Cheng Zhang, Chee Wei Phang, Qingsheng Wu, & Xueming Luo

# Nonlinear Effects of Social Connections and Interactions on Individual Goal Attainment and Spending: Evidences from Online Gaming Markets

Although it seems intuitive for firms to leverage social connections and interactions to influence consumers' goal attainment and spending, the authors present a caveat of such strategies. Using two large-scale data sets with more than 5 million people-day observations from online gaming markets, Studies 1 and 2 show consistently nonlinear effects. Although some social connections and interactions boost goal attainment and spending (positive linear term), after a certain point too many of them have a diminished marginal effect (negative squared term). The results are robust to a wide array of modeling techniques addressing self-selection, unobserved individual heterogeneity, and endogeneity. In addition, novices can benefit more from greater social connections and interactions, yet also suffer more from the diminishing effects. Regarding the underlying mechanism, the follow-up experiment Study 3 shows that consistent with the information processing theory, some social connections and interactions can provide information support for goal attainment, but too many of them can introduce an information overload problem and, thus, hamper goal attainment intention. Together, these findings refute a simple, linear view of the effects of social connections and interactions and provide pivotal theoretical and practical implications.

*Keywords*: social connections, social interactions, goal attainment, spending, nonlinear effects

*Online Supplement*: http://dx.doi.org/10.1509/jm.16.0038

"Human existence is social through and through."

—Dy (1994, p. 3)

People often form social connections and interact with others (Cacioppo and Patrick 2008; Reisberg et al. 2002). Through social connections and interactions, people gain access to resources such as information and advice that can help them attain goals (Burt 1992). Tapping into this idea, many firms set up brand community pages on Facebook so that their fans may connect and interact with each other. SparkPeople, an online health service, allows its members to add fitness buddies, emphasizing that "the more you surround yourself with people who support your goals, the greater your chance of success will be" (Mueller 2009).

However, is there a caveat in leveraging social connections and interactions to influence consumers' goal attainment and spending? Studies in other consumer contexts seem to suggest that this is the case. For instance, by surveying users of a social networking site (SNS), Maier et al. (2015) highlight a "dark side" of social connections: having too many friends on a SNS may lead to a negative information overloading problem. In a shopping environment, Argo, Dahl, and Manchanda (2005) find that even when not interacting, the mere presence of too many other shoppers can lead to negative effects on consumer emotions and brand preference.

To answer this question and to quantify the effects of social connections and interactions, we analyzed objective behavioral data sets from two online gaming markets involving 11,720 and 817,546 people, respectively, in a panel of more than 5 million

Cheng Zhang is Professor of Information Systems, School of Management, Fudan University (e-mail: zhangche@fudan.edu.cn). Chee Wei Phang is Professor of Information Systems, School of Management, Fudan University (e-mail: phangcw@fudan.edu.cn). Qingsheng Wu is Associate Professor of Marketing, Antai College of Economics & Management, Shanghai Jiaotong University (e-mail: qswu@sjtu.edu.cn). Xueming Luo is Charles Gilliland Distinguished Chair, Professor of Marketing, Management Information Systems and Strategy, and Director/Founder of the Global Center of Big Data and Mobile Analytics, Fox School of Business, Temple University (e-mail: luoxm@temple.edu). The corresponding authors of this publication are Qingsheng Wu and Chee Wei Phang. The authors gratefully acknowledge the corporate partner for providing the unique and comprehensive anonymous data sets, the financial support of the National Natural Science Foundation of China (#71372112, 71522006, 71490721, 71232008), and the constructive feedback from the *JM* review team, J.P. Dubé, Nathan Fong, Jessica Keech, K. Sudhir, Yuchi Zhang, and participants in the workshop seminar series in the Global Center for Big Data and Mobile Analytics. P.K. Kannan served as area editor for this article.


ISSN: 0022-2429 (print)
1547-7185 (electronic)

*Journal of Marketing*
Vol. 81 (November 2017), 132–155
DOI: 10.1509/jm.16.0038

people-day observations (in Studies 1 and 2). The results show that social connections and interactions positively influence consumer goals and spending. However, their positive effects diminish after a certain point in a salient, nonlinear pattern. That is, some social connections and interactions are beneficial, but the marginal benefits are reduced when they become too numerous. In addition, we identify substantial heterogeneity with individual experience. Novices are more subject to the effects of social connections and interactions, yet such effects also diminish more severely for unseasoned people. To explore the underlying mechanism, our follow-up experiment (Study 3) reveals that, consistent with the information processing theory, some social connections and interactions can provide information support for goal attainment, but too many of them can introduce information overload and, thus, hamper goal attainment intention.

Our research offers several contributions. Theoretically, to the extent of our knowledge, this study is among the first to reveal a nonlinear effect of social connections and interactions on consumers' goal attainment and spending, thus refuting a simple, linear effect. This curvilinear effect is crucial, because it might change our views in theorizing more nuanced, in-depth effects of social connections and interactions (vis-à-vis most previous studies, which have assumed a linear, positive effect). Specifically, social connections and interactions can not only be advantageous but also engender overloading concerns that should be forewarned. Indeed, Grant and Schwartz (2011) explicitly call for research on the nonlinear nature of factors that are generally perceived to be good (e.g., strengths, virtues, and positive experiences), as well as "their mediating mechanisms and boundary conditions" (p. 70). They remark, "Despite the intuitive familiarity of the inverted U, psychologists have failed to appreciate fully its prevalence and importance" (p. 62). Furthermore, they caution that "when researchers fail to discover nonmonotonic relationships, the methodological artifact of range restriction may be the culprit" (p. 71). Our findings also contribute by identifying the boundary condition of experience level in the nonlinear effects of social interactions. People with less experience benefit more from social connections and interactions but also suffer more from diminishing returns from these connections and interactions. Thus, we directly respond to the call of Grant and Schwartz (2011) to not only uncover nonlinear patterns but also identify the mediating mechanisms and boundary conditions.

Managerially, the findings may help shape practices on how managers should exploit social connections and interactions to increase consumers' goal attainment and spending. Given that goal attainment is challenging, it is common for people to quit their goals halfway through despite their good intentions (Capizzi and Ferguson 2005; Koo and Fishbach 2012).[1] Social connections and interactions may help in this regard, and it seems a missed opportunity if managers do not leverage them. Yet managers need to understand that their utility could also diminish because of the information overload problem. This insight is important because managers should be aware of any repercussions from over-exploiting social connections. They may prevent the information overload problem by incorporating monitoring mechanisms to prevent excessive information. Furthermore, they should take a differential strategy toward experienced and novice users; the latter can benefit more from greater social connections and interactions yet suffer more from the diminishing effects than the former.

## Conceptual Background and Hypotheses

Social connections and social interactions are interrelated. As Karlan (2007, p. 53) notes, social connections are "the links and commonalities that bind a group of people together and determine their social interactions." Thus, on the one hand, social connections are precursors of social interactions; even when people are not interacting, the presence of a social connection provides the confidence that one can interact with the people with whom (s)he is connected (e.g., friends added in Facebook or WhatsApp). On the other hand, the occurrences of social interactions between two people can be considered activations of their social connections. For conceptual definitions, empirical measures, and implications of key constructs, see Table 1.

Prior research has investigated the roles of social connections and social interactions in various human cognitions and behaviors. In the social psychology and economics literature, research has investigated the effects of social connections and interactions on people's happiness (Bartolini, Bilancini, and Pugno 2013), health and well-being (Jetten et al. 2014), group contributions (Falk, Fischbacher, and Gächter 2013), microfinance default (Feigenberg, Field, and Pande 2013), and investment response to social programs (Macours and Vakis 2014). The focus has been on the positive effects of social connections and interactions, with the general assumption that they afford the exchange and sharing of resources and support that can promote a psychological state or behavior. For instance, social connections are assumed to provide information and support that can lead to people's welfare (Bartolini, Bilancini, and Pugno 2013), and social interactions are deemed to enhance information flows about a program and increase people's support of the program (Macours and Vakis 2014).

Research in consumer/marketing literature has focused on how social connections and interactions can be exploited to promote consumers' attitude and emotion (Argo, Dahl, and Manchanda 2005; Ranaweera and Jayawardhena 2014), spending (Kurt, Inman, and Argo 2011; Manchanda, Packard, and Pattabhiramaiah 2015), and product adoption (Aral and Walker 2011). For instance, online social connections can promote adoption of the product (Aral and Walker 2011), and social interactions can stimulate spending (Manchanda, Packard, and Pattabhiramaiah et al. 2015) and attitude change (Ranaweera and Jayawardhena 2014). Similarly, these studies have focused on uncovering the positive implications of social connections and interactions. There is one exception by Argo, Dahl, and Manchanda (2005). Their study reveals that, even without interactions, the presence of other shoppers in a retail environment can promote one's positive emotions but only up to a point, after which the effect diminishes and has a negative impact on consumer emotions and brand preference.

[1]Nearly half of participants drop out of weight-loss programs (Matthews 2012). In the online learning context, the dropout rate may be over 90% (Yang et al. 2013).

**TABLE 1**
**Variables' Definition, Measure, and Implication**

| Key Variable | Definition | Measure | Exemplar Studies | Managerial Implications |
|---|---|---|---|---|
| Social connections | The connections among consumers that allow for resource exchange | Studies 1 and 2 (objective data): Number of other participants whom a person has added to his or her friend list in the game. Study 3: Randomly assigned scenario-based experiment (survey data). | Bartolini, Bilancini, and Pugno (2013); Feigenberg, Field, and Pande (2013) | Social connections may help promote goal attainment and spending. Yet it is important to recognize that such effects may diminish after reaching a certain point of social connections. |
| Social interactions | The interactions among consumers that allow for resource exchange | Studies 1 and 2 (objective data): Interaction occurrences including teaming up to accomplish tasks, sending gifts, and chatting with friends. The game system automatically records these interactions and computes a score indicating their interaction extent. Study 3 (survey data): Randomly assigned scenario-based experiment. | Bartolini, Bilancini, and Pugno (2013); Feigenberg, Field, and Pande (2013); Manchanda, Packard, and Pattabhiramaiah (2015) | Social interactions help promote goal attainment and spending. Yet it is important to recognize that such effects may diminish after a certain point. |
| Goal attainment | The achievement of a set goal | Studies 1 and 2 (objective data): Game level attained. Participants try to accomplish a total of 80 predetermined levels with increasing difficulties. Each level presents a mission consisting of several tasks that a participant needs to achieve to advance to the next level. Study 3 (survey data): Goal attainment intention. | Gollwitzer (1999); Grant (2003) | Firms may set goals for consumers (e.g., weight loss plans, online self-learning courses, loyalty programs, saving schemes) and encourage consumers to attain the goals. |
| Consumer spending | How much consumers spent in attaining a set goal | Amount of money spent in the game. | Kurt, Inman, and Argo (2011); Manchanda, Packard, and Pattabhiramaiah et al. (2015) | Spending represents a key return on investment for firms in increasing the social connections and social interactions among consumers (i.e., how much money is generated for the firm). |
| Experience | How long a consumer has been engaging in a goal behavior | Tenure in game (number of days that have elapsed since a player registered in the game). | Bandura (1988); Venkatesh (2000) | Nonlinear effects of social connections and interactions depend on the experience of the individual; thus, managers may design individual-based interventions to promote or limit social connections and interactions. |

Research in other literature streams has likewise focused on different outcomes, such as intention to shop online (Lee et al. 2011) and technology adoption and use (e.g., Maier et al. 2015; Onnela and Reed-Tsochas 2010; Sykes, Venkatesh, and Gosain 2009) in the information systems literature, employees' perceptions and attitudes toward organization (e.g., Ho and Levesque 2005) and work performance (e.g., Chan, Li, and Pierce 2014) in the organization literature, and voter preference change (Baker, Ames, and Renno 2006) and turnout (Bond et al. 2012) in the political science literature (for a review, see Table A1 in the Web Appendix). Again, the objective of these studies has been to unravel the positive effects of social connections and interactions. The only exception is the study by Maier et al. (2015), which finds that having too many social connections in a SNS may lead to a negative overload feeling, which in turn lowers people's satisfaction with and intention to use the SNS.

In summary, extant studies have highlighted the pervasive roles of social connections and social interactions in a variety of human cognitions and behaviors. The majority of them have assumed the positive effects of social connections and interactions on the outcomes of interest, with the general belief that they act as the means through which various types of information are disseminated (e.g., product information, word of mouth, emotional and behavioral cues, knowledge). Only very few exceptions have noted the potentially negative sides of social connections and interactions (i.e., Argo, Dahl, and Manchanda 2005; Maier et al. 2015). However, it remains unclear whether social connections and interactions have a nonlinear effect on consumers' goal attainment and spending behaviors—and, if so, what the mechanisms involved are.

### *Hypotheses on Social Connections/Interactions and Goal Attainment*

We hypothesize that some social connections/interactions are functional in providing useful information or tips that can facilitate goal attainment. However, beyond a certain point, the information overload problem arises; the cost of processing information becomes salient and diminishes the utility of the information for goal attainment. Our thesis is grounded in the information processing perspective (Bettman 1979). This perspective is a general theory of human cognition, which views people as information processors who process information to solve problems and make decisions (Lord and Putrevu 1993; Miller, Galanter, and Pribram 1960). Information is viewed as providing the utility for problem solving; thus, people are motivated to seek and process information in their goal attainment, which typically entails a series of problems to solve. However, information processing is not cost free; processing information requires cognitive efforts and resources on the part of the human information processors. Because humans are limited information processors (Newell and Simon 1972), too much information, despite its utility, is likely to introduce an information overload problem (Eppler and Mengis 2004). Thus, while some information is useful for problem solving, too much information could introduce information overload. This echoes Grant and Schwartz's (2011, p. 62) contention that "all positive traits, states, and experiences have costs that at high levels may begin to outweigh their benefits, creating the nonmonotonicity of an inverted U."

We expect similar logic to explain why social connections and interactions are likely to demonstrate a nonlinear effect on consumers' goal attainment and spending. By forming social connections with others, people obtain access to useful information that may be helpful in their goal attainment. Such information can take the forms of tips and experiences that social others have acquired and accumulated during their goal-attainment process, which can be shared to the focal individuals through social interactions. This information may help people understand the complexity of the problem and make better moves to accomplish their goal (Kelman 2006; Lord, Lee, and Choong 2001). Even without interactions, the mere presence of others may also influence people (Argo, Dahl, and Manchanda 2005; Luo 2005). The presence of social connections may provide psychological comfort through the notion that whenever one encounters a problem during the goal-attainment process, information needed for solving the problem is readily accessible. Thus, social connections and interactions should promote goal attainment.

However, too much information could introduce overload problems because of the increasing cost of processing the information, which diminishes its utility (Eppler and Mengis 2004; Miller, Galanter, and Pribram 1960; Newell and Simon 1972). In other words, too many social connections and interactions may give rise to too much information for a person to process, thus discounting the positive effect of these connections and interactions. Specifically, having too many social connections and interactions with others means that a person is likely to be exposed to and overloaded with a variety of information (Banduhira and Locke 2003; Freeman, Romney, and Freeman 1987). Such diverse information may include the right and wrong behaviors for goal attainment, which can be impediments when there are too many. In line with the findings of Argo, Dahl, and Manchanda (2005) and Maier et al. (2015), we expect that the positive effect of social connections/interactions on goal attainment may diminish after reaching a point when information overloading becomes salient.

> $H_1$: There is a nonlinear relationship between social connections/interactions and consumer goal attainment, such that (a) some social connections/interactions can facilitate goal attainment (i.e., positive linear term), but (b) too many of them have a reduced marginal effect on goal attainment (i.e., negative squared term).

### *Hypotheses on Social Connections/Interactions and Spending*

We expect a similar nonlinear relationship between social connections/interactions and consumer spending. Previous research has noted that a primary reason social others may promote one's spending is that they serve as sources of useful product information (Urbany, Dickson, and Wilkie 1989). Consumers may process this information to decide which product to buy (Bettman 1979). Thus, social others (Burnkrant and Cousineau 1975; Lord, Lee, and Choong 2001) may help a person to be more informed (i.e., understand a product better) and gain confidence in spending. Consumers may obtain the information through interactions with others or by directly observing social connections in their group. They may follow the purchases made by their social connections to keep up with what others have achieved through the product. For instance, seeing that many "fitness buddies" successfully lost weight after using a new health product, a consumer may be stimulated to buy the product, too. Thus, social connections/interactions should promote consumer spending.

However, when social connections/interactions become overwhelming, people's spending desire could be dampened. This may again be due to information overload problems (Bandura and Locke 2003; Eppler and Mengis 2004). Specifically, when many people provide product information and opinions, the cost of processing the information increases and diminishes the utility of the information to aid purchase making. Moreover, the information obtained, either directly through interactions or indirectly by observing those social connections, is likely to be diverse and even contradictive when it reaches a certain level, which may cause confusion regarding what to buy. Indeed, too much information can instigate choice paralysis (Thompson, Hamilton, and Rust 2005) and lead people to become less decisive in purchasing. Therefore,

> $H_2$: There is a nonlinear relationship between social connections/interactions and consumer spending, such that (a) some social connections/interactions can facilitate spending (i.e., positive linear term), but (b) too many of them have a reduced marginal effect on spending (i.e., negative squared term).

### Hypotheses on the Moderating Role of Individual Experience

We also hypothesize some heterogeneity in the effects, and we expect individual experience, or the length of time that people have been engaging in a goal attainment behavior, to moderate the nonlinear effects in $H_1$ and $H_2$. Because information processing is conducted by human beings with past experiences (Moital 2006), it is important to consider how the nonlinear effects of social connections/interactions are amplified or attenuated by individual experience.

People's past experiences constitute an important basis on which their confidence in goal attainment are formed (Bandura 1988). As people gain experience in the process of attaining a goal in an environment, they accumulate more information on how best to solve problems toward attaining their goal. This should make them more confident in their ability to attain the goal (Venkatesh 2000). In this sense, experienced people may rely less on others for information support (obtained through direct interactions with others or indirect observations of their social connections) in attaining a goal. This should make them subject to the influence of social connections/interactions to a lesser extent.

In contrast, novices may yearn more for information support from social others given their lack of experience (Finkelstein and Fishbach 2012). The less experience a person has, the more likely it is that (s)he will depend on social others for information to support his or her goal attainment. In addition, novices may be more vulnerable to the information overload problems caused by having too many social connections/interactions, thus impeding their goal attainments. Previous research has suggested that novices process information differently than experienced people (Alba and Hutchinson 1987). Specifically, as familiarity with a behavior increases, experienced people can better decipher the most relevant information central to the behavior and are better able to derive utility from a larger amount of information. In contrast, novices are more susceptible to information overload that impedes goal attainment because they are less able to differentiate helpful from unhelpful social connections and interactions. As such, we test the moderating role of individual experience as follows:

> $H_3$: The nonlinear role of social connections/interactions in $H_1$ and $H_2$ is moderated by individual experience, such that novices have both (a) stronger positive effects from some social connections/interactions and (b) stronger negative marginal effects from too many social connections/interactions than experienced people.

To test our hypotheses, we first analyzed two sets of objective field data from two online game markets that can detect the nonlinear nature of social connections/interactions (Studies 1 and 2). We then conducted a scenario-based experiment to replicate the results and uncover the underlying mechanisms (Study 3).

## Study 1: Field Data

In Study 1, we aimed to comprehensively examine the nonlinear nature of social connections/interactions for goal attainment and spending in a context fitting for the purpose—massively multiplayer online role-playing game (MMORPG) markets. The three-dimensional simulated goal-based MMORPG markets can be considered an epitomic social world, in which people connect, interact, and engage in goal attainment while making product purchases (i.e., game items; Chappell et al. 2006; Hsu and Lu 2007; Yee 2006). Thus, the game environment provides an ideal setting for gauging the role of social connections and interactions on goal attainment and spending. Indeed, scholars have noted that online games such as MMORPGs present an apt environment to study human behaviors (Bainbridge 2007; Borbora et al. 2011; Shim et al. 2011). For instance, Shim et al. (2011, p. 1) argue that online games serve as "unprecedented tools to theorize and empirically model the social and behavioral dynamics of individuals.... The opportunity this offers for social scientists to test their theories empirically is unparalleled." In addition, Bainbridge (2007, p. 472) holds that online gaming "naturally generates a vast trove of diverse but standardized data about social and economic interactions."

Furthermore, online games are consonant with today's trend of gamification strategies used by companies to engage consumers (Hofacker et al. 2016). For instance, Treehouse, a virtual training academy for young professionals, designs its courses in manageable chunks; as students work through the courses, they earn badges and points that allow them to track their goal progress and impress potential employers. Companies have used Keas, an employee wellness platform, to maintain lower group health insurance costs by challenging employees with health tasks and offering awards for goal attainment. Other companies that employ similar gamification strategies include Starbucks (Wong 2014) and McDonald's (Adamous 2011) (for other examples of firm-employed gamification strategies, see Stanley [2014]). Thus, it is apparent that online games have pervasive applications in the consumer landscape; coupled with their ability to accurately and progressively track user behaviors, they provide an ideal context for studying the nature and effects of social interactions. The latter is particularly important for revealing the nonlinear nature of social connections/interactions, which would be left undetected if alternative approaches with only a limited range of manipulations were used.

We obtained our objective behavioral data from one of the world's largest online games[2] outside the United States, whose name is concealed per our corporate partner's request. The act of joining the game is recognized as a consumer's willingness to engage in a goal-driven behavior. An overarching goal is pre-established for the participants (i.e., to accomplish all the game missions) and divided into smaller tasks (i.e., to advance from easier to more challenging levels). To begin the game, participants select a character from a range of hero classes (e.g., warriors, archers) and use their selected avatar to perform pre-given tasks, such as slaying dragons, destroying objects, and finding treasures. Apart from the functional tasks, players may also engage in economic-related behavior—particularly spending. Although the game is free to play, people can spend real money on equipment to enhance their game abilities and on virtual clothing to improve the visual appearance of their avatar. The confined environment also means that it is less vulnerable to uncontrollable interferences, thus allowing for the nature of the effects of social connections/interactions to be better established.

People may add other players as friends in the game. This enables us to capture social connections, as friends are a common manifestation of social connections (Kurt, Inman, and Argo 2011). Consistent with prior literature, we understand "friends" to be relationships ranging from the stage in which two people like each other and seek out each other's company to the stage of friendly relations (Kurt, Inman, and Argo 2011; Price and Arnould 1999). Previous research has indicated that across the range of stages, the behavioral outcomes from the relationships concerned (e.g., compliance to a request) are similar (Burger et al. 2001; Dolinski, Nawrat, and Rudak 2001; Hsu and Lin 2008). In particular, being friends in the game allows participants to communicate easily, share information and tips, and complete tasks together (e.g., destroying objects, finding treasures; note that these constitute only parts of the requirements for an individual player to advance to the next level). Friends differ from strangers in that the parties involved have a history of prior interactions (Funder and Colvin 1988; Stinson and Ickes 1992). It has been shown that having brief interactions (e.g., a short conversation) can lead people to treat each other as if they are friends (Burger et al. 2001; Dolinski, Nawrat, and Rudak 2001).

Overall, the goal-based virtual game environment enables us to precisely identify and quantify the extent of a person's social connections and interactions and their impacts on goal attainment (the extent to which players achieve the set goal of the game; i.e., completion of all game missions) and spending (how many in-game items purchased) behaviors. In addition, real-world user demographics, such as age and race, are less salient in the virtual environment because users present themselves in the form of an avatar that shields their age and race. Next, we describe the core measures employed in this study, followed by data analyses.

[2]Online gaming is an important industry. Starting from Zynga's Farmville in 2009, which helped online social games become mainstream, the number of people who play online games through social networks in the United States alone is projected to reach 97 million people by 2017 (eMarketer 2013).

### Measures

We measured social connections as the number of other participants a player added to his or her friend list in the game. When two people in the game agree to be friends, the system records the time stamp and the identity of each player. We measured social interactions using interaction occurrences such as teaming up to accomplish tasks, sending gifts, and chatting with friends. The game system automatically records these interactions and computes a score indicating the players' social interaction extent (SIE). Because this score measures a dyadic friendship, we average a player's social interaction score with each of his or her friends. Specifically, when a user forms a team with his or her friends to accomplish a task or fight enemies, the players are treated as having interacted, and the computer program records their interactions. The calculation is dyadic, meaning that every two friends will be counted as interacted. For example, if three friends A, B, and C team up, the interaction is counted between AB, BC, and AC. The calculation also considers task difficulty and numbers of enemies defeated together, with scores ranging between 1 and 30. The higher the task difficulty and the more enemies defeated, the higher the interaction score assigned by the computer program. The program also calculates the situation in which two friends interact with each other directly (e.g., one giving a virtual gift to other). The calculation is also dyadic and considers the value of gift they exchange as a weight of the social interaction, with scores ranging between 10 and 200. The interaction computation system is employed in many social interaction settings to quantify the extent of interactions among friends in online games.

We measured goal attainment as the game level a participant managed to attain. In the game in our study, participants try to accomplish a total of 80 predetermined levels of increasing difficulty. Each level presents a mission consisting of several tasks that a participant needs to achieve to advance to the next level. Participants are motivated to accomplish all game levels because the game's storyline and tasks are tied to their level. As such, they are motivated to persist for the storyline to more fully unfold until they accomplish the final mission. Finally, we measured consumer spending as the total amount of real money that a player spent in the game to buy equipment or virtual clothing.

### Control Variables

We also control for several variables that could affect the results:

- Experience was measured as the number of days that elapsed since a participant registered in the game.
- Trading amount is the amount of virtual currency (not real money) participants use to buy and sell secondhand items (e.g., game equipment) with other participants and in-game shops. We separately coded "trading out" as the amount of virtual currency a participant spent to purchase equipment and "trading in" as the amount a participant earned from selling.
- Number of deaths is the number of times a game character dies in a game. Death may motivate participants to challenge enemies again and thus increase their interest in goal attainment. Yet death may also frustrate participants by signaling effort futility.

- Avatar gender is the gender a player chooses for the role character. A male player may select a female avatar (but more than 87% of male avatars are played by males, according to our corporate partner). After they begin the game, participants cannot change their avatar gender. During game play, participants can see the image of each other's avatar. The avatars are designed by the company to be clearly gendered (0 for male and 1 for female).

Our analyses were conducted at the individual level. The data set contains 11,720 active avatars who played the game at least once in our observation period (i.e., from April 8, 2012 through May 15, 2012), providing 348,940 person-day observations in total. Among them, 5,603 avatars made friends in the game. They added 12.50 social connections (in-game friends) on average (SD = 16.84), and their average social interaction score between friends is 195.20 (SD = 305.48). The remaining 6,117 avatars made no friends. The average game level attained by all avatars was 21.67 (SD = 15.81). On average, participants spent 518.31 RMB in the game.[3] They have a mean experience of playing the game for 41.36 days (SD = 42.12) at the time of our observation. In Table 2, Panels A and B, we provide the descriptive statistics and correlations among the variables. When comparing the difference of all variables employed in the study between the subgroups of players with and without friends (see Table 2, Panel A), the impacts that social connections make on goal attainment and spending can be clearly observed. Next, we go beyond this model-free evidence and test the statistical significance of the nonlinear relationships that we hypothesize.

### *Two-Phase Panel Tobit II Model for Goal Attainment and Spending*

We first developed a two-phase panel Tobit II model to analyze a player's interrelated game behavior decisions: players decide to make a friend (or not) and, conditional on the friending decision in the game, we examine how their goal attainment and spending are affected by social connections and social interactions. This model accounts for endogeneity that the decisions of goal attainment and spending are affected by the decision of making friends in the game. Only when players decide to make friends would their goal attainment and spending be affected by social connections and interactions (i.e., no friends would mean no social connections or interactions). Thus, we have specified a logit function for the friend-making decision in the first phase and a separate Tobit function for the goal attainment or spending amount in the second phase, conditional on the likelihood of friend making (Bucklin and Sismeiro 2003; Luo, Andrews, Song, et al. 2014). In this way, we account for sample selection issues (Heckman 1979) and apply the Mundlak–Chamberlain approach for panel sample estimation (Chamberlain 1982; Mundlak 1978).

Specifically, in our panel Tobit II modeling system, let $P_{it}$ be a binary variable indicating whether a player i makes friend on day t. Let $P^*_{it}$ be the latent variable related to $P_{it}$. $R_{it}$ indicates the goal attainment or spending amount conditional on making friends (i.e., $P_{it} = 1$), and $R^*_{it}$ is the latent variable related to $R_{it}$. The system of the equations can be expressed as follows:

$$P_{it} = \begin{cases} 1 & \text{if } P^*_{it} > 0 \\ 0 & \text{if otherwise} \end{cases}, \text{ and}$$

$$R_{it} = \begin{cases} R^*_{it} & \text{if } P_i = 1 \\ 0 & \text{if otherwise} \end{cases} \text{ where}$$

$$P^*_{it} = \theta_1 \text{Exp}_{it} + \theta_2 \text{Gender}_i + \varepsilon_{it}, \text{ and}$$

$$\begin{aligned} R^*_{it} = {} & \gamma_1 \text{Social\_Connection}_{it} + \gamma_2 \text{Social\_Connection}^2_{it} \\ & + \gamma_3 \text{Social}_{\text{Interaction}_{it}} + \gamma_2 \text{Social}^2_{\text{Interaction}_{it}} + \gamma_5 \text{Exp}_{it} \\ & + \gamma_6 \text{Gender}_i + \gamma_7 \text{Tradein}_{it} + \gamma_8 \text{Tradeout}_{it} + \gamma_9 \text{Death}_{it} + \mu_{it}, \end{aligned}$$

where θ and γ are estimated coefficients of the variables in the model, and μ and ε are residuals of the estimation. In the first phase, important factors that can affect a player's friend making include his or her game experience until the end of observation period (i.e., $\text{exp}_{it}$) and avatar gender (i.e., $\text{gender}_i$, 0 = male, 1 = female). Game experience is important because the time players spend in the game may influence their likelihood to make friends in the game. Furthermore, avatar gender is important because it may also influence a player's friend-making behaviors. As Taylor (2003) notes, women play and derive pleasure from online games differently from men. In the second phase, we have social connections made and SIE, and their squared terms. Because experience and gender also affect users' goal attainment and spending behaviors, we include them in the second phase. However, some other covariates may also take effect. For example, we consider a player's trading in and trading out amount in the model (i.e., $\text{tradein}_{it}$ and $\text{tradeout}_{it}$) because the theory of sunk cost implies that players' previous efforts in the game may influence their likelihood of staying in the game and spending. In addition, we include the number of times an avatar "died" (death amount) in the model (i.e., $\text{death}_{it}$) because the controllability of failures is critical to players' attribution of subsequent behaviors (Weiner 1995, 2000), and frustration caused by failures may influence players' likelihood of goal attainment and spending.

In Table 3, Panels A and B, we present the results with stepwise models, with goal attainment and spending as the dependent variables. More specifically, Model A1 shows the first-phase probit model result of the Tobit II model. Model A2 (B2) examines the linear and nonlinear relationships between quantity of social connections (QSC)—that is, number of friends in the game—and players' goal attainment (spending). Model A3 (B3) examines the linear and nonlinear relationships between SIE and goal attainment (spending). Model A4 (B4) includes all effects. We mean-centered all continuous variables to minimize the threat of multicollinearity in equations with squared terms. We also log-transformed the spending variable.

$H_{1a–b}$ predicted a nonlinear role of social connections and social interactions in individual goal attainment. As Table 3, Panel A, shows, the coefficients of QSC (b = .671) and SIE (b = .012) are positive ($p < .01$). Furthermore, the coefficients of $\text{QSC}^2$ (b = −.009) and $\text{SIE}^2$ (b = −.001) are negative ($p < .01$). Thus, $H_{1a–b}$ is supported. We further depict the nonlinear relationships in Figure A1 in the Web Appendix. The figure

[3]For data anonymity concerns, the spending was rescaled by a constant ratio.

**TABLE 2**
**Summary Statistics (N = 11,720 users)**

**A: Definitions and Summary Statistics of Variables**

| Variables | Definitions | M | SD | Percentile 25% | Percentile 50% | Percentile 75% | Without Friend (6,117 Users) | With Friend (5,603 Users) |
|---|---|---|---|---|---|---|---|---|
| 1. Game level attained | An avatar's game level achieved | 21.67 | 15.81 | 8 | 20 | 33 | 11.8 | 32.5 |
| 2. Quantity of social connections (QSC) | An avatar's virtual friend amount | 5.98 | 13.21 | 0 | 0 | 3 | 0 | 12.5 |
| 3. Social interaction extent (SIE) | Interaction extent between an avatar and his or her friends | 93.32 | 232.62 | 0 | 0 | 24.5 | 0 | 195.2 |
| 4. Gender | Avatar gender recorded (1 = female, 0 = male) | .42 | .49 | 0 | 0 | 1 | .44 | .41 |
| 5. Experience | Number of days elapsed since an avatar registered | 41.36 | 42.12 | 9 | 9 | 99 | 21.6 | 62.9 |
| 6. Spending | An avatar's cash spending | 518.31 | 23,121.40 | 0 | 0 | 0 | 4,433.5 | 6,001.9 |
| 7. Trade-in amount | Amount of virtual currency an avatar earned | 2,626.53 | 43,939.34 | 0 | 0 | 0 | 688.4 | 13,961.0 |
| 8. Trade-out amount | Amount of virtual currency an avatar spent | 7,033.66 | 127,359.10 | 0 | 0 | 0 | 683.5 | 4,747.8 |
| 9. Number of deaths | Number of times an avatar died in the game | 17.41 | 122.18 | 0 | 0 | 2 | 5.1 | 30.8 |

**B: Correlation Matrix of Variables**

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| 1. Game level attained | — | | | | | | | | |
| 2. Quantity of social connections (QSC) | .73*** | — | | | | | | | |
| 3. Social interaction extent (SIE) | .60*** | .60*** | — | | | | | | |
| 4. Gender | −.02** | −.07*** | −.03*** | — | | | | | |
| 5. Experience | .67*** | .54*** | .42*** | .06*** | — | | | | |
| 6. Spending | .02** | .03*** | .03*** | .01 | .01*** | — | | | |
| 7. Trade-in amount | .10*** | .12*** | .09*** | −.01 | .06*** | .02*** | — | | |
| 8. Trade-out amount | .07*** | .08*** | .05*** | .01 | .07*** | .01 | .42*** | — | |
| 9. Number of deaths | .26*** | .28*** | .22*** | −.01 | .15*** | .03*** | .10*** | .05*** | — |

** $p < .05$.
*** $p < .01$.
Notes: Trade-in and trade-out amount are calculated by virtual currency in the game, which is different from real money. The trading amount is not comparable to the cash spending amount and was rescaled for data anonymity concerns.

**TABLE 3**
**Main Results**

| Variable | Model A1 DV = Friend Making (Y/N) | A: DV = Goal Attainment | | | B: DV = Spending | | |
|---|---|---|---|---|---|---|---|
| | | Model A2 | Model A3 | Model A4 | Model B2 | Model B3 | Model B4 |
| Gender | −.267*** | | | | | | |
| Experience | .015*** | | | | | | |
| QSC | | .697*** | | .671*** | .007*** | | .005*** |
| $QSC^2$ | | −.010*** | | −.009*** | .001*** | | .001*** |
| SIE | | | .014*** | .012*** | | .001*** | .001*** |
| $SIE^2$ | | | −.001*** | −.001*** | | −.001*** | −.001*** |
| Gender | | .974*** | .737*** | 1.006*** | −.056*** | −.064*** | −.056*** |
| Experience | | −.028*** | −.062*** | −.032*** | −.001 | −.001 | −.001 |
| Trade-in amount | | −.001 | .001*** | −.001 | .001** | .001** | .001** |
| Trade-out amount | | .001 | .001 | .001 | .001*** | .001*** | .001*** |
| Death amount | | .010*** | .015*** | .008*** | .031*** | .032*** | .031*** |
| Inv. Mills ratio | | −12.244*** | −17.524*** | −11.581*** | .155* | .063 | .143* |
| Significance | | .001 | .001 | .001 | .001 | .001 | .001 |
| $\chi^2$ | | 139,880.08 | 93,608.23 | 42,467.99 | 3,193.21 | 2,948.03 | 3,251.32 |
| $R^2$ | | .666 | .554 | .730 | .066 | .063 | .068 |

*$p < .10$.
**$p < .05$.
***$p < .01$.
Notes: Number of observations = 348,940; censored observations = 189,688. Because the first-part probit model result is consistent across Models A2/B2 to Models A4/B4, we present it only once as Model A1 here to highlight findings from the second-part model.

illustrates that social connections and social interactions have a positive effect on individual goal attainment and spending (positive linear term), but too many of them have a reduced marginal effect (negative squared term) on individual goal attainment and spending.

$H_{2a–b}$ predicted a nonlinear role of social connections and social interactions in individual spending. As Table 3, Panel B, shows, the coefficients of QSC (b = .005) and SIE (b = .001) are positive ($p < .01$). The coefficient of the $SIE^2$ is negative (b = –.001, $p < .01$), but not $QSC^2$ (b = .001, $p < .01$). This indicates that as the QSC increases, players' spending increases as well. Thus, $H_{2b}$ is supported, but not $H_{2a}$. Figure A1 in the Web Appendix also illustrates that SIE has a positive effect on individual spending (positive linear term), but too much has a reduced marginal effect (negative squared term).[4]

[4]By estimating the inflection points of our main results in Models A4 and B4 in Table 3 with differential calculus method, we find that the diminishing effects of social connections and interactions on goal attainment become salient after users made 37 friends or when their interaction extent score reached 1,943. After the inflection point, a 10% increase of friend number (interaction extent) leads to .8% (1.0%) decrease in leveling up in the game. Similarly, the diminishing effect of social interactions on spending occurs after users' interaction extent reaches a score of 2,107. After that point, a 10% increase of interaction extent led to a 2.7% decrease in players' spending trend. To calculate an inflection point in a regression model, we conduct the following approximation: given that our model is in a quadratic function form of $y_i = a_i + \beta_i x_i + \gamma_i x_i^2 + \varepsilon_i$, and the estimated outcome is $\bar{y} = a + \beta\bar{x} + \gamma(\bar{x})^2$, its expectation value can be expressed as $E(y_i) = E(a_i) + E(\beta_i)E(x_i) + E(\gamma_i)E(x_i^2) = a + \beta E(x_i) + \gamma E(x_i^2)$ when $E(\varepsilon_i) = 0$ and $Cov(x_i, \varepsilon_i) = 0$ (assuming that we have controlled endogeneity successfully). Following the differential calculus method, we approximate the inflection point of the function as $-\beta/2\gamma$.

### *Propensity Matching to Account for Self-Selection*

To deal with self-selection, we performed a matching technique, which provides a means to analyze observational data with causal inference (Rosenbaum and Rubin 1983; Rubin and Waterman 2006). As discussed previously, consumers' heterogeneity in terms of avatar gender, sunk cost concerns in terms of experience and trading patterns, and behavioral attribution concerns in terms of number of deaths in our context may confound the friend-making behavior during game play, preventing us from making causality inferences on goal attainment and spending. To mimic some characteristics of treatment selection, we used the nearest-neighbor matching technique, which is one type of propensity score–matching method that selects a set of closest controls for each treated case one at a time (Ho et al. 2011) to create differently ranked groups that are as similar to each other as possible. This allows us to identify the treatment effect (i.e., friend making, in our case) as if in a randomized experiment (Austin 2011; Stuart 2010). Essentially, propensity score is defined as the latent probability of receiving the treatment given the covariates (Rosenbaum and Rubin 1983). We build a matching model by using the propensity score (Imbens and Lemieux 2008; Joffe and Rosenbaum 1999) with covariates including avatar gender, experience, trading amount, trading frequency, and number of deaths. In our data, we have 6,117 observations in the control groups (i.e., players who did not make any friends) and 5,603 observations in the treatment groups (i.e., players who made one or more friends).

Results in Table A2 in the Web Appendix show that after matching, the means of the two groups' covariates are much closer to each other. This table also reports the absolute standardized difference in means (Rosenbaum and Rubin 1983) for each covariate, which is the most commonly used numerical measure of balance of covariate distribution between two groups and is defined as $\left|\bar{X}_{q,1} - \bar{X}_{q,0}\right|/D_{q,0}$, where $\bar{X}_{q,1}$ and $\bar{X}_{q,0}$ denote the means of covariate $X_q$ for the treatment and control groups, respectively. $D_{q,0}$ denotes the standard deviation of $X_q$ for the treatment group. The absolute standardized difference in means suggest .25 as a reasonable balance criterion (Stuart 2010). The mean standardized differences have been markedly reduced and satisfied the balance requirement after we matched the data. Matching results further reveal that players with friends obtained a higher goal-attainment level (coef. = 11.886, SE = .090, z = 131.90, $p < .001$) and spent more (coef. = .057, SE = .005, z = 12.50, $p < .001$).

Then, we reran the two-phase Tobit model on the matched data set that better controls individual heterogeneity. Results shown in Table A3 in the Web Appendix are consistent with the preceding findings. With goal attainment as the dependent variable, the coefficients of QSC (b = .592) and SIE (b = .011) are positive ($p < .01$) while the coefficients of their squared terms are negative ($QSC^2$: b = –.009, $SIE^2$: b = –.001; $p < .01$), indicating a nonlinear role of QSC and SIE in individual goal attainment. With spending as the dependent variable, the coefficients of QSC (b = .06) and SIE (b = .001) are positive ($p <$ .01), while the coefficient of the $SIE^2$ is negative (b = –.001, $p <$ .01) but not $QSC^2$ (b = .001, $p < .01$). This indicates a nonlinear role of SIE (but not QSC) in individual spending.

### Addressing Heterogeneity and Endogeneity

Because latent individual-specific differences (e.g., level of interest, people's personal values) may not be apparent in the data, unobserved heterogeneity in the effects is a concern that may affect the estimation outcome.[5] A strength of our panel data is that we can account for unobserved heterogeneity with individual-specific model parameters. Thus, to account for unobserved heterogeneity to the full extent and to avoid incorrect inferences, we first develop a hierarchical Bayesian model that can allow for individual-specific heterogeneity of the parameters (Kim and Kumar 2017; Kumar et al. 2011; Sun, Dong, and McIntyre 2017). At the top level, we model the drivers of each user's goal attainment and spending amount, after accounting for individual-specific parameters:

$$\begin{aligned}
(5)\quad \text{Goal_Attainment}_{it} = {} & \alpha_{0it} + \alpha_{1i}\text{Social_Connection}_{it} \\
& + \alpha_{2i}\text{Social_Connection}_{it}^2 \\
& + \alpha_{3i}\text{Social_Interaction}_{it} \\
& + \alpha_{4i}\text{Social_Interaction}_{it}^2 \\
& + \alpha_{5i}\text{Gender}_i + \alpha_{6i}\text{Tradein}_{it} \\
& + \alpha_{7i}\text{Tradeout}_{it} + \alpha_{8i}\text{Death}_{it} + \varepsilon_{it}, \\
\text{Spending}_{it} = {} & \beta_{0it} + \beta_{1i}\text{Social_Connection}_{it} \\
& + \beta_{2i}\text{Social_Connection}_{it}^2 \\
& + \beta_{3i}\text{Social_Interaction}_{it} \\
& + \beta_{4i}\text{Social_Interaction}_{it}^2 \\
& + \beta_{5i}\text{Gender}_t + \beta_{6i}\text{Tradein}_{it} \\
& + \beta_{7i}\text{Tradeout}_{it} + \beta_{8i}\text{Death}_{it} + \varepsilon_{it},
\end{aligned}$$

where the Bayesian model includes the base-level parameters ($\alpha_{0it}$, $\beta_{0it}$), which capture all other user-day-specific factors. Because $\alpha_{0it}$ and $\beta_{0it}$ may exhaust the degree of freedom and cannot be identified, we decompose them as follows:

$$(6)\quad \begin{aligned} \alpha_{0it} &= \alpha_{0i} + \alpha_{0t}, \text{ and} \\ \beta_{0it} &= \beta_{0i} + \beta_{0t}, \end{aligned}$$

where $\alpha_{0i}$ and $\beta_{0i}$ measure the baseline purchase rate of user i, and $\alpha_{0t}$ and $\beta_{0t}$ capture the baseline day effect. At the lower level, we model the individual-specific effects of social connections and interactions and their square terms ($\alpha_{1i}$, $\alpha_{2i}$, $\alpha_{3i}$, $\alpha_{4i}$, $\beta_{1i}$, $\beta_{2i}$, $\beta_{3i}$, and $\beta_{4i}$) with two parameters, the grand mean effect and error term, as shown in the following equation:

$$(7)\quad \begin{bmatrix} \alpha_{0i} \\ \alpha_{1i} \\ \alpha_{2i} \\ \alpha_{3i} \\ \alpha_{4i} \end{bmatrix} = \begin{bmatrix} \varpi_{01} \\ \varpi_{02} \\ \varpi_{03} \\ \varpi_{04} \\ \varpi_{05} \end{bmatrix} + \begin{bmatrix} \xi_{0i} \\ \xi_{1i} \\ \xi_{2i} \\ \xi_{3i} \\ \xi_{4i} \end{bmatrix} \text{ and } \begin{bmatrix} \beta_{0i} \\ \beta_{1i} \\ \beta_{2i} \\ \beta_{3i} \\ \beta_{4i} \end{bmatrix} = \begin{bmatrix} \delta_{01} \\ \delta_{02} \\ \delta_{03} \\ \delta_{04} \\ \delta_{05} \end{bmatrix} + \begin{bmatrix} \zeta_{0i} \\ \zeta_{1i} \\ \zeta_{2i} \\ \zeta_{3i} \\ \zeta_{4i} \end{bmatrix}.$$

Furthermore, to address possible endogeneity of social connections and interactions, we use the number of "circle" friends, or the number of friends' friends, as the instrument variable (Sun, Dong, and McIntyre 2017) in the following models:

$$\begin{aligned}
(8)\quad \text{Social_Connection}_{it} = {} & \theta_{10} + \theta_{11}\text{Circle}_{it} + \theta_{12}\text{Gender}_i \\
& + \theta_{13}\text{Exp}_{it} + \eta_{1it}, \text{ and} \\
\text{Social_Interaction}_{it} = {} & \theta_{20} + \theta_{21}\text{Circle}_{it} + \theta_{22}\text{Gender}_t \\
& + \theta_{23}\text{Exp}_t + \eta_{2it}.
\end{aligned}$$

The Bayesian estimation results appear in Table 4. As Table 4, Panel A, shows for goal attainment, the posterior mean coefficients of QSC ($\alpha_{1i}$ = 2.181) and SIE ($\alpha_{3i}$ = .169) are significantly positive, and their squared terms are negative ($QSC^2$: $\alpha_{2i}$ = –.012, $SIE^2$: $\alpha_{4i}$ = –.001). Thus, $H_1$ is supported regarding the nonlinear role of social connections and interactions for players' goal attainment. As Table 4, Panel B, shows for spending, the posterior mean coefficients of QSC ($\beta_{1i}$ = .016) and SIE ($\beta_{3i}$ = .001) are positive, and their squared terms are negative ($QSC^2$: $\beta_{2i}$ = –.001, $SIE^2$: $\beta_{4i}$ = –.001). These findings support the nonlinear role of social connections and interactions for players' goal spending. Thus, $H_2$ is also supported by Bayesian estimation with individual-specific heterogeneity in the parameters. As we expected, the players' friends' circle variable has a significant coefficient of .031 and .396 as an instrument variable for social connections and interactions, respectively (see Table 4, Panels C and D). Figure 1 presents histograms of posterior means of social connections and interactions on goal attainment and spending. Because the mass of the posterior mean distributions for the linear terms of social connections and interactions is indeed positive (right of zero), while that of the squared terms is negative (left of zero), these Bayesian estimates of individual-specific parameters provide strong support for $H_1$ and $H_2$.

Furthermore, we applied a mixed-effect hierarchical modeling approach consisting of both fixed effects and random coefficients effects (Raudenbush and Bryk 2002; Verbeke and Molenberghs 2000). Through the mixed-effect modeling (Luo 2007), the estimation allows for the possibility that people could have different goal attainment and spending because of latent individual-specific heterogeneity in both the

[5]We acknowledge the editor, area editor, and one reviewer for this insight.

**TABLE 4**
**Results of Bayesian Estimation Accounting for Individual-Level Unobservable Heterogeneity**

| Variable | Posterior Mean Coefficient | SD | 95% Credible Interval |
|---|---|---|---|
| **A: DV = Goal Attainment** | | | |
| Constant | 16.700 | 1.331 | [14.238, 19.007] |
| Gender | –2.000 | .114 | [–2.226, –1.773] |
| Experience | .042 | .002 | [.038, .047] |
| Trade-in amount | .001 | .001 | [–.001, .001] |
| Trade-out amount | –.001 | .001 | [–.001, .001] |
| Death amount | .019 | .009 | [.002, .036] |
| QSC | 2.181 | .283 | [1.624, 2.722] |
| $QSC^2$ | –.012 | .003 | [–.016, –.006] |
| SIE | .169 | .004 | [.009, .0250] |
| $SIE^2$ | –.001 | .001 | [–.001, –.001] |
| **B: DV = Spending** | | | |
| | **Posterior Mean Coefficient** | **SD** | **95% Credible Interval** |
| Constant | –.323 | .197 | [–.742, –.045] |
| Gender | .023 | .021 | [–.018, .065] |
| Experience | –.001 | .001 | [–.002, –.001] |
| Trade-in amount | .017 | .002 | [.013, .020] |
| Trade-out amount | .001 | .001 | [.001, .001] |
| Death amount | .001 | .001 | [–.001, .001] |
| QSC | .016 | .007 | [.002, .029] |
| $QSC^2$ | –.001 | .001 | [–.002, –.001] |
| SIE | .001 | .001 | [.001, .003] |
| $SIE^2$ | –.001 | .001 | [–.001, .001] |
| **C: QSC with IV** | | | |
| **Variable** | **Posterior Mean Coefficient** | **SD** | **95% Credible Interval** |
| Constant | .159 | .017 | [.126, .192] |
| Friend's circle (IV) | .031 | .001 | [.031, .031] |
| Gender | –1.140 | .019 | [–1.178, –1.102] |
| Experience | .054 | .001 | [.054, .055] |
| **D: SIE with IV** | | | |
| | **Posterior Mean Coefficient** | **SD** | **95% Credible Interval** |
| Constant | 8.207 | .600 | [7.032, 9.382] |
| Friend's circle (IV) | .396 | .001 | [.394, 398] |
| Gender | –6.549 | .688 | [–7.898, –5.200] |
| Experience | 1.016 | .009 | [.999, 1.033] |

Note: IV = instrument variable; coefficients are significant if zero is not included in the 95% credible interval of the hierarchical Bayesian estimates.

constants (i.e., random intercepts $\mu_{0i}$ and $\pi_{0i}$) and the slopes for the effects of social connection and interaction (i.e., $\mu_{1i}$ and $\pi_{1i}$).

(9)
$$\begin{aligned}\text{Goal\_Attainment}_{it} = {} & \mu_{0i} + \mu_{1i}\text{Social\_Connection}_{it} \\ & + \mu_{2i}\text{Social\_Connection}^2_{it} \\ & + \mu_{3i}\text{Social\_Interaction}_{it} \\ & + \mu_{4i}\text{Social\_Interaction}^2_{it} \\ & + \mu_{5i}\text{Gender}_t + \mu_{6i}\text{Tradein}_{it} \\ & + \mu_{7i}\text{Tradeout}_{it} + \mu_{8i}\text{Death}_{it} + \varepsilon_{9it},\end{aligned}$$

$$\begin{aligned}\mu_{0i} &= \alpha_0 + \alpha_{0i}, \\ \mu_{1i} &= \alpha_1 + \alpha_{1i}, \\ \mu_{2i} &= \alpha_2 + \alpha_{2i}, \\ \mu_{3i} &= \alpha_3 + \alpha_{3i}, \\ \mu_{4i} &= \alpha_4 + \alpha_{4i},\end{aligned}$$

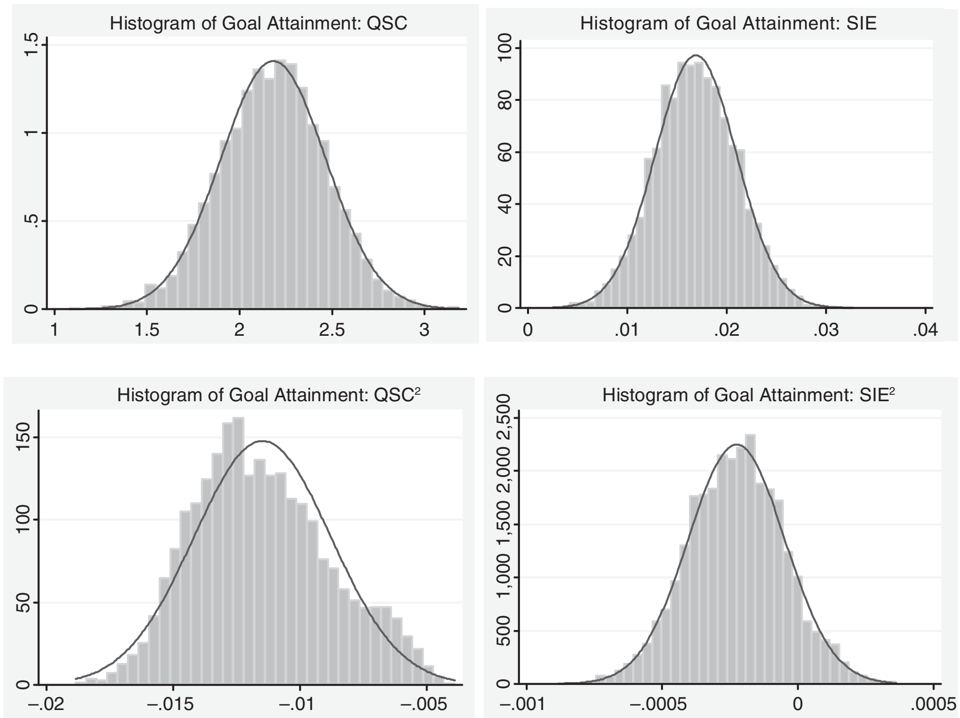
$$\begin{aligned}\text{Spending}_{it} = {} & \pi_{0i} + \pi_{1i}\text{Social\_Connection}_{it} \\ & + \pi_{2i}\text{Social\_Connection}^2_{it} \\ & + \pi_{3i}\text{Social\_Interaction}_{it} \\ & + \pi_{4i}\text{Social\_Interaction}^2_{it} \\ & + \pi_{5i}\text{Gender} + \pi_{6i}\text{Tradein}_{it} \\ & + \pi_{7i}\text{Tradeout}_{it} + \pi_{8i}\text{Death}_{it} + \varepsilon_{10it},\end{aligned}$$

$$\begin{aligned}\pi_{0i} &= \beta_0 + \beta_{0i}, \\ \pi_{1i} &= \beta_1 + \beta_{1i}, \\ \pi_{2i} &= \beta_2 + \beta_{2i}, \\ \pi_{3i} &= \beta_3 + \beta_{3i}, \\ \pi_{4i} &= \beta_4 + \beta_{4i}.\end{aligned}$$

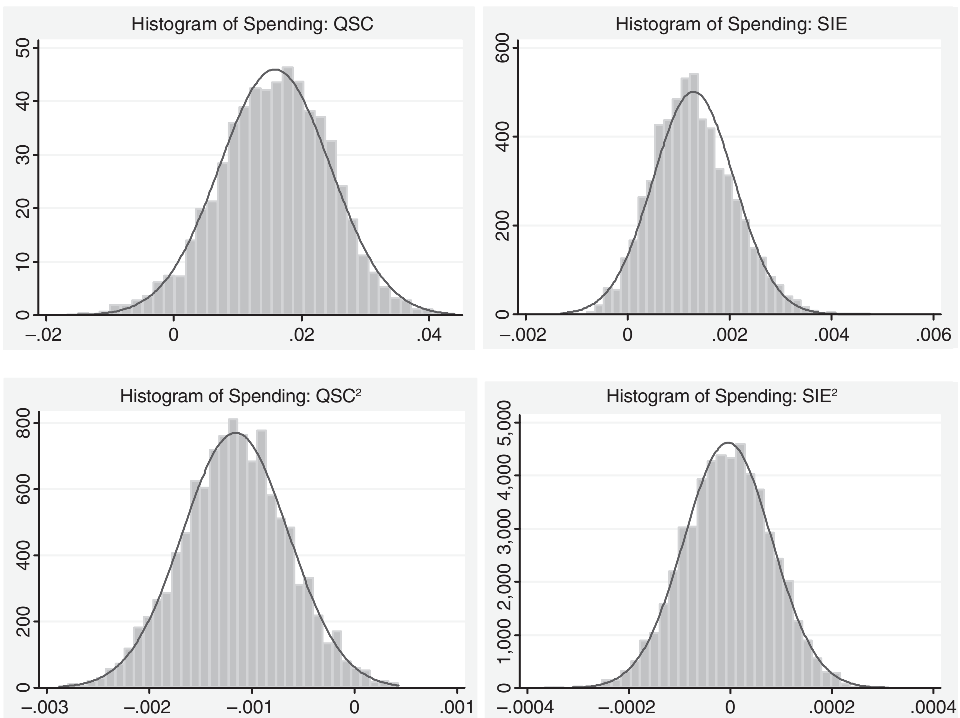
We also considered the temporal effects with the lagged goal attainment and spending, as well as the instrument variable of friend circle, as we did in the hierarchical Bayesian estimation.

**FIGURE 1**
**Histogram of Posterior Mean for the Effects of QSC and SIE on Goal Attainment and Spending**

**A: Goal Attainment**




**Panel B: Spending**




Notes: x-axis = posterior mean values; y-axis = frequency of the posterior means.

**TABLE 5**
**Results of Mixed-Effect Hierarchical Model for Individual-Level Unobservable Heterogeneity**

| | A: DV = Goal Attainment | | | | B: DV = Spending | | | |
|---|---|---|---|---|---|---|---|---|
| Variable | Coefficient (SE) | z | P > \|z\| | 95% Conf. Interval | Coefficient (SE) | z | P > \|z\| | 95% Conf. Interval |
| Constant | 9.539 (.108) | 87.74 | .001 | [9.326, 9.752] | .055 (.008) | 7.01 | .001 | [.040, .070] |
| Gender | .495 (.129) | 3.84 | .001 | [.242, .748] | .022 (.006) | 4.01 | .001 | [.011, .033] |
| Experience | .006 (.001) | 6.49 | .001 | [.004, .007] | –.004 (.001) | –18.58 | .001 | [–.004, –.003] |
| Trade-in amount | .001 (.001) | 1.38 | .169 | [–.001, .001] | .001 (.001) | 27.49 | .001 | [.001, .001] |
| Trade-out amount | .001 (.001) | 1.35 | .177 | [–.001, .001] | .001 (.001) | 3.24 | .001 | [.001, .001] |
| Death amount | .003 (.001) | 15.69 | .001 | [.002, .004] | .009 (.001) | 27.23 | .001 | [.008, .009] |
| Lagged (t – 1) | .459 (.001) | 459.00 | .001 | [.457, .461] | .123 (.002) | 73.80 | .001 | [.120, .126] |
| QSC | .237 (.011) | 19.83 | .001 | [.214, .261] | .003 (.003) | 1.15 | .251 | [–.002, .008] |
| $QSC^2$ | –.004 (.001) | –18.71 | .001 | [–.005, –.004] | –.001 (.001) | –2.51 | .012 | [–.001, –.001] |
| SIE | .002 (.001) | 2.16 | .031 | [.001, .004] | .002 (.001) | 9.73 | .001 | [.002, .003] |
| $SIE^2$ | –.001 (.001) | –7.50 | .001 | [–.001, –.001] | –.001 (.001) | –7.18 | .001 | [–.001, –.001] |
| Experience × QSC | –.004 (.001) | –12.87 | .001 | [–.003, –.005] | –.001 (.001) | –3.24 | .001 | [–.001, –.001] |
| Experience × $QSC^2$ | .001 (.001) | 2.11 | .035 | [.001, .001] | –.001 (.001) | –0.51 | .603 | [–.001, .001] |
| Experience × SIE | –.001 (.001) | –3.56 | .001 | [–.001, –.001] | –.001 (.001) | 4.46 | .001 | [.001, .001] |
| Experience × $SIE^2$ | .001 (.001) | 6.70 | .001 | [.001, .001] | .001 (.001) | .18 | .860 | [–.001, .001] |
| Wald $\chi^2$ | | 216,700.76 | | | | 7,806.14 | | |
| Significance | | .001 | | | | .001 | | |

Notes: Number of observations = 337,220.

The results are robust and consistent with previous findings. As Table 5 shows, the mean coefficients of QSC ($\alpha_{1i}$ = .237) and SIE ($\alpha_{3i}$ = .002) on goal attainment are positive, and their squared terms are negative ($QSC^2$: $\alpha_{2i}$ = –.004, $SIE^2$: $\alpha_{4i}$ = –.001). The mean coefficients of QSC ($\beta_{1i}$ = .003) and SIE ($\beta_{3i}$ = .002) are positive, and their squared terms are negative ($QSC^2$: $\beta_{2i}$ = –.001, $SIE^2$: $\beta_{4i}$ = –.001). Again, these results provide strong and robust evidence for both $H_1$ and $H_2$ with individual-specific heterogeneity in the parameters. Figure 2 illustrates four players' individual-specific heterogeneity in the effects of social connections and interactions on goal attainment and spending. It shows the robustness of our main results even after accounting for individual-level unobserved heterogeneity.

### *Testing the Moderating Effect of Individual Experience*

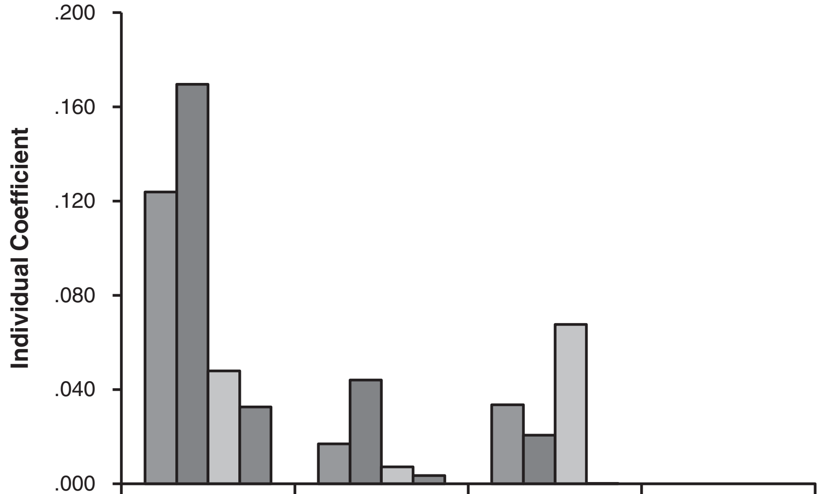
$H_3$ predicts that the nonlinear roles of social connections and social interactions in individual goal attainment and spending are moderated by experience, such that novices will experience stronger positive effects from some social connections/interactions but also stronger negative marginal effects from too many social connections/interactions. Table 6 shows the moderating effect for individual goal attainment and spending, following stepwise analysis logic. As Models A2–A4 show, there is a negative interaction impact between experience and social connections/interactions, and the interaction between experience and the squared term of social connections/interactions are positive (both $ps < .01$). The results suggest that as experience increases, the positive linear effect decreases, but the negative nonlinear effect also decreases. Thus, the nonlinear role of social connections and social interactions in goal attainment is amplified for novices. As Models B2–B4 show, there is a negative interaction between experience and social connections/interactions, and the coefficients of experience × squared term interactions are positive (both $ps < .01$). These results support $H_{3a–b}$. Thus, we identify individual experience level as a boundary condition of the nonlinear effects of social connections and social interactions.

Figure A2 in the Web Appendix depicts the nonlinear relationships between social interactions and spending for more (vs. less) experienced players. As the figure shows, social interactions have a more positive effect on individual spending for novices (i.e., the low-experience line is initially above the high-experience line, confirming that some social interactions are more influential for novices). However, too many social interactions also have greater diminished effect for novices (i.e., after approximately 350 social interactions, the low-experience line is below the high-experience line, confirming that novices are more vulnerable to the dysfunctional side of too many social interactions). Although the total effects do not become negative within our data range, the trend of the lines may suggest that an extremely large number of social interactions could eventually produce a negative total effect. Nevertheless, the patterns support the nonlinear effects of social interactions: some social interactions are beneficial, but their marginal benefits are reduced at too high a level.[6]

[6]Furthermore, we conducted a marginal analysis of experience's interaction effect (Lin, Lucas, and Shmueli 2013). Results show that a one-day increase in more experienced users' duration in the game is associated with a .05% decrease in leveling up (i.e., –.0142) and a .18% decrease in spending (i.e., –.0013) per day. The amount is small for each player every day but can accumulate to a large number that should not be neglected over time: it translates to approximately \$460 (–.0013 × 11,720 users × 30 days) per month based on our sample subset. The impact scale extends easily as the user population increases. However, take Supercell, a leading game developer, as an example. It had 100 million daily active players in early 2016 (Galang 2016). We approximate the impact to the company to be \$3.9 million (–.0013 × 100 million users × 30 days) per month. Overall, these estimations highlight the economic importance of customizing the social connections and interactions for novices and experienced users, respectively.

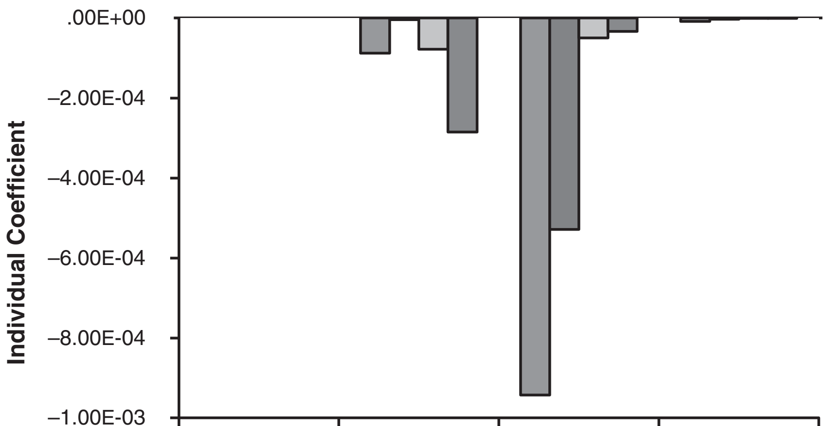
**FIGURE 2**
**Examples of Individual Heterogeneity of QSC and SIE on Goal Attainment and Spending**

**A: Individual Heterogenous Impact of Social Connection and Interaction on Goal Attainment and Spending**




| | QSC on Goal | SIE on Goal | QSC on Spending | SIE on Spending |
|---|---|---|---|---|
| Player 131 | .124 | .017 | .034 | 7.72E-19 |
| Player 2,159 | .170 | .044 | .021 | 4.48E-19 |
| Player 5,814 | .048 | .007 | .068 | 1.70E-18 |
| Player 7,099 | .033 | .004 | .000 | 4.18E-21 |

**B: Individual Heterogenous Impact of Squared Social Connection and Interaction on Goal Attainment and Spending**




| | QSC Squared on Goal | SIE Squared on Goal | QSC Squared on Spending | SIE Squared on Spending |
|---|---|---|---|---|
| Player 131 | –4.09E-22 | –8.76E-05 | –9.43E-04 | –8.82E-06 |
| Player 2,159 | –7.69E-22 | –4.30E-06 | –5.29E-04 | –2.81E-06 |
| Player 5,814 | –1.18E-22 | –7.81E-05 | –4.99E-05 | –5.19E-07 |
| Player 7,099 | –2.64E-22 | –2.85E-04 | –3.37E-05 | –1.73E-07 |

**TABLE 6**
**Moderating Effects of Experience**

| | A: DV = Goal Attainment | | | | B: DV = Spending | | | |
|---|---|---|---|---|---|---|---|---|
| **Variable** | **Model A1** | **Model A2** | **Model A3** | **Model A4** | **Model B1** | **Model B2** | **Model B3** | **Model B4** |
| Gender | −.267*** | | | | −.267*** | | | |
| Experience | .015*** | | | | .015*** | | | |
| Gender | | .615*** | .689*** | .740*** | | −.146*** | −.090*** | −.154*** |
| Experience | | −.007*** | −.058*** | −.015** | | .005*** | .001 | .005*** |
| Trade-in amount | | −.001 | .001*** | −.001 | | .001** | .001** | .001** |
| Trade-out amount | | .001 | .001 | .001 | | .001*** | .001*** | .001*** |
| Death amount | | .010*** | .015*** | .009*** | | .031*** | .032*** | .030*** |
| QSC | | .747*** | | .717*** | | .011*** | | .008*** |
| $QSC^2$ | | −.013*** | | −.011*** | | .001*** | | .001*** |
| SIE | | | .015*** | .012*** | | | .001*** | .001*** |
| $SIE^2$ | | | −.001*** | −.001*** | | | −.001*** | −.001*** |
| Experience × QSC | | −.003*** | | −.003*** | | −.001*** | | −.001*** |
| Experience × $QSC^2$ | | .001*** | | .001*** | | .001*** | | .001*** |
| Experience × SIE | | | −.001*** | .001 | | | −.001*** | −.001*** |
| Experience × $SIE^2$ | | | .001*** | .001*** | | | .001*** | .001*** |
| Inv. Mills ratio | | −10.291*** | −17.19*** | −10.080 | | .736*** | .229*** | .775*** |
| Significance | | .001 | .001 | .001 | | .001 | .001 | .001 |
| $\chi^2$ | | 152,514.89 | 94,974.67 | 195,983.60 | | 3,317.15 | 3,317.15 | 3,317.15 |
| $R^2$ | | .671 | .556 | .735 | | .070 | .063 | .073 |

*$p < .05$.
**$p < .01$.
Notes: Number of observations = 34,940; censored observations = 189,688. Because the first-part probit model result is consistent across Models A2/B2 to Models A4/B4, we present it only once as Model A1 here to highlight findings from the second-part model.

### *Additional Checks of Endogeneity, Dynamic Effects, Ceiling Effects, and Friendship Patterns*

An additional endogeneity concern could arise between experience, goal attainment, and spending (i.e., users with more experience may attain higher goal attainment or vice versa). We performed analyses on the basis of experience residual. The results in Table A4 in the Web Appendix show consistent nonlinear relationships between social connections/interactions and goal attainment and spending, thus minimizing this concern. More specifically, with goal attainment as the dependent variable, the coefficients of QSC (b = .811) and SIE (b = .014) are positive ($p < .01$), while the coefficients of their squared terms are negative ($QSC^2$: b = −.011, $SIE^2$: b = −.001; $p < .01$), indicating their nonlinear role in individual goal attainment. With spending as the dependent variable, the coefficients of QSC (b = .02, $p < .05$) and SIE (b = .001, $p < .01$) are positive, while the coefficient of the $SIE^2$ is negative (b = −.001, $p < .05$) but not $QSC^2$ (b = .001, $p < .01$). This indicates a nonlinear role of SIE but not QSC in individual spending.

We performed panel analysis with different time lags (time lags = 1, 2, and 3 days) to account for potential temporal effects. As shown in Table A5 in the Web Appendix, with goal attainment as the dependent variable, the coefficients of QSC and SIE are positive, whereas the coefficients of their squared terms are negative in various time lag settings, indicating a nonlinear role of social interactions in individual goal attainment. With spending as the dependent variable, the coefficients of QSC and SIE are positive, but only the coefficients of $SIE^2$ are negative in various time lag settings, indicating a nonlinear role of SIE (but not QSC) in individual spending. The results are consistent with the preceding findings across various time lags.

To further verify the dynamic effects of social connections and social interactions on goal attainment and spending, we consider a weekly-level two-phase panel Tobit II model and a cross-sectional-level (no dynamic results) Tobit II model to compare the daily-level analysis. The analysis helps determine whether the dynamic process of friend making (i.e., when a user makes friend in some days but does not do so in other days) affects the finding. As shown in Table A6 in the Web Appendix, with goal attainment as the dependent variable, the coefficients of QSC and SIE are positive, while the coefficients of their squared terms are negative at both the weekly and cross-sectional levels of analysis. This indicates a consistent nonlinear role of QSC and SIE in individual goal attainment. With spending as the dependent variable, the coefficients of QSC and SIE are positive, while only the coefficient of $SIE^2$ is negative, indicating a nonlinear role of SIE (but not QSC) in individual spending. The results are largely in line with the main analyses and show a clear consistent pattern under various dynamic conditions.

Another perspective to consider the dynamic effects is to test the models with cumulative social connections and interactions. Unlike noncumulative daily social connections and interactions in the current models, the cumulative measures take into account users' social connections and interactions before a particular point in time. As shown in Table A7 in the Web Appendix, with goal attainment as the dependent variable, the coefficients of QSC (b = .001) and SIE (b = .001) are positive ($p < .01$) while the coefficients of their squared terms are negative ($QSC^2$: b = –.001, $SIE^2$: b = –.001; $p < .01$). This indicates nonlinear roles of cumulative QSC and SIE in individual goal attainment. With spending as the dependent variable, the coefficients of QSC (b = .053, n.s.) and SIE (b = .012, $p < .01$) are positive, while the coefficient of $SIE^2$ is negative (b = –.001, $p < .10$) but not $QSC^2$ (b = .001, n.s.). This indicates a nonlinear role of cumulative SIE (but not QSC) in individual spending. The results are again largely consistent with the main analysis findings.

Because being friends in the game allows users to communicate, share information, and complete tasks together, there could be a confounding factor of group goal on individual goal attainment. While individual users are rewarded separately for their own performance for leveling up, their friends also pursue their own goals in addition to helping their in-game friends when they play together. In this way, friends' performance might affect a focal user's goal attainment. For example, when a user repeatedly sees many of his or her friends achieving their goals in terms of avatar level, (s)he might be encouraged or demotivated in his or her own goal attainment. Thus, we further consider the group goal effect by adding friends' levels as a control variable. As shown in Table A8 in the Web Appendix, with goal attainment as the dependent variable, the coefficients of QSC (b = .539) and SIE (b = .011) are positive ($p < .01$) while the coefficients of their squared terms are negative ($QSC^2$: b = –.007, $SIE^2$: b = –.001; $p < .01$). This indicates nonlinear roles of QSC and SIE in individual goal attainment. With spending as the dependent variable, the coefficients of QSC (b = .05) and SIE (b = .001) are positive ($p < .01$) while the coefficient of $SIE^2$ is negative (b = –.001, $p < .01$) but that of $QSC^2$ is not (b = .001, $p < .01$). This indicates a nonlinear role of SIE (but not QSC) in individual spending. The results are also consistent with the main analyses, thus minimizing the concerns regarding group goal influence.

We conducted two additional analyses. First, rather than a nonlinear effect, a potential ceiling effect may exist. If the ceiling effect exists, we should observe a constant pattern across different users (i.e., the same ceiling due to the same social connections and interactions). However, the results in Table 3 indicate that the negative squared terms of social connections/interactions for goal attainment and spending are larger for less experienced users than more experienced users. This means that the effects of social connections/interactions on goal attainment drop more heavily for the less experienced group than for the more experienced group as social connections/interactions increase. In addition, Figure A2 in the Web Appendix clearly supports the notion of different nonlinear effects across less versus more experienced users. The less experienced users still experience a nonlinear pattern of the relationships but do not seem to be subject to any "ceiling" effect within our data range. Thus, these findings alleviate the concern of a ceiling effect and support the nonlinear effects of social connections and social interactions.

In addition, users with close friends (deep relationships with a few most important friends) may have different behaviors from those with wider circle of friends with whom they rarely interact. These various types of users may be affected by social connections/interactions differently and warrant special attention. In our context, friendship patterns may affect users' goal attainment differently. To address this possibility, we conducted a subsample test to investigate the impact of friendship patterns on users' goal attainment. In line with users' QSC and SIE, we classified users into four groups along the two aspects by their mean values: 2 (QSC: users with more vs. fewer friends) × 2 (SIE: users with more vs. fewer social interactions). For example, the user group with fewer friends but more interactions is more likely to receive stronger social interactions from fewer friends than the other three groups. The user group with more friends but fewer interactions with each friend is more likely to receive weaker social interactions from more friends than the other three groups. As shown in Table A9 in the Web Appendix, the user group with fewer friends and more interactions is affected by social connections/interactions in a nonlinear way, in support of the notion that close friends influence users' goal attainment. The positive effect also diminishes after reaching a certain level. This nonlinear influence is consistent with the main findings based on the overall samples. In the user group with more friends and more social interactions, users are similarly affected by social connections/interactions in a nonlinear way as with the group with few friends but many interactions. Compared with the latter group, however, the influence from QSC is weaker given the lower coefficient (b = .378, while the coefficient in the more friends/more interactions group is b = .995). Combining the observations from the two groups, it is plausible to argue that for users with fewer close friends, each friend's impact becomes stronger. However, it is also notable that in the more friends/more interactions group, after reaching a certain level, the positive effect diminishes less than that in the few friends/more interactions group (b = –.003 vs. b = –.068, respectively). In the user group with few friends and few interactions, we observe a similar nonlinear influence from social connections/interactions. Because users in this group have few friends and interactions, increases in social connections/interactions influence users' goal attainment significantly, though there is still a negative marginal effect after reaching a certain level. In the user group with more friends but few interactions, we observe the similar nonlinear influence from QSC. Overall, the findings support the notion that close friends matter, implying different social interaction patterns between "first-tier" and "second-tier" friend circles. Still, the nonlinear effects appear to be quite robust across the different friendship patterns.

## Study 2: Second Field Data Set to Test the Generalizability of Findings

To examine the generalizability of our findings, we replicate the analysis using a new data set from another online game market. The game setting is similar to the previous game in terms of goal attainment and spending but differs in the storyline context, social interaction mechanism design, and data scale. The second game is designed in a more Western fairytale style, whereas the first game's storyline and background are more oriented to Asian cultures. Tasks and items in the game are therefore different. In addition, the second game's social interaction mechanism design is simpler than that in the first game. Although users can also make friends in the game, the system does not calculate friends' interactions. In addition, the second game data set provides a longer observation period and larger data set for investigation than the first game. Specifically, the data set contains the information of 817,546 newly registered users in a three-month period between January 1, 2011 and March 30, 2011. Altogether, the data set provides 5,067,960 person-day observations. Among them, 94,821 users made an average of 7.1 friends in the game, whereas the rest did not make friends during the observation period.

This game does not record friends' interactions, so we calculate the team connections among friends as a proxy of their SIE, which is also used as part of the formula for calculating the SIE in the first game. Because users with or without in-game friends can form a team to play and achieve goals together in the game, we identify and capture SIE using actual instances of these teaming-up occurrences. For example, if a user teamed up three times with a friend on a day, we count the SIE between the two users as three on that day.

As we show in Table 7, with goal attainment as the dependent variable, the coefficients of QSC (b = .025) and SIE (b = .104) are positive ($p < .01$). Furthermore, the coefficients of the $QSC^2$ (b = –.001) and $SIE^2$ (b = –.012) are negative ($p <$ .01). Thus, again, $H_{1a–b}$ is supported. With spending as the dependent variable, the coefficients of QSC (b = .003) and SIE (b = .017) are positive ($p < .01$). The coefficients of $QSC^2$ and $SIE^2$ are negative ($b$ = –.001/–.010, $p < .01$). Thus, $H_{2a–b}$ is supported.

Table 7 also depicts the moderating effect of experience for individual goal attainment and spending. Specifically, with goal attainment as the dependent variable, there is a negative interaction between experience and QSC (b = –.001, $p < .01$) and experience and SIE (b = –.003, $p < .01$), and the coefficients of experience interacted with the squared terms are positive (experience × $QSC^2$: b = .001, experience × $SIE^2$: b = .01; $p <$ .01). Thus, the nonlinear role of social connections/interactions in goal attainment is moderated by individual experience. With spending as the dependent variable, there is also a negative interaction between experience and QSC (b = –.001, $p < .01$) and experience and SIE (b = –.001, $p < .01$), and the coefficients of experience interacted with the squared terms are positive (experience × $QSC^2$: b = .001, experience × $SIE^2$: b = .001; $p <$ .01). These results suggest that the nonlinear role of social connections/interactions in individual spending is moderated by experience. Thus, we also find support for $H_{3a–b}$ in this data set.

Finally, we also checked for possible ceiling effect and whether our results are robust across different friendship patterns (varied by QSC and SIE). The results are reported in the "Additional Checks of Ceiling Effects and Friendship Patterns" section in the Web Appendix.

## Study 3: Scenario-Based Experiment for the Underlying Mechanisms

Study 3 involves a scenario-based experiment to achieve two objectives: (1) to replicate the main results of our objective data analysis and (2) to uncover the mechanisms underlying why

**TABLE 7**
**Use of Another Field Data Set to Test Generalizability**

| Variable | Model A1 DV = Friend Making (Y/N) | Model A2 DV = Goal Attainment | Model A3 DV = Goal Attainment | Model B1 DV = Friend Making (Y/N) | Model B2 DV = Spending | Model B3 DV = Spending |
|---|---|---|---|---|---|---|
| Gender | 2.232*** | | | 2.232*** | | |
| Experience | .011*** | | | .011*** | | |
| Gender | | −.763*** | −.265*** | | −.001 | .017 |
| Experience | | .012*** | .017*** | | −.001*** | −.001 |
| Trade-in amount | | .001 | .001* | | .001*** | .001*** |
| Trade-out amount | | −.001 | −.001 | | .001*** | .001*** |
| Death amount | | .018*** | .017*** | | .007*** | .007*** |
| QSC | | .011*** | .025*** | | .002*** | .003*** |
| $QSC^2$ | | −.001*** | −.001*** | | −.001*** | −.001*** |
| SIE | | .080*** | .104*** | | .016*** | .017*** |
| $SIE^2$ | | −.008*** | −.012*** | | −.001*** | −.001*** |
| Experience × QSC | | | −.001*** | | | −.001*** |
| Experience × $QSC^2$ | | | .001*** | | | .001*** |
| Experience × SIE | | | −.003*** | | | −.001** |
| Experience × $SIE^2$ | | | .001*** | | | .001*** |
| Inv. Mills ratio | | −.502*** | −.134*** | | −.006*** | .007*** |
| Significance | | .001 | .001 | | .001 | .001 |
| $\chi^2$ | | 61,397.8 | 68,455.92 | | 45,648.49 | 45,686.92 |
| $R^2$ | | .041 | .042 | | .027 | .027 |

*$p < .10$.
**$p < .05$.
***$p < .01$.
Notes: Number of observations = 5,067,960; censored observations = 1,167,420. Because the first-part probit model result is consistent across Models A2/B2 to Model A4/B4, we present it only once as Model A1 here to highlight findings from the second-part model.

social connections and interactions demonstrate a nonlinear effect. We engaged a professional market research company to conduct the scenario-based experiment. The experiment comprised six scenarios designed to capture different extents of social connections and interactions: low (5), moderate (10), and too much (30) friend presence (corresponding to number of social connections), and low (5), moderate (10), and too many (30) informational tips provided (as a proxy of SIE).[7]

We employed a computer game called "Contraption Maker"[8] as the context of the experiment because the game appeals to general audiences of all ages and can be learned within a short time. It is also sufficiently cognitively challenging (i.e., it requires cognitive thinking, not just speed of response or motor skill), making support from social others (problem-solving information and tips) relevant. The market research company publicized the experiment on its website to its panel members, with a brief explanation that the experiment was to obtain their frank perceptions about a game (to avoid possible guessing of the research objective). We offered an incentive of 10 RMB (approximately $1.50 USD) in the form of a mobile reward card to motivate participation. When participants clicked "enter" to take the survey, they were shown a demo video (approximately 30 seconds) that introduced the game and explained how a simple task was solved to give them an idea of how to play the game (see Figure A3 in the Web Appendix).

The participants were then told that other players would be added to the game as "in-game friends" to help them push through the challenges. This was followed by randomly showing one of the video versions (approximately 30 seconds) designed to correspond to the six social connections and interactions conditions. For instance, in the mere-presence-of-friends conditions, participants would see the process of solving a task in the presence of either 5, 10, or 30 friends (all else being equal) in their friend list shown in the bottom-right panel of the game interface (see Figure A4 in the Web Appendix). In the friends-providing-information conditions, the video would show that friends were providing information (game tips) during the process (5, 10, or 30 tips provided in a chat window at equal intervals during the video, all else being equal) (see Figure A4 in the Web Appendix). Participants were told to imagine that the scenario was real (i.e., they are to play the game in the presence of in-game friends/with information tips received from in-game friends) and to watch the video carefully. We took great care to ensure that the participants watched the video by incorporating a timer that prevented them from proceeding to the next page before finishing the video. After watching the video, the participants were directed to provide their responses to the items designed to capture the focal constructs.

We obtained 768 complete responses from all six groups (each group had a similar sample size). In addition, we also included a control group in which only a basic video without the presence of friends or their provision of information support was

[7]We conducted a series of small-scale pretests to identify the approximate point at which too many social connections and interactions are likely to become salient in our context.

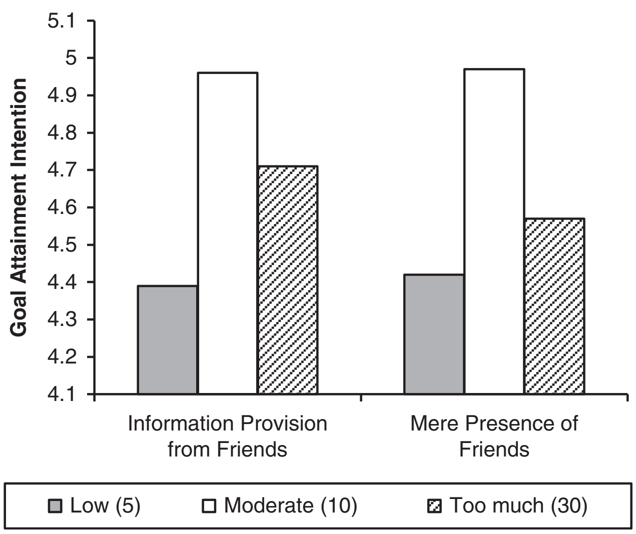
[8]Contraption Maker (http://contraptionmaker.com/) is a puzzle-solving game in which players build machines with a set of given objects to solve predetermined problems.

shown (105 complete responses). This resulted in 873 total responses from the follow-up study.

We measured the following key constructs in the survey: goal attainment intention, perceived information support, perceived information overload, and perceived goal impediment. Our hypotheses argue that some social connections/interactions are favorable because of the information support (actual or perceived) they provide for goal attainment, but too many of them can be detrimental because they introduce an information overload problem. We also examined the following control variables to take in account their potential influences: game self-efficacy, because individual confidence in game playing is likely to affect players' game goal attainment intention; social dependency, because individual dependency on social others for help may affect how social connections/interactions matter to players; personal intolerance toward interference, because people low in such tolerance may more easily feel impeded in their goal attainment when experiencing interference from others; and experience, because whether players had experience playing the game may influence their intention toward goal attainment. The measurements of the constructs are shown in Table A10 in the Web Appendix.

Results from the survey experiment largely replicated those of the objective data analyses. Compared with the control group (no social interactions), the mean goal attainment intention (i.e., intention toward attaining the overall game goal) of the groups with social connections/interactions are significantly higher, with respect to both the information provision ($M_{\text{no social interactions}}$ = 3.89, $M_{\text{friends providing information}}$ = 4.69; $F(1, 433) = 15.45$, $p < .001$) and the mere presence ($M_{\text{no social interactions}}$ = 3.89, $M_{\text{friends' presence}}$ = 4.65; $F(1, 433) = 16.17$, $p < .001$) conditions. The difference remains significant when comparing the respective groups with the lowest mean goal attainment intention in each of the two conditions (information provision and mere presence; see Figure 3). Figure 3 shows that among the groups under both the friends-information-provision and mere-presence conditions, there is a significant rise of mean goal attainment intention from the low to the moderate conditions. However, this intention drops when moving from the moderate to the "too much" (friends' providing 30 pieces of information tips/presence of 30 friends) conditions, although the decreases are not significant. This again indicates the diminishing effects of social connections and interactions on goal attainment, thus replicating our objective data analyses.

**FIGURE 3**
**Mean Goal Attainment Intentions Across the Social Connections and Interactions Conditions**



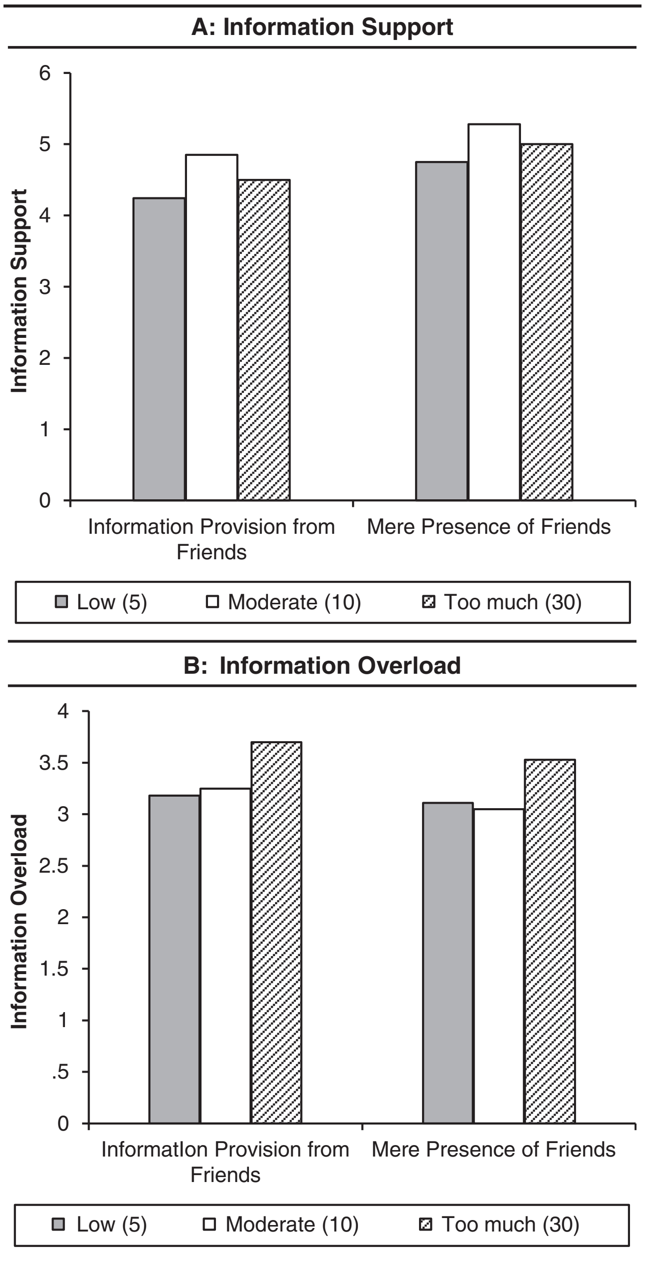

Furthermore, in our hypotheses we posit that some social connections/interactions can provide information support (actual or perceived) that promotes goal attainment, but too many can introduce information overload and impede goal attainment. Figure 3 shows that, for both the information provision and mere presence conditions, people perceived greater information support (or possibility to obtain greater information support) when ten friends were providing information tips (or when ten friends were present) compared with when five friends were providing information tips (or when five friends were present) ($M_{5\text{ friends providing information}}$ = 4.24, $M_{10\text{ friends providing information}}$ = 4.85; $F(1, 218) = 6.36$, $p < .05$; $M_{5\text{ friends' presence}}$ = 4.75, $M_{10\text{ friends' presence}}$ = 5.28; $F(1, 218) = 5.42$, $p < .05$). Again, there is a drop of perceived information support when the number reached 30, although the differences were not significant.

In addition, Figure 4 shows that people perceived similar levels of information overload in the low and moderate levels of both the information provision and mere presence conditions. However, they perceived significantly higher information overload when the number reached 30 (e.g., taking the moderate condition as a baseline: $M_{10\text{ friends providing information}}$ = 3.25, $M_{30\text{ friends providing information}}$ = 3.70; $F(1, 218) = 3.92$, $p < .05$; $M_{10\text{ friends' presence}}$ = 3.05, $M_{30\text{ friends' presence}}$ = 3.53; $F(1, 218) = 5.60$, $p < .05$). This indicates that participants indeed felt overloaded when presented with informational tips from 30 friends or felt a psychological burden when seeing that 30 friends were present who might interact with them during game play.

The observations in this study provide indications of the nonlinear effects of social connections and interactions as well as the possible mediating effects of perceived information support and information overload. To more formally test the mediating mechanisms, we conducted bootstrap mediation and a Sobel test using SmartPLS. To capture the effects of the three social connections and interactions conditions (low, moderate, and too much), we created two dummies (IP1 and IP2 for friends' information provision and MP1 and MP2 for friends' presence): IP1/MP1 compares the moderate social interactions/connections with the low social interactions/connections conditions (0 = moderate level, 1 = low level): IP2/MP2 compares the moderate social interactions/connections with the "too much" social interactions/connections conditions (0 = moderate level, 1 = "too much" level).

Our analyses show that the positive effect of social connections/interactions may indeed result from perceived information support. That is, in the friends-providing-information conditions, IP1 has a negative and significant effect on perceived information support (–.11, $p < .05$). This suggests that compared with the base of moderate social interactions, low social interactions would decrease perceive information support, as we

**FIGURE 4**
**Perceived Information Support and Information Overload Across the Social Connections and Interactions Conditions**




expected. In addition, perceived information support positively affects goal attainment intention (.22, $p < .001$). A Sobel test indicates that the mediation effect of information support between IP1 and goal attainment is significant at $p < .05$. In the friends'-mere-presence conditions, MP1 similarly has a negative and significant effect on perceived information support (–.11, $p < .05$), which then positively affects goal attainment intention (.30, $p < .001$). A Sobel test indicates that the mediation effect of information support between MP1 and goal attainment is weakly significant at $p < .10$.

Our analyses also support that the negative side of social connections/interactions works through information overload and then goal impediment. That is, in the friends-providing-information conditions, IP2 has a positive and significant effect on perceived information overload (.14, $p < .05$). This suggests that compared with the base of moderate social interactions, too many social interactions would increase perceive information overload, as we expected. In addition, perceived information overload increased goal impediment (.57, $p < .001$). A Sobel test indicates that the mediation effect of information overload between IP2 and goal impediment is significant at $p < .05$. Furthermore, goal impediment has a negative and significant effect on goal attainment intention (–.17, $p < .01$). In the friends'-mere-presence conditions, MP2 similarly has a positive and significant effect on perceived information overload (.13, $p < .05$), which then increased perceived goal impediment (.42, $p < .001$). A Sobel test indicates that the mediation effect of information overload between MP2 and goal impediment is significant at $p < .05$. In turn, perceived goal impediment negatively affects goal attainment intention (–.15, $p < .01$).

Together, these findings suggest the following chained path relationships: (1) social connections/interactions conditions → information support → goal attainment, which may explain their positive effects (when social connections/interactions are at a moderate vs. a low level); (2) social connections/interactions conditions → information overload → goal attainment, which may explain their negative side (when social connections/interactions are beyond a moderate level).[9] Overall, the follow-up experiment largely replicates our objective data analysis findings and provides further insights into their underlying mechanisms.

## Discussion

The profusion of social connections and interactions provides invaluable resources that can be leveraged to influence consumer behaviors. The conventional wisdom is that because social connections and interactions have positive implications on consumer behaviors, firms should leverage them. Our study shows that when people are subject to a greater number social connections and interactions, they are indeed more likely to persist in goal attainment and spend more money. However, these positive effects diminish after a certain level, thus demonstrating a nonlinear role of social connections and interactions. Our follow-up experiment reveals that social connections and interactions may create positive effects through the provision of information support; yet, when there are too many social connections/interactions, information overload kicks in and diminishes their positive effects. Overall, the results from both objective longitudinal data and survey data enhance our understanding of the roles and limits of social connections and interactions, which have broad research and practical implications.

[9]In the analyses, we also controlled for alternative explanations related to game self-efficacy, social dependency, personal intolerance toward interference, and experience (i.e., whether one had played the game before). In the friends-providing-information conditions, none of these explanations were significant except game self-efficacy (.39, $p < .001$). In the friends'-mere-presence conditions, only game self-efficacy (.29, $p < .001$) and personal intolerance toward interference (.15, $p < .01$) were significant.

### Implications for Research

This study offers several implications for further research. First, our findings highlight a view of diminishing marginal utility of social connections and interactions. Thus, further research investigating social connections/interactions may note their limits and consider their nonlinear nature in hypothesis development and data analyses. Most prior studies have focused on the positive linear effects of social connections/interactions (e.g., Bartolini, Bilancini, and Pugno 2013; Jetten et al. 2014; Kurt, Inman, and Argo 2011; Ranaweera and Jayawardhena 2014), so an extension of our research may provide a more balanced theoretical view of such pervasive resources in consumers' everyday life (Ratner 2013). This responds to Grant and Schwartz's (2011) to uncover more evidence of the nonlinear nature of things that are generally perceived to be good.

Second, our study contributes to the literature by demonstrating the roles and limits of social connections and interactions in promoting two key behavioral outcomes of marketers' interest: individual goal attainment and spending. In addition, our follow-up experiment reveals the theoretical mechanisms of their nonlinear effects. Specifically, we show that some social interactions can provide information support that enhances goal attainment, but too many of them heighten information overload and impede goal attainment. Thus, we broaden the understanding of the nature of social connections and interactions on the two focal outcomes and their underlying mechanisms.

Third, our findings contribute by identifying the boundary condition of experience level in the nonlinear effects of social connections and interactions. People with less experience are subject to their greater positive impacts, yet the impacts also diminish more acutely for these individuals. This contribution also responds to Grant and Schwartz's (2011) call to not only uncover nonlinear patterns but also identify their boundary conditions.

### Managerial Implications

A recent phenomenon of "social media fatigue" is that users withdraw from social media because too much time and effort are consumed on friending and social interactions (Bright, Kleiser, and Grau 2015). This may suggest that users begin feeling overwhelmed by their growing social networks and yearn for something more manageable. Indeed, a *CNN* article has noted that "in an age when people are encouraged to collect hundreds of Facebook 'friends' and thousands of Twitter followers, some social media users, particularly young ones, are going smaller" (Gross 2014). Consistent with these observations, our results suggest that while managers may still increase their users' exposure to social connections and interactions, caution needs to be taken because too many of them have a negative marginal effect on consumers' goal attainment and spending. In addition, managers may want to take notice of the salient heterogeneity of the nonlinear effects across more versus less experienced people. Novices benefit more from social connections and interactions but, paradoxically, suffer more from the diminishing returns.

Moreover, as our follow-up experiment indicates, the positive effects of social connections and interactions on goal attainment may result from their provision of information support. Thus, managers should consider how they can facilitate social others to provide information in support of a person's goal attainment. For instance, tools and features that can help the instant communication of information among a social group can be designed such that people can readily access the information whenever needed. Interfaces that clearly show the presence of friends may give users the confidence of information support availability. However, managers need to be careful of information overload, as this is a culprit that diminishes the positive effect of social connections and interactions. Thus, they should design features that aid in organizing information to minimize the information overload or incorporate monitoring mechanisms that prevent the excessive information problem.

### Limitations and Future Research Directions

There are several limitations that suggest opportunities for further research. First, most participants in our research (the online game environment) originate from one culture. Previous research on national culture has shown that people in different cultures tend to differ in their receptiveness to social others (Hall 1976), which implies that people could perceive and be affected by social connections/interactions differently. Further research might extend our study to other cultural contexts to assess whether cultural factors play a role (Hofacker et al. 2016). Another limitation is related to the follow-up experiment study. Although it provides additional insights into what may account for the positive and negative sides of social connections/interactions, it mainly serves a supplementary role and may not be exhaustive. In addition, it focuses on one dependent variable (i.e., goal attainment intention). Further research could explore other perceptions about social connections and interactions and investigate other behavioral outcomes in digital marketing with online gaming (Hofacker et al. 2016) and mobile targeting (Andrews et al. 2016; Li et al. 2017; Luo, Andrews, Fang, et al. 2014).

In conclusion, our study underscores the roles and limits of social connections and interactions for individual goal attainment and spending. In a series of studies, we illustrate that that social connections and interactions can have a nonlinear effect. In line with the information processing theory, social connections and interactions can have a positive impact, but too much information can "overload" the individual, thus hampering goal attainment. In addition, the nonlinear effect has substantial heterogeneity across less versus more experienced people. We hope the findings from this study can inspire further research to obtain a more holistic understanding of the effects of social connections and interactions, thus allowing these pervasive resources to be better leveraged for greater business and customer value.

## REFERENCES

Adamou, Betty (2011), "McDonald's: The Masters of Gamification," GameAccess.com (August 26), http://researchaccess.com/2011/08/mcdonald%E2%80%99s-the-masters-of-gamification/.

Alba, Joseph W., and J. Wesley Hutchinson (1987), "Dimensions of Consumer Expertise," *Journal of Consumer Research*, 13 (4), 411–54.

Andrews, Michelle, Xueming Luo, Zheng Fang, and Anindya Ghose (2016), "Mobile Ad Effectiveness: Hyper-Contextual Targeting with Crowdedness," *Marketing Science*, 35 (2), 218–33.

Aral, Sinan, and Dylan Walker (2011), "Creating Social Contagion through Viral Product Design: A Randomized Trial of Peer Influence in Networks," *Management Science*, 57 (9), 1623–39.

Argo, Jennifer J., Darren W. Dahl, and Rajesh V. Manchanda (2005), "The Influence of a Mere Social Presence in a Retail Context," *Journal of Consumer Research*, 32 (2), 207–12.

Austin, Peter C. (2011), "An Introduction to Propensity Score Methods for Reducing the Effects of Confounding in Observational Studies," *Multivariate Behavioral Research*, 46 (3), 399–424.

Bainbridge, William S. (2007), "The Scientific Research Potential of Virtual Worlds," *Science*, 317 (5837), 472–76.

Baker, Andy, Barry Ames, and Lucio R. Renno (2006), "Social Context and Campaign Volatility in New Democracies: Networks and Neighborhoods in Brazil's 2002 Elections," *American Journal of Political Science*, 50 (2), 382–99.

Bandura, Albert (1988), "Perceived Self-Efficacy: Exercise of Control Through Self-Belief," *Annual Series of European Research in Behavior Therapy*, 2, 27–59.

Bandura, Albert, and Edwin A. Locke (2003), "Negative Self-Efficacy and Goal Effects Revisited," *Journal of Applied Psychology*, 88 (1), 87–99.

Bartolini, Stefano, Ennio Bilancini, and Maurizio Pugno (2013), "Did the Decline in Social Connections Depress Americans' Happiness?" *Social Indicators Research*, 110 (3), 1033–59.

Bettman, James R. (1979), *Information Processing Theory of Consumer Choice*. Boston: Addison Wesley.

Bond, Robert M., Christopher J. Fariss, Jason J. Jones, Adam D. Kramer, Cameron Marlow, Jaime E. Settle, et al. (2012), "A 61-Million-Person Experiment in Social Interactions and Political Mobilization," *Nature*, 489 (7415), 295–98.

Borbora, Zoheb, Jaideep Srivastava, Kuo W. Hsu, and Dmitri Williams (2011), "Churn Prediction in MMORPGs Using Player Motivation Theories and Ensemble Approach," *2011 IEEE Third International Conference on Social Computing (SocialCom)*, 157–64.

Bright, Laura F., Susan B. Kleiser, and Stacy L. Grau (2015), "Too Much Facebook? An Exploratory Examination of Social Media Fatigue," *Computers in Human Behavior*, 44 (March), 148–55.

Bucklin, Randolph E., and Catarina Sismeiro (2003), "A Model of Web Site Browsing Behavior Estimated on Clickstream Data," *Journal of Marketing Research*, 40 (3), 249–67.

Burger, Jerry M., Shelley Soroka, Katrina Gonzago, Emily Murphy, and Emily Somerwell (2001), "The Effect of Fleeting Attraction on Compliance Request," *Personality and Social Psychology Bulletin*, 27 (12), 1578–86.

Burnkrant, Robert E., and Alain Cousineau (1975), "Informational and Normative Social Interactions in Buyer Behavior," *Journal of Consumer Research*, 2 (3), 206–15.

Burt, Ronald S. (1992), *Structural Holes*. Cambridge, MA: Harvard University Press.

Cacioppo, John T., and William Patrick (2008), *Loneliness: Human Nature and the Need for Social Connection*. New York: W.W. Norton.

Capizzi, Michael T., and Rick Ferguson (2005), "Loyalty Trends for the Twenty-First Century," *Journal of Consumer Marketing*, 22 (2), 72–80.

Chamberlain, Gary (1982), "Multivariate Regression Models for Panel Data," *Journal of Econometrics*, 18 (1), 5–46.

Chan, Tat Y., Jia Li, and Lamar Pierce (2014), "Learning from Peers: Knowledge Transfer and Sales Force Productivity Growth," *Marketing Science*, 33 (4), 463–84.

Chappell, Darren, Virginia Eatough, Mark N. Davies, and Mark Griffiths (2006), "'EverQuest'—It's Just a Computer Game Right? An Interpretative Phenomenological Analysis of Online Gaming Addiction," *International Journal of Mental Health and Addiction*, 4 (3), 205–16.

Dolinski, Dariusz, Magdalena Nawrat, and Izabela Rudak (2001), "Dialogue Involvement as a Social interactions Technique," *Personality and Social Psychology Bulletin*, 27 (11), 1395–406.

Dy, Manuel B., Jr. (1994), *Contemporary Social Philosophy*. Quezon City, Philippines: JMC Press.

eMarketer (2013), "Gaming on Mobile Leads All Other Online Platforms," (August 13), http://www.emarketer.com/Article/Gaming-on-Mobile-Leads-All-Other-Online-Platforms/1010125.

Eppler, Martin J., and Jeanne Mengis (2004), "The Concept of Information Overload: A Review of Literature from Organization Science, Accounting, Marketing, MIS, and Related Disciplines," *Information Society*, 20 (5), 325–44.

Falk, Armin, Urs Fischbacher, and Simon Gächter (2013), "Living in Two Neighborhoods – Social Interaction Effects in the Laboratory," *Economic Inquiry*, 51 (1), 563–78.

Feigenberg, Benjamin, Erica Field, and Rohini Pande (2013), "The Economic Returns to Social Interaction: Experimental Evidence from Microfinance," *Review of Economic Studies*, 80 (4), 1459–83.

Finkelstein, Stacy R., and Ayelet Fishbach (2012), "Tell Me What I Did Wrong: Experts Seek and Respond to Negative Feedback," *Journal of Consumer Research*, 39 (1), 22–38.

Freeman, Linton C., A. Kimball Romney, and Sue C. Freeman (1987), "Cognitive Structure and Informant Accuracy," *American Anthropologist*, 89, 310–25.

Funder, David C., and Randall C. Colvin (1988), "Friends and Strangers: Acquaintanceship, Agreement, and the Accuracy of Personality Judgment," *Journal of Personality and Social Psychology*, 55 (1), 149–58.

Galang, Gel (2016), "'Clash of Clans' Dev Supercell Enjoy 100M Active Players Every Day Boosted by 'Clash Royale'," *International Business Times* (March 8), http://www.ibtimes.com.au/clash-clans-dev-supercell-enjoy-100m-active-players-every-day-boosted-clash-royale-1507605.

Gollwitzer, P.M. (1999), "Implementation Intentions: Strong Effects of Simple Plans," *American Psychologist*, 54 (7), 493–503.

Grant, Adam M. (2003), "The Impact of Life Coaching on Goal Attainment, Metacognition and Mental Health," *Social Behavior & Personality An International Journal*, 31 (3), 253–63.

Grant, Adam M., and Barry Schwartz (2011), "Too Much of a Good Thing: The Challenge and Opportunity of the Inverted-U," *Perspectives on Psychological Science*, 6 (1), 61–76.

Gross, Doug (2014), "Social Media Users Are Migrating to Smaller Circles," *CNN* (March 25), http://edition.cnn.com/2014/03/25/tech/social-media/smaller-social-networks.

Hall, Marshall (1976), *The Theory of Groups*. Providence, RI: American Mathematical Society.

Heckman, James J. (1979), "Sample Selection Bias as a Specification Error," *Econometrica*, 47 (1), 153–61.

Ho, D., K. Imai, G. King, and E. Stuart (2011), "MatchIt: Nonparametric Preprocessing for Parametric Causal Inference," *Journal of Statistical Software*, 42 (8), 1–28.

Ho, Violet T., and Laurie L. Levesque (2005), "With a Little Help from My Friends (and Substitutes): Social Referents and Influence in Psychological Contract Fulfillment," *Organization Science*, 16 (3), 275–89.

Hofacker, Charles F., Ko de Ruyter, Nicholas H. Lurie, Puneet Manchanda, and Jeff Donaldson (2016), "Gamification and Mobile Marketing Effectiveness," *Journal of Interactive Marketing*, 34 (May), 25–36.

Hsu, Chin L., and Judy C. Lin (2008), “Acceptance of Blog Usage: The Roles of Technology Acceptance, Social Influence and Knowledge Sharing Motivation,” *Information & Management*, 45 (1), 65–74.

Hsu, Chin L., and Hsi P. Lu (2007), “Consumer Behavior in Online Game Community: A Motivational Factor Perspective,” *Computers in Human Behavior*, 23 (3), 1642–59.

Imbens, Guido W., and Thomas Lemieux (2008), “Regression Discontinuity Designs: A Guide to Practice,” *Journal of Econometrics*, 142 (2), 615–35.

Jetten, Jolanda, Catherine Haslam, Alexander S. Haslam, Genevieve Dingle, and Janelle M. Jones (2014), “How Groups Affect Our Health and Wellbeing: The Path from Theory to Policy,” *Social Issues and Policy Review*, 8 (1), 103–30.

Joffe, Marshall M., and Paul R. Rosenbaum (1999), “Invited Commentary: Propensity Scores,” *American Journal of Epidemiology*, 150 (4), 327–33.

Karlan, Dean S. (2007), “Social Connections and Group Banking,” *Economic Journal*, 117 (517), 52–84.

Kelman, Herbert C. (2006), “Interests, Relationships, Identities: Three Central Issues for Individuals and Groups in Negotiating Their Social Environment,” *Annual Review of Psychology*, 57, 1–26.

Kim, Kihyun H., and V. Kumar (2017), “The Relative Influence of Economic and Relational Direct Marketing Communications on Buying Behavior in B2B Markets,” *Journal of Marketing Research* (published electronically March 20), DOI: 10.1509/jmr.16.0283

Koo, Minjung, and Ayelet Fishbach (2012), “The Small-Area Hypothesis: Effects of Progress Monitoring on Goal Adherence,” *Journal of Consumer Research*, 39 (3), 493–509.

Kumar, V., S. Sriram, Anita Luo, and Pradeep K. Chintagunta (2011), “Assessing the Effect of Marketing Investments in a Business Marketing Context,” *Marketing Science*, 30 (5), 924–40.

Kurt, Didem, Jeffrey J. Inman, and Jennifer J. Argo (2011), “The Influence of Friends on Consumer Spending: The Role of Agency–Communion Orientation and Self-Monitoring,” *Journal of Marketing Research*, 48 (4), 741–54.

Lee, Matthew K., Na Shi, Christy M. Cheung, Kai H. Lim, and Choon L. Sia (2011), “Consumer’s Decision to Shop Online: The Moderating Role of Positive Informational Social Influence,” *Information & Management*, 48 (6), 185–91.

Li, Chenxi, Xueming Luo, Cheng Zhang, and Xiaoyi Wang (2017), “Sunny, Rainy, and Cloudy with a Chance of Mobile Promotion Effectiveness,” *Marketing Science* (published electronically June 20), DOI: 10.1287/mksc.2017.1044.

Lin, Mingfeng, Henry C. Lucas, and Galit Shmueli (2013), “Too Big to Fail: Large Samples and the p-Value Problem,” *Information Systems Research*, 24 (4), 906–17.

Lord, Kenneth R., Myung-Soo Lee, and Peggy Choong (2001), “Differences in Normative and Informational Social Interactions,” *Advances in Consumer Research*, Vol. 28, Mary C. Gilly and Joan Meyers-Levy, eds. Valdosta, GA: Association for Consumer Research, 280–85.

Lord, Kenneth R., and Sanjay Putrevu (1993), “Advertising and Publicity: An Information Processing Perspective,” *Journal of Economic Psychology*, 14 (1), 57–84.

Luo, Xueming (2005), “How Does Shopping with Others Influence Impulsive Purchasing?” *Journal of Consumer Psychology*, 15 (4), 288–94.

Luo, Xueming (2007), “Consumer Negative Voice and Firm-Idiosyncratic Stock Returns,” *Journal of Marketing*, 71 (3), 75–88.

Luo, Xueming, Michelle Andrews, Zheng Fang, and Cheewei Phang (2014), “Mobile Targeting,” *Management Science*, 60 (7), 1738–56.

Luo, Xueming, Michelle Andrews, Yiping Song, and Jaakko Aspara (2014), “Group-Buying Deal Popularity,” *Journal of Marketing*, 78 (2), 20–33.

Macours, Karen, and Renos Vakis (2014), “Changing Households’ Investment Behaviour Through Social Interactions with Local Leaders: Evidence from a Randomised Transfer Programme,” *Economic Journal*, 576 (124), 607–33.

Maier, Christian, Sven Laumer, Andreas Eckhardt, and Tim Weitzel (2015), “Giving Too Much Social Support: Social Overload on Social Networking Sites,” *European Journal of Information Systems*, 24 (5), 447–64.

Manchanda, Puneet, Grant Packard, and Adithya Pattabhiramaiah (2015), “Social Dollars: The Economic Impact of Customer Participation in a Firm-Sponsored Online Customer Community,” *Marketing Science*, 34 (3), 367–87.

Matthews, Susan E. (2012), “Nearly Half Drop Out of Weight-Loss Programs,” LiveScience (August 1), http://www.livescience.com/22025-weight-loss-program-drop-outs.html.

Miller, George A., Eugence Galanter, and Karl H. Pribram (1960), *Plans and the Structure of Behavior*. New York: Holt, Rinehart & Winston.

Moital, Miguel (2006), “An Evaluation of the Factors Influencing the Adoption of Ecommerce in the Purchasing of Leisure Travel by the Residents of Cascais,” doctoral thesis, Bournemouth University.

Mueller, Jen (2009), “Find a Fitness Buddy,” SparkPeople (July 21), http://www.sparkpeople.com/resource/fitness_articles.asp?id=102.

Mundlak, Yair (1978), “On the Pooling of Time Series and Cross Section Data,” *Econometrica*, 46 (1), 69–85.

Newell, Allen, and Herbert A. Simon (1972), *Human Problem Solving*. Englewood Cliffs, NJ: Prentice Hall.

Onnela, Jukka P., and Felix Reed-Tsochas (2010), “The Spontaneous Emergence of Social Influence in Online Systems,” *Proceedings of the National Academy of Sciences of the United States of America*, 107 (43), 18375–80.

Price, Linda L., and Eric J. Arnould (1999), “Commercial Friendships: Service Provider-Client Relationships in Context,” *Journal of Marketing*, 63 (4), 38–56.

Ranaweera, Chatura, and Chanaka Jayawardhena (2014), “Talk Up or Criticize? Customer Responses to WOM About Competitors During Social Interactions,” *Journal of Business Research*, 67 (2), 2645–56.

Ratner, Rebecca (2013), “Consumer Goal Pursuit,” *Journal of Consumer Research*, 40 (2), vi–viii.

Raudenbush, Stephen W., and Anthony S. Bryk (2002), *Hierarchical Linear Models: Applications and Data Analysis Methods*, 2nd ed. Thousand Oaks, CA: Sage Publications.

Reisberg, Barry, Emile H. Franssen, Liduin E.M. Souren, Stefanie R. Auer, Imran Akram, and Sunnie Kenowsky (2002), “Evidence and Mechanisms of Retrogenesis in Alzheimer’s and other Dementias: Management and Treatment Import,” *American Journal of Alzheimer’s Disease and Other Dementias*, 17 (4), 202–12.

Rosenbaum, Paul R., and Donald B. Rubin (1983), “The Central Role of the Propensity Score in Observational Studies for Causal Effects,” *Biometrika*, 70 (1), 41–55.

Rubin, Donald B., and Richard P. Waterman (2006), “Estimating the Causal Effects of Marketing Interventions Using Propensity Score Methodology,” *Statistical Science*, 21 (2), 206–22.

Shim, Kyong J., Nishith Pathak, Muhammad A. Ahmad, Colin DeLong, Zoheb Borbora, Amogh Mahapatra, et al. (2011), “Analyzing Human Behavior from Multiplayer Online Game Logs: A Knowledge Discovery Approach,” *IEEE Intelligent Systems*, 26 (1), 85–89.

Stanley, Robert (2014), “Top 25 Best Examples of Gamification in Business,” ClickSoftware.com (March 24), http://blogs.

clicksoftware.com/index/top-25-best-examples-of-gamification-in-business.

Stinson, Linda, and William Ickes (1992), “Empathic Accuracy in the Interactions of Male Friends and Male Strangers,” *Journal of Personality and Social Psychology*, 62 (5), 787–97.

Stuart, Elizabeth A. (2010), “Matching Methods for Causal Inference: A Review and a Look Forward,” *Statistical Science*, 25 (1), 1–21.

Sun, Yacheng, Xiaojing Dong, and Shelby McIntyre (2017), “Motivation of User-Generated Content: Social Connectedness Moderates the Effects of Monetary Rewards,” *Marketing Science*, 36 (3), 329–37.

Sykes, Tracy A., Viswanath Venkatesh, and Sanjay Gosain (2009), “Model of Acceptance with Peer Support: A Social Network Perspective to Understand Employees’ System Use,” *Management Information Systems Quarterly*, 33 (2), 371–93.

Taylor, T.L. (2003), “Multiple Pleasures Women and Online Gaming,” *Convergence*, 9 (1), 21–46.

Thompson, Debora V., Rebecca W. Hamilton, and Roland T. Rust (2005), “Feature Fatigue: When Product Capabilities Become Too Much of a Good Thing,” *Journal of Marketing Research*, 42 (6), 431–42.

Urbany, Joel E., Peter R. Dickson, and William L. Wilkie (1989), “Buyer Uncertainty and Information Search,” *Journal of Consumer Research*, 16 (2), 208–15.

Venkatesh, Viswanath (2000), “Determinants of Perceived Ease of Use: Integrating Control, Intrinsic Motivation, and Emotion into the Technology Acceptance Model,” *Information Systems Research*, 11 (4), 342–65.

Verbeke, Geert, and Geert Molenberghs (2000), *Linear Mixed Models for Longitudinal Data*. New York: Springer.

Weiner, Bernard (1995), *Judgments of Responsibility: A Foundation for a Theory of Social Conduct*. New York: Guilford Press.

Weiner, Bernard (2000), “Attributional Thoughts About Consumer Behavior,” *Journal of Consumer Research*, 27 (3), 382–87.

Wong, Kimberly (2014), Starbucks Attributes the Success of Its Loyalty Programmes to Gamification,” Total Customer (April 30), http://www.totalcustomer.org/2014/04/30/starbucks-attributes-success-loyalty-programmes-gamification/.

Yee, Nick (2006), “Motivations for Play in Online Games,” *Cyberpsychology & Behavior*, 9 (6), 772–75.