competence. Visualizing the top rank may not have the same effect on active exercisers' perception of personal competence and motivation to exercise more as it might on moderate and inactive exercisers. Thus, we expect that awareness cues are more effective in strengthening the effect of performance ranking for moderate and inactive exercisers.

> **HYPOTHESIS 4:** *Awareness cues are more effective in strengthening the effect of performance ranking in online gamified competitions on moderate and inactive exercisers' exercise behavior compared to that of active exercisers.*

Awareness cues serve as a visual medium that provides social information for individuals to construct a picture about the social situation of others and perceive connection with others in a virtual setting (Stawarz et al., 2015). Specifically, multiple relation cues afforded by fitness activity trackers, such as historical activity or competition records, allow individuals to view their competition history and become aware of the strength of rivalry with their competitors. Exercisers are able to identify the repeated competitive stimulus from visible indicators of past opponents as well as prior competition outcomes (Andersen et al., 2006). Such information can help refresh their memory of whether they had been evenly matched, remind them of the competitive residue accumulated, and help them form expectations of whether they might outperform or underperform against competitors by learning how good they are (Kilduff et al., 2010). Individuals prefer to focus on the ego-bolstering information that is favorable for their self-evaluation, which is especially acute under situations of threat (Wills, 1981). For moderate and inactive exercisers who have relatively low perceived competence, the visualization of superior competitors could pose a threat for them, which may lead them to seek for more ego-bolstering information. Thus, an awareness of opponents who are inferior to them could boost their perceived self-efficacy and be more encouraging for subsequent exercise behavior. On the other hand, active exercisers tend to possess higher levels of exercise capability and perceived personal competence (McAuley, 1994). The visualization of past competitive interactions may therefore simply reaffirm their sense of competitiveness. With the reminder of being competitive, active exercisers may develop an expectancy to outperform competitors again in the following competition and thus may not exert further effort in exercising.

> **HYPOTHESIS 5:** *Awareness cues are more effective in strengthening the effect of rivalry intensity in online gamified competitions on moderate and inactive exercisers' exercise behavior compared to that of active exercisers.*

3. Methods

3.1 Research Context and Data Description

We collected the dataset for this study from a popular online fitness platform that embeds the integrated use of mobile fitness apps and wearable devices (e.g., a smart wristband) within a competition context.[5] Mobile fitness apps and wearable devices enable users to track their exercise activities through GPS or sensors. Data synchronization on the platform allows users to be informed of various health parameters (e.g., distance jogged, calories expended) in a timely manner. The platform allows users to initiate a competition with others online, and then the competition performance of all the participants in the competition is evaluated based on their offline exercise distance tracked by their fitness activity trackers (i.e., via a mobile fitness app or a smart wristband). The initiated competitions are displayed and accessible to all the users on the platform. Users can sign up for a competition online by paying a race deposit with virtual currency.[6] The deposits from all the participants are pooled to constitute the total reward,[7] which is then reallocated based on the competition outcomes. Each competition has a

[5] Due to a confidentiality agreement, we are not allowed to reveal the name of the platform.
[6] The deposit refers to the virtual currency that participants need to pay to participate in a competition.
[7] The reward of a competition is composed of all the deposits paid by each participant in the competition. The pooled reward has been controlled in our analysis since the pooled reward is the outcome of multiplying the deposit by the number of participants in a race, which is also controlled in our analysis. Although the reward obtained in the form of virtual currency can be used to redeem products, the exchange rate with real currency is very low.

specified start and end time, and all participants need to exercise (i.e., run or jog) within that time period using their fitness activity trackers to track the exercise. Participants' tracked exercise details are synchronized with the platform via the specified fitness activity trackers (i.e., mobile app or wearable device). Participants can obtain performance ranking information through the leaderboard in a competition. The online fitness platform contains user profile pages, social feeds on daily exercise activities, and information notifications.

Our dataset contains information on all the competitions completed during the study period. For each competition, we collected information regarding the start and end time, the number of participants, the competition type,[8] the deposit, the total reward, each player's exercise performance achieved at the end of the competition (i.e., exercise distance tracked by fitness activity trackers), and the tracking device used in the competition (i.e., a mobile fitness app or a smart wristband). Further, we collected participants' information from their personal pages, including (anonymous) unique ID, gender, city of residence, cumulative exercise distance (in kilometers), and cumulative points.[9] We aggregated the individual-competition data into individual-week level, and our final data set for empirical analysis at the individual-week level consists of 122,828 observations for 25,583 individuals over approximately forty-eight months.

3.2 Variables

We describe the measures for all focal and control variables below. Table 1 presents the descriptive statistics of all the variables. The correlations among all the variables are presented in Appendix Table A2.

Outcome variable. The outcome variable of interest is an individual's exercise distance (*EXER_DIST*) during a certain period (i.e., a week). Exercise distance, as an important indicator of exercise behavior, has been widely used to capture individuals' exercise behavior

[8] There are three types of competitions on the platform, i.e., one-to-one, multiplayer, and group competition.
[9] The cumulative points refer to the amount of virtual currency that an individual has accumulated since joining the platform.

in the literature (e.g., Wininger, 2007). We operationalize an individual's exercise behavior in a week as the individual's average exercise distance (i.e., total exercise distance/frequency of exercise in week *t*). In the context of this study, individuals' exercise distance in kilometers was tracked by a mobile fitness app or wearable device (e.g., a smart wristband) and then synchronized to the online fitness platform.

Performance gap indicates the improvement or deterioration in exercise performance (i.e., the exercise distance tracked by fitness activity tracker) compared to the past performance levels. It refers to the discrepancy between individuals' exercise performance in week *t–1* and their average exercise performance in the past. Following prior literature, we specify the performance gap using a "spline" function, which allows the change of variable coefficient at a predetermined point (Kim et al., 2015; Marsh & Cormier, 2001). Specifically, we split the performance gap into two variables: (1) positive performance gap (*POS_PERF_GAP*, i.e., for when the last exercise performance is *above* the average historical exercise performance level) and (2) negative performance gap (*NEG_PERF_GAP*, i.e., for when the last exercise performance is *below* the average historical exercise performance level). The positive performance gap is measured as the difference between the focal exerciser's last exercise performance and the average historical performance level if the former is above the latter, and as zero otherwise. The negative performance gap is measured as the absolute difference between the focal exerciser's last exercise performance and the average historical performance level if the former is below the latter, and as zero otherwise.

Performance ranking (*RANKING*) represents an individual's relative standing in terms of exercise performance (i.e., the exercise distance tracked by the fitness activity trackers) among participants. In an *N*-participant competition, the best-performing participant with the longest exercise distance will be ranked as first, followed by the one with the second-longest distance, and so on (participants will be ranked from 1 to *r* based on their exercise distance, *r*

$\leq N$). We calculated an individual's relative ranking in an N-participant competition as $(N–r+1)/N$.[10] The larger the value, the higher an individual ranks in a specific N-participant competition. To obtain an individual's exercise performance ranking in a week, we first identified all the competitions that individual i had joined in that week, and then aggregated individual i's exercise performance rankings in the identified competitions by averaging all these rankings in that week.

Rivalry intensity *(RIVALRY_INTST)* captures the strength of the competitive relationship between an individual and their competitors in online gamified competitions in week $t–1$ and before. Based on prior literature (Kilduff et al., 2010), we operationalized the rivalry intensity as a competitiveness index that captures the extent to which individual i and competitor n were evenly matched in prior joint competitions. Specifically, we identified all the competitions that individual i participated in and all the unique competitors in a week. Then for each dyad of individual i and competitor n, the competitive index was calculated by the winning rate of the inferior participant (i.e., either individual i or competitor n who won fewer competitions) (Kilduff et al., 2010). The competitiveness index ranges from 0, indicating a completely lopsided match-up, to 0.5, indicating a perfectly even match-up. Finally, we obtained the rivalry intensity between individual i and all competitors by averaging across the dyadic measures.

Awareness cues *(AWARE_CUES)* captures the level of awareness cues (e.g., ranking information and history of prior competition records) afforded by the fitness activity trackers. Research suggests that media differ in the amount of cues available and the level of social presence affordance (Yoo & Alavi, 2001). Fitness activity trackers differ in the capability of

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[10] We greatly appreciate the reviewer's suggestion on the measure of performance ranking. There are concerns with using an individual's actual ranking (e.g., ranks 1st, 2nd, 3rd, …r^{th} in an N-participant competition, $r \leq N$) as the measure here. The number of participants in a competition can affect the true meaning of an individual's ranking achieved in that competition. For instance, an individual who ranks the second in a two-player competition is the loser with bottom ranking, while the individual who ranks second in a 10-player competition is actually a top player. Thus, we use $(N–r+1)/N$) to calculate an individual's ranking ratio to alleviate such a concern.

affording awareness cues for interpersonal interactions. For instance, in contrast to wearable devices (e.g., a smart wristband),[11] mobile fitness apps are a self-contained system for users to interact with others, and provides automatic cues of others' statuses (e.g., competitions participated in and leaderboard ranking) to facilitate social interactions. Thus, we operationalized awareness cues by the percentage of using a mobile fitness app as an activity tracker in all the competitions in which individual *i* participated in a week.

Control variables. This study also considers several control variables that could affect individuals' exercise behaviors, including aspects related to the competition, individual, and season. The characteristics of competitions that individuals participate in can affect their exercise behavior. For instance, (1) the number of competitors, which counts the unique number of opponents that an individual competed against in all the competitions in a week; (2) deposit, which measures the average amount of virtual currency that a participant needs to pay for all the competitions participated in during a week; and (3) competition type, which indicates the different types of competition—one-to-one, multiplayer or group—and is measured by the percentage of a specific type of competition that an individual participated in during a week.

We also accounted for individual characteristics that could affect exercise behavior. Beyond the demographic characteristics such as gender,[12] we controlled for an individual's cumulative exercise distance. Extrinsic motivation is an important incentive for driving individuals' behaviors. Thus, we also controlled for individuals' cumulative points since joining the platform and number of winnings in prior competitions. Lastly, we controlled for seasonal effects because levels of exercise activity can vary with the season (Tucker &

[11] In the context of our study, wearable device activity trackers primarily includes the smart wristbands and smartwatches that allow users to monitor and track their daily exercise activities. Smart wristbands with a simple light-emitting diode (LED) display and smartwatches with an advanced liquid-crystal display (LCD) can provide and visually present health parameters such as exercise distance/steps, calories burned, heart rate, etc. However, these two device types cannot provide real-time social information such as leaderboard information unless they are synchronized with the mobile fitness app.
[12] We acknowledge that other individual attributes such as health status (e.g., height, weight, and disease) and age are not available, since these are considered highly sensitive or private data types. Nevertheless, such individual attributes are controlled for as fixed or random effects in our empirical models.

Gilliland, 2007). Specifically, the four seasons (i.e., spring, summer, autumn, and winter) were coded as dummy variables indicating the season that a specific week falls into. Additionally, week dummies were controlled to account for week-specific fluctuations in exercise behaviors.

Table 1. Summary Statistics

Variables	Mean	Std. Dev.	Min	Max
EXER_DIST	49.74	51.98	0.04	135.50
POS_PERF_GAP	16.76	42.70	0.00	680.39
NEG_PERF_GAP	8.16	24.14	0.00	482.98
RANKING	0.47	0.29	0.02	1.00
RIVALRY_INTST	0.32	0.22	0.00	0.50
AWARE_CUES	0.83	0.37	0.00	1.00
NUM_COMPETITORS	33.03	38.24	1.00	1284.00
DEPOSIT	548.30	1061.32	0.00	10000.00
ONE-TO-ONE_RACE	0.04	0.18	0.00	1.00
MULTIPLAYER_RACE	0.87	0.29	0.00	1.00
GROUP_RACE	0.09	0.24	0.00	1.00
GENDER	0.69	0.46	0.00	1.00
CUM_POINTS	29209.02	3035.16	0.00	126706.00
CUM_KM	734.61	1596.56	0.00	9552.75
NUM_WINNINGS	10.14	28.81	0.00	1255.00
SPRING	0.29	0.45	0.00	1.00
SUMMER	0.31	0.46	0.00	1.00
AUTUMN	0.23	0.42	0.00	1.00
WINTER	0.17	0.38	0.00	1.00

Notes: Number of observations = 122,828; number of individuals = 25,583. All variables are at the individual-week level.

4. Empirical Analysis and Results

4.1. Model Specification

Exercisers may exhibit different exercise levels. Cluster analysis enables us to identify homogeneous groups of similar individuals while preserving the heterogeneity across these groups. Specifically, cluster analysis is used to segment individuals into different groups whose members are alike, sharing similar characteristics compared to those in other groups (Afifi & Clark, 1990). This allows us to determine which exercisers are likely to be in a certain group and how the group's characteristics are different from those of the other groups. Based on the

RFM framework (Hughes, 1994), we adapted the three key attributes of RFM by considering the recency, frequency, and magnitude of exercise activity as defined in Section 2.1, and posit that an exerciser can be classified into one of the three groups, i.e., active, moderate, or inactive. To determine an exerciser's group or segment status, we employed *K*-means cluster analysis and assumed the population of interest has K ($K \leq C$) clusters, and each member of the population belongs exclusively to one of the K clusters.

To examine the effects of online gamified competition across different groups of exercisers, we specified a panel-level linear regression model, as shown in Equation (1),

$$EXER\_DIST_{it} = \alpha_i^{Seg} + \beta_1^{seg} POS\_PERF\_GAP_{i(t-1)} + \beta_2^{seg} NEG\_PERF\_GAP_{i(t-1)} + \beta_3^{Seg} RANKING_{i(t-1)} + \beta_4^{seg} RIVALRY\_INTST_{i(t-1)} + \beta_5^{seg} AWARE\_CUES_{it} + \beta_6^{seg} RANKING_{i(t-1)} * AWARE\_CUES_{it} + \beta_7^{seg} RIVALRY\_INTST_{i(t-1)} * AWARE\_CUES_{it} + \beta_8^{seg} CONTROLS + \varepsilon_{it} \quad (1)$$

where the *seg* superscript denotes an individual *i*'s segment or group status, i.e., active, moderate, or inactive.

4.2. Estimation and Results

Our empirical analysis involved two steps. First, following the RFM framework with adapted key attributes, we segmented the exercisers by the *K*-means clustering analysis using an exerciser's average weekly exercise recency, frequency, and magnitude (as measured by exercise distance and duration). Second, we estimated both linear fixed-effect and random-effect models, and then performed the Hausman test for model selection for each segment respectively. The Hausman test results (active segment: χ^2=2202.51, p<0.001; moderate segment: χ^2=794.81, p<0.001; inactive segment: χ^2=3047.98, p<0.001) indicate that a fixed-effect model is preferred for the analysis of all the three segments.

Given the number of segments or clusters are not known prior to the *K*-means clustering analysis, we carried out the analysis for alternative values of the number of clusters and then determined the number of clusters K based on a mix of criteria (Wedel & Kamakura, 2012). The criteria information for each solution is presented in Table 2. The plots with the criteria information for different k values are shown in Figure 1. The reduction of the within-cluster-sum of squared errors (WSS) becomes much smaller for $k > 3$. The η^2 for $k=3$ is 0.87, indicating an 87% reduction of the WSS, and the proportional reduction (PRE) of the WSS for cluster solution $k=3$ is 47.6% compared to the two-cluster solution. Based on the four criteria in Table 2 and Figure 1, a three-cluster solution is revealed to be the most parsimonious solution.

The detailed summary statistics for the three-cluster solution's adapted RFM metrics are presented in Table 3. Based on these descriptive statistics, we labeled Cluster 1 as the *active* segment, Cluster 2 as the *moderate* segment, and Cluster 3 as the *inactive* segment. Cluster 1 is the smallest but most active segment, with 11.83% of the exercisers, and average weekly exercise metrics showing lowest recency, highest frequency, and largest distance and duration. Cluster 2 is the "middle" segment, with around 20.05% of the exercisers, and average weekly exercise metrics showing recency, frequency, and distance and duration that straddle those of exercisers in Clusters 1 and 3. Cluster 3 is the largest but most inactive segment, with around 68.12% of the exercisers, and average weekly exercise metrics showing highest recency, lowest frequency, and smallest distance and duration among the three clusters.

Table 2. Model Fit for Alternative Cluster Solutions

# of K	WSS	log(WSS)	η^2	PRE
1	34344294	17.35	0.00	–
2	8679443	15.97	0.75	0.75
3	4549810	15.33	0.87	0.48
4	3065136	14.94	0.91	0.33
5	2385201	14.68	0.93	0.22
6	2017101	14.52	0.94	0.15
7	1644028	14.31	0.95	0.19
8	1431302	14.17	0.96	0.13

Notes: *WSS refers to the within-cluster-sum of squared errors; log(WSS) refers to the logarithm of the within-cluster-sum of squared errors; η^2 coefficient measures the proportional reduction of the WSS for each cluster* *solution k compared with the total sum of squares; PRE refers to the proportional reduction of the WSS for cluster solution k compared with the previous solution with k–1 clusters.*

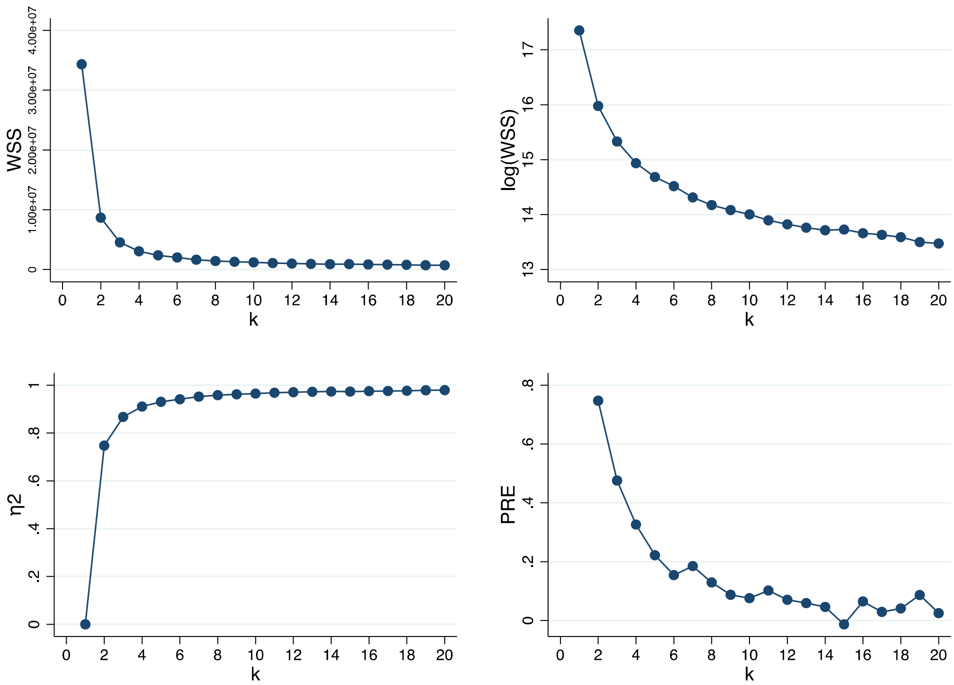

Figure 1. WSS, log(WSS), η^2, and PRE for all *K* Cluster Solutions

Table 3. Descriptive Statistics of the Three Clusters

Variables	Clusters		
	1 Active	2 Moderate	3 Inactive
Cluster size (%)	11.83	20.05	68.12
Weekly exercise recency (days)	19.72	22.16	29.01
Weekly exercise frequency	4.35	2.65	1.31
Weekly exercise distance (km)	108.93	45.66	6.99
Weekly exercise duration (hour)	14.42	8.19	2.13

Table 4 presents the parameter estimates of the linear fixed-effect model for the three segments. As our results show, the positive performance gap between an individual's last exercise performance and their historical average exercise performance has a positive relation to the exercise behavior in terms of exercise distance for the three groups of exercisers (β_1^{active} =0.140, p<0.001; $\beta_1^{moderate}$ =0.197, p<0.001; $\beta_1^{inactive}$ =0.092, p<0.001). We performed pair-wise comparisons among the coefficients of the three segments, and the results suggest that the coefficients are significantly different compared to each other ($F_{active\_moderate}$ = 373.08, p<0.001; $F_{moderate\_inactive}$ = 77.37, p<0.001; $F_{active\_inactive}$ = 576.08, p<0.001). The effect of the positive performance gap is more salient for active and moderate exercisers. H1a is thus supported. In contrast, when an individual's last exercise performance is below their historical average exercise performance level, the negative performance gap is negatively associated with the exercise behavior for all the three groups (β_2^{active}= –0.041, p<0.001; $\beta_2^{moderate}$= –0.062, p<0.001; $\beta_2^{inactive}$= –0.100, p<0.001). The negative effects are significantly different compared to each other ($F_{active\_moderate}$=27.87, p<0.001; $F_{moderate\_inactive}$=12.58, p<0.001; $F_{active\_inactive}$=22.65, p<0.001), and are the strongest for inactive exercisers. H1b is thus supported. Performance ranking is positively associated with exercise behavior for all three segments (β_3^{active}=0.372, p<0.001; $\beta_3^{moderate}$=0.982, p<0.001; $\beta_3^{inactive}$=0.428, p<0.01). The positive effects among the three segments are significantly different compared to each other ($F_{active\_moderate}$=55.62, p<0.001; $F_{moderate\_inactive}$=28.78, p<0.001; $F_{active\_inactive}$=15.75, p<0.001), and are relatively stronger for moderate and inactive exercisers compared to active exercisers. Hence, H2 is supported. We also find a positive relationship between rivalry intensity and exercise behavior for active and inactive exercisers (β_4^{active}=0.211, p<0.001; $\beta_4^{inactive}$=0.025, p<0.01). The effects are significantly different compared to each other ($F_{active\_moderate}$=52.30, p<0.001; $F_{moderate\_inactive}$=19.12, p<0.001; $F_{active\_inactive}$=3.92, p<0.05), and are more pronounced for active exercisers. H3 is thus partially supported.

Further, we find that awareness cues attenuate the effect of performance ranking on exercise behavior for moderate and inactive exercisers ($\beta_6^{moderate}$= –0.258, p<0.01; $\beta_6^{inactive}$= –0.636, p<0.001). The interaction effect is positive but insignificant for active exercisers. The pair-wise comparisons reveal that the coefficients of the three segments are significantly different compared to each other ($F_{active\_moderate}$=33.96, p<0.001; $F_{moderate\_inactive}$=22.48,

p<0.001; $F_{active\_inactive}$ =15.32, p<0.001). H4 is thus not supported. Next, we find that awareness cues significantly strengthen the effect of rivalry intensity on exercise behavior for exercisers from all the three segments (β_7^{active}=0.221, p<0.001; $\beta_7^{moderate}$=0.322, p<0.01; $\beta_7^{inactive}$=0.439, p<0.001). The interaction effects are significantly different compared to each other ($F_{active\_moderate}$=49.76, p<0.001; $F_{moderate\_inactive}$=10.14, p<0.01; $F_{active\_inactive}$= 9.85, p<0.01), and are stronger for inactive and moderate segments. Thus, H5 is supported.

Table 4. Model Estimation Results

Variables	Segments		
	Active	Moderate	Inactive
POS_PERF_GAP	0.140***	0.197***	0.092***
	(0.006)	(0.006)	(0.003)
NEG_PERF_GAP	–0.041***	–0.062***	–0.100***
	(0.003)	(0.006)	(0.017)
RANKING	0.372***	0.982***	0.428**
	(0.034)	(0.078)	(0.153)
RIVALRY_INTST	0.211***	0.040	0.025**
	(0.049)	(0.097)	(0.010)
AWARE_CUES	–0.544***	–1.143***	–0.578***
	(0.037)	(0.078)	(0.137)
*RANKING*AWARE_CUES*	0.035	–0.258**	–0.636***
	(0.041)	(0.085)	(0.157)
*RIVALRY_INTST*AWARE_CUES*	0.221***	0.322**	0.439***
	(0.029)	(0.104)	(0.129)
Control Variables			
NUM_COMPETITORS	0.016***	0.015***	0.012***
	(0.001)	(0.001)	(0.001)
DEPOSIT	0.029***	0.051***	0.017*
	(0.004)	(0.006)	(0.007)
MULTIPLAYER_RACE	0.513***	0.857***	0.462***
	(0.032)	(0.058)	(0.104)
GROUP_RACE	0.269***	1.129***	0.538***
	(0.034)	(0.062)	(0.109)
CUM_KM	0.073***	0.222***	0.424***
	(0.005)	(0.013)	(0.017)
CUM_POINTS	0.236***	1.151***	2.161***
	(0.030)	(0.136)	(0.329)
NUM_WINNINGS	–0.003***	–0.019***	–0.077***
	(0.001)	(0.001)	(0.004)
SPRING	0.041	0.190*	–0.245*
	(0.042)	(0.083)	(0.107)
SUMMER	0.086	0.181	-0.130
	(0.049)	(0.095)	(0.128)
AUTUMN	–0.090	–0.040	–0.119
	(0.049)	(0.090)	(0.122)

WEEK_DUMMY	Included	Included	Included
CONSTANT	–0.835*	–13.527***	–27.225***
	(0.382)	(1.730)	(4.130)
R^2	0.211	0.242	0.154
AIC	68177	75949	83084
BIC	68761	76516	83668
Number of exercisers	3026	5130	17427
Notes: Coefficients are presented in the table. Standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001.			

4.3. Robustness Checks

We conducted further analyses to corroborate our main results in several ways. First, we accounted for the possible correlation of the exercise behaviors within an individual using robust estimates of standard errors. The results with robust standard errors are presented in Table 5, columns (1) to (3). We note that most of the estimated coefficients remain qualitatively consistent with our main results, except that the effect of performance ranking and rivalry intensity for the inactive segment, and the interaction effect of awareness cues on performance ranking and rivalry intensity for the moderate segment become marginally significant at $p<0.1$.

Second, exercise behavior may increase the likelihood of ranking ahead and change the benchmark of using past exercise performance level for self-evaluation, leading to the possible endogeneity of performance ranking, positive and negative performance gap. To alleviate the potential endogeneity of these variables, we adopted the Gaussian copula approach which is an instrument-free method and does not require the availability of outside information to construct the instruments (Park & Gupta, 2012). Specifically, the Gaussian copula approach models the joint distribution of the endogenous regressors and the error term, and makes inferences on the model parameters by maximizing the likelihood from the joint distribution (Park & Gupta, 2012; Tran & Tsionas, 2015). This approach has been adopted as an important method for addressing endogeneity in marketing research (e.g., Rutz & Watson, 2019; Zhang et al., 2017). Specifically, we used individuals' weekly average exercise distance as the outcome variable and estimated the Gaussian copula regression for each segment. Table 5, columns (4) to (6), presents the results of the Gaussian copula correction method. Most results of the focal variables remain qualitatively consistent with those in our main results, other than the effect of rivalry intensity and the interaction effect of awareness cues on performance ranking for the inactive segment.

Table 5. Results for Robustness Checks

Variables	Robust Standard Errors			Gaussian Copula Approach		
	Active (1)	Moderate (2)	Inactive (3)	Active (4)	Moderate (5)	Inactive (6)
POS_PERF_GAP	0.140***	0.197***	0.092***	0.102***	0.082***	0.062***
	(0.008)	(0.008)	(0.003)	(0.026)	(0.011)	(0.002)
NEG_PERF_GAP	–0.041***	–0.062***	–0.100***	–0.042***	–0.071***	–0.118***
	(0.005)	(0.009)	(0.024)	(0.006)	(0.008)	(0.008)
RANKING	0.372***	0.982***	0.428†	0.061**	0.913***	0.374***
	(0.072)	(0.136)	(0.230)	(0.022)	(0.082)	(0.064)
RIVALRY_INTST	0.211*	0.040	0.025†	0.276***	0.212***	0.013
	(0.085)	(0.162)	(0.015)	(0.025)	(0.046)	(0.015)
AWARE_CUES	–0.544***	–1.143***	–0.578*	–0.154***	–0.307***	–0.199***
	(0.098)	(0.148)	(0.236)	(0.018)	(0.048)	(0.026)
*RANKING*AWARE_CUES*	0.035	–0.258†	–0.636**	0.013	–0.335**	–0.072
	(0.084)	(0.151)	(0.234)	(0.021)	(0.072)	(0.054)
RIVALRY_INTST AWARE_CUES*	0.221***	0.322†	0.439*	0.192***	0.225**	0.237***
	(0.049)	(0.166)	(0.192)	(0.027)	(0.076)	(0.053)
CONSTANT	–0.835	–13.527**	–27.224**	–1.326*	–7.471***	–9.362***
	(0.539)	(4.901)	(8.833)	(0.316)	(1.365)	(1.440)
CONTROLS	Included	Included	Included	Included	Included	Included
R^2	0.211	0.242	0.154	-	-	-
AIC	68175	75947	83082	-	-	-
BIC	68750	76506	83657	-	-	-
Number of exercisers	3026	5130	17427	3026	5130	17427
Notes: Coefficients are presented in the table. Standard errors in parentheses † p<0.1, * p<0.05, ** p<0.01, *** p<0.001. The Gaussian copula estimation was run for more than 1000 bootstraps.						

Third, one may have concerns on potential endogeneity bias resulting from the exercisers who self-selected to participate in the online gamified competitions. The decision to participate in the online gamified competitions can depend on individual characteristics such as existing exercise level. To address such concerns, we estimated a Heckman probit two-step selection model for each segment to account for the potential endogeneity due to self-selection (Heckman 1976; 1979). In the first step, an exerciser's decision to participate in online gamified competitions was predicted based on their related characteristics such as gender, cumulative exercise distance, cumulative points, and home region.[13] Exercisers' home region was used as the exclusion restriction variable, because the different regions in China differ greatly in economic development status. Research has suggested that socioeconomic status is positively related to individuals' participation in physical activity (Eime et al., 2015). In the second step, the effect of online gamified competitions on exercisers' behavior (i.e., average weekly exercise distance) was assessed. The results are shown in Table 6 and are mostly qualitatively consistent with our main results. Considering that individuals might try or sample online platforms with gamified competitions due to curiosity or feeling of freshness, and are not serious about joining and exercising in a competition, we considered exercisers with only one competition record as a proxy for those who are not selected in the first step estimation. We also did the estimation using exercisers with two or three competition records, and the results are consistent with the ones presented in Table 6.

Table 6. Results for Heckman Selection Model

Variables	Segments		
	Active	Moderate	Inactive
POS_PERF_GAP	0.139***	0.197***	0.097***
	(0.006)	(0.006)	(0.003)
NEG_PERF_GAP	–0.040***	–0.060***	–0.093***
	(0.003)	(0.006)	(0.017)
RANKING	0.357***	0.958***	0.434**
	(0.034)	(0.078)	(0.153)
RIVALRY_INTST	0.220***	0.002	0.028**
	(0.049)	(0.097)	(0.010)
AWARE_CUES	–0.529***	–1.113***	–0.541***
	(0.037)	(0.079)	(0.137)
*RANKING*AWARE_CUES*	0.011	–0.248**	–0.633***
	(0.041)	(0.085)	(0.157)
*RIVALRY_INTST*AWARE_CUES*	0.228***	0.285**	0.491***
	(0.029)	(0.105)	(0.129)
CONSTANT	–0.220	–11.915***	–33.122***
	(0.381)	(1.739)	(4.223)
CONTROLS	Included	Included	Included
R^2	0.206	0.239	0.137
AIC	67187	75562	82884
BIC	67779	76137	83476
Number of exercisers	3026	5130	17427

[13] Based on the regional division of China and the subjects' city of residence information, we have seven home regions: Northeast, North, Central, East, South, Southwest, and Northwest.

Notes: Coefficients are presented in the table. Standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001.

5. Discussion

5.1. Key Findings

In this study, we examine how online gamified competition can shape individuals' exercise behaviors across different exerciser groups. Specifically, drawing on temporal self-comparison theory and social comparison theory, we theorize online gamified competition as involving temporal self-comparison and social comparison processes, and empirically examine the impact on the different segments' exercise behavior of temporal comparison with past self in terms of performance (i.e., positive or negative performance gap), performance feedback from social comparison with peers (i.e., performance ranking), relationship with social comparison referents (i.e., rivalry intensity), and the moderating effect of awareness cues afforded by fitness activity trackers.

Deviating from the one-size-fits-all discussions of prior studies (e.g., Leahey & Rosen, 2014; Raju et al., 2010), our results reveal that online gamified competition has differential effects on different segments' exercise behavior. Prior studies have suggested that temporal self- and social comparisons serve as fundamental information sources for individuals' self-evaluation (Zell & Alicke, 2009). Consistent with this point, our results further enrich the prior knowledge by showing that exercisers respond differently to these two modes of performance comparison. First, we find that, if the latest exercise performance has improved relative to the historical exercise performance level, the increase in exercise behavior in terms of exercise distance is greater for active and moderate exercisers than that for inactive ones. On the other hand, when the latest exercise performance has deteriorated relative to the historical exercise performance level, the decrease in exercise behavior in terms of exercise distance is more drastic for inactive exercisers compared to active and moderate exercisers. Further, our results show that, compared to active exercisers, moderate and inactive exercisers are influenced more by positive performance feedback from social comparison with peers as enabled by performance ranking in online gamified competitions. Consequently, the positive effect of performance ranking on the exercise behavior of moderate and inactive exercisers is stronger than that of active exercisers.

Second, our results reveal that rivalry intensity has a stronger positive effect on the active exerciser segment's exercise behavior relative to the inactive exerciser segment. For active exercisers with a relatively high perception of personal competence, competing with equally skilled opponents with intense rivalry can yield higher levels of competitiveness and desire to win, resulting in a proportionately higher extent of exercise behaviors. In contrast, inactive exercisers with a lower level of exercise activity may feel less confident in their ability to outperform opponents with intense rivalry, and may not be able to perceive the same level of enjoyment and arousal as active exercisers do, which thus results in a lower extent of exercise behavior increase. However, the effect is insignificant for moderate exercisers. This might be attributed to the excessive pressure from the competitiveness and challenge from the accumulated competitive residue, which may trigger their reactance against the pressure (Ryan & Deci, 2000).

Third, contrary to our expectation, the moderating effect of awareness cues on the impact of performance ranking is stronger but negative for moderate and inactive exercisers. This might be attributed to the potential complacency or excessive self-satisfaction derived from the amplified achievement of a high ranking (Kawall, 2006). Compared to active exercisers, moderate exercisers tend to be affected more by more controlling regulation, and thus are more likely to be affected by and excessively satisfied with the amplified extrinsic value of a high ranking. Inactive exercisers with a lower exercise level tend to have a less stable sense of self in terms of exercise capability and are more easily satisfied by the amplified positive performance feedback through social comparison. Further, our results reveal the role of fitness activity trackers in visualizing the social relations with competitors. We find that rivalry between competitors as visualized by awareness cues encourages moderate and inactive exercisers to engage in more exercise behaviors.

5.2. Theoretical Contributions

Our study represents a leading effort to theorize and empirically examine the role of gamified information systems with competition as a core design element in shaping different user segments' exercise behavior. First, our study contributes to the understanding of a key design principle of gamified information systems, i.e., personalization. The personalization principle posits that user characteristics and differences need to be considered in the design of gamified information systems so that they are better received by users (Liu et al., 2017). Prior studies on the impact of competition-based health promotion programs have mostly failed to consider the heterogeneity among individuals (Raju et al., 2010; Stunkard et al., 1989). The one-size-fits-all discussions may create divergent findings and are unable to provide insightful explanations for different groups. We fill this gap by considering the heterogeneity among exercisers. In particular, we have employed the RFM framework with key exercise behavior metrics to classify exercisers into three groups with different exercise levels, and then empirically examined how exercisers in each group with different exercise behavior characteristics respond to the impact of online gamified competition in diverse ways.

Second, in contrast to prior literature that primarily focuses on competitions among individuals or groups (e.g., Tauer & Harackiewicz, 2004), we have gone beyond the boundary of interpersonal or inter-group competitions, and captured the intrapersonal and temporal aspects of comparison by considering the competition with the past oneself. More specifically, drawing on temporal self-comparison theory and social comparison theory, we have gone beyond the monolithic concept of competition in past literature, and deconstructed competition into two different nuanced dimensions, i.e., temporal comparison with past self and social comparison with peers. We empirically examined how the performance feedbacks from the two distinct comparison processes (i.e., positive and negative performance gaps from temporal self-comparison, and performance ranking from social comparison) affect exercise behaviors across different exerciser segments. Our findings in terms of the performance feedback from two distinct modes of comparison can also shed light on how to effectively improve task feedback in the design of gamified information systems—for instance, in terms of positive or negative, or relative or absolute, feedback that should be given to motivate exercise behaviors.

Third, our study contributes to the competition literature by accounting for the social relationship between competitors in an online repeated competition scenario. Previous related research has been mainly conducted mainly in laboratory settings and pits participants against one another in an offline one-shot competition setting (e.g., Stunkard et al., 1989), which fails to capture the relationships developed through historical competitive interactions among competitors. We fill this gap by examining the impact of the competitive relationship with opponents (i.e., rivalry intensity), and our findings imply that competing against opponents with intense rivalry is more stimulating for active exercisers.

Fourth, our study adds to the nuanced understanding of how target system technology (i.e., a fitness activity trackers) interacts with gamification design elements (i.e., competition) to jointly affect individuals' exercise behavior. Prior studies mainly focus on the core function of tracking and monitoring empowered by fitness activity trackers (e.g., Bravata et al., 2007; Lyons et al., 2014), and thus have overlooked the facilitating role of fitness activity trackers as target system technology (Patel et al., 2015). Our results suggest that, beyond tracking and monitoring, fitness activity trackers such as mobile fitness apps can help visualize the social comparison process by providing various awareness cues. Differing from self-contained offline competitions, online competitions integrated with fitness activity trackers not only offer exercisers a means of self-tracking their physical activity, but also provide affordances through which the competitive interaction process can be visualized. Compared to offline competitions, such visibility bridges the information gap among participants who are not co-located in online gamified competitions and facilitates the social comparison process with peers.

5.3. Practical Implications

This study offers important implications on practice. First, our study demonstrates that performance feedback from two distinct modes of performance comparison, i.e., positive and negative performance gaps derived from temporal comparison with past self, and performance ranking derived from social comparison, affect individuals' exercise behavior in different ways. This finding should encourage health IT providers to utilize different forms of performance feedback and integrate appropriate comparison benchmarks into gamification system designs. For example, a performance feedback system can emphasize the increase in relative standing among peers specifically for moderate and inactive exercisers, and highlight the positive performance improvements achieved for active and moderate exercisers. Moreover, negative performance gap information should be avoided or framed in an appropriate manner for inactive exercisers.

Second, considering that rivalry intensity has divergent effects across different exerciser segments, designers can take advantage of the diverse responses from different user segments and recommend opponents with different levels of rivalry for corresponding user groups. For instance, compared to moderate and inactive exercisers, it would be more motivating to recommend evenly matched opponents with strong rivalry for active exercisers to compete against. Further, from a system design perspective, the design of activity trackers needs to be geared toward conveying and visualizing customized competitive information for different types of users. For example, it is much easier for inactive individuals to forgo their exercise activity, so platform designers may need to retain those particular individuals by boosting their confidence through revealing the participants who are inferior to them.

Third, given the existence of different sensitivities to incentive factors across exercisers, consumer health IT providers are encouraged to develop segment-specific interventions in order to better target and engage users, and shape their exercise behaviors. Compared to inactive and moderate exercisers, active exercisers tend to have higher exercise capability and more established exercise behavior. An intervention strategy targeted at active exercisers need to focus more on the provision of personal standards information such as the discrepancy between their latest and historical exercise performance, as well as the rivalry intensity with opponents. For inactive and moderate exercisers, the intervention can be customized to focus more on increasing their perception of personal competence and thus promoting their interests in exercising by providing more favorable feedback from social comparison.

5.4. Limitations and Future Research

While this research has highlighted several notable findings and contributions, we acknowledge that there are limitations that present opportunities for future research. First, our data sample comes from a single though popular online fitness platform, but the phenomenon of utilizing competitions to promote exercise behaviors has become prevalent across multiple online social platforms (e.g., Fitbit and Strava). We encourage researchers to extend our findings by exploring other platforms to investigate the features and designs used to promote exercise behaviors. Second, to alleviate the concern of potential endogeneity, we have used the Gaussian copula approach and Heckman selection model. Future research may employ field experiments to derive a more robust causal perspective. Third, our study can direct attention to examining the gamified competition approach in terms of shaping other health behavior changes.

6. Conclusion

Our study contributes toward a comprehensive understanding of the role of gamified information systems with competition as a core design element in shaping different exerciser groups' exercise behaviors. We have taken into account the individual differences in exercise behaviors, and categorized exercisers into three groups (i.e., active, moderate, and inactive) based on an adapted RFM framework with key exercise behavior metrics. Grounded in temporal self-comparison theory, social comparison theory, and literature on visibility of ICT systems, we explicated the theoretical mechanisms by which the key factors of online gamified competition, such as positive and negative performance gap, performance ranking, relationship with social comparison referents, and awareness cues afforded by fitness activity trackers, affect individuals' exercise behaviors across different segments. Our results reveal that online gamified competition has differential effects on exercise behavior in terms of exercise distance across different exerciser groups. Our findings indicate that, instead of a one-size-fits-all approach, it is critical to consider individual differences in developing interventions to better target and engage users, and shape their exercise behaviors. Gamification designs have been increasingly utilized in information systems and mobile apps to nudge change in people's behaviors and it is imperative that IS researchers develop sound theories to shape the design and implementation of gamified systems and apps.

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