The Evolution of Customer Relationships in Game Contexts: An Empirical Examination of Design Dimensions, Processes, and Social Dynamics in Large-Scale Networks

DISSERTATION
of the University of St.Gallen,
School of Management,
Economics, Law, Social Sciences
and International Affairs
to obtain the title of
Doctor of Philosophy in Management

submitted by

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Dissertation no. 4822

Rosch-Buch, Scheßlitz 2019

The University of St.Gallen, School of Management, Economics, Law, Social Sciences and International Affairs hereby consents to the printing of the present dissertation, without hereby expressing any opinion on the views herein expressed.

St.Gallen, October 23, 2018

The President:

Prof. Dr. Thomas Bieger

This Dissertation is dedicated to my beloved
Mother, Father, and Sisters.

Acknowledgements

Writing a dissertation is a game-changing experience. As in games, you master different levels, improve your skills with increasing challenges, defeat several bosses, and either come off as the winner or the loser. Having finalized my dissertation, published one of my articles in a top-tier journal, spent one year as a visiting scholar at Columbia University, and gained valuable work experience over the course of many client projects, I can say—without a doubt—that I won this game. However, this victory would not have been possible without the support of several coaches and teammates.

First and foremost, I would like to express my gratitude to my primary supervisor, *Prof. Dr. Andreas Herrmann*, who has supported me with his excellent scientific advice, motivating enthusiasm, and interest in my research at all stages of the dissertation process. I would also like to thank my co-supervisor, *Prof. Dr. Torsten Tomczak*, not only for his great academic and personal guidance, but also for his encouragement. In addition, I am indebted to *Prof. Dr. Tobias Schlager*, my former postdoctoral mentor, who belongs to some of the sharpest and most creative minds I have met over the course of my career. He shared inspiring ideas with me, consistently pushed me to the next level, and thereby boosted the quality of this dissertation.

Moreover, I am grateful for my former colleagues from the University of St.Gallen, for contributing to this work through their constructive feedback, ideas, or simply existence: *Dr. Anna Zakharova*, *Dr. Alexander Wieneke*, *Tobias Mirsch*, *Dr. Alexander Schulte-Mattler*, *Dr. Antje Budzanowski*, and *Dr. Thomas Kochanek*. However, one person I want to express my special thanks to is *Dr. Andreas Hess*, who has been my teammate from the very first day at the University of St.Gallen and supported me with his smart insights, relentless encouragement, and friendship. His enthusiastic and energetic character was and still is a motivation for me.

Finally, I want to show my appreciation for my parents and sisters, particularly for my little sister, *Katja Berger*, that probably knows each of my articles as well as I do. She not only supported me with valuable ideas for the manuscript, but was also willing to listen to my problems and frustrations associated with crafting this dissertation. I hope that I can return the favor when she is starting with her own dissertation.

St.Gallen, October 23, 2018

Axel Berger

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Summary

The digital era has caused ground-breaking shifts in consumer behavior and culture. One of the most significant developments is homo ludens, namely man the player, implying that an increasing number of consumers has become attracted by the activity of playing games. While marketing practitioners agree that games create novel and promising opportunities for managing customer relationships, little is known about the *evolution of customer relationships in game contexts* as well as their associated business impact. Addressing this gap in research, the current dissertation consists of three articles, examining how *design dimensions, processes, and social dynamics in large-scale networks* affect the different customer relationship stages; that is, how firms can initiate relationships between their consumers and brands (article 1), intensify existing customer relationships (article 2), or prevent customers from terminating their relationship with a firm (article 3).

The first article shows that only gamified interactions that are highly interactive and optimally challenging facilitate consumers' self–brand connections, because such games lead to emotional and cognitive brand engagement. The study also identifies conditions under which consumers do not become engaged with a brand, namely when firms restrict their decisional control either to voluntarily participate in the game or to spend as much time as desired playing the game. The second article uses longitudinal field data from a massive multilayer online game to show that peers' sharing of purchase information is contagious and has a positive, yet temporarily decaying effect on customers' spending in social networks. The study also reveals that social characteristics of customers' ego and global network account for this effect. Specifically, customers not only spend more on products when they are shared by knowledgeable, interconnected, and numerous peers, but also when customers—themselves—operate as information "brokers" in the social network. Finally, the third article uses longitudinal field data from a massive multiplayer online game to show that customers' exposure toward already defected peers has a positive influence on customer churn, whereas their interconnectedness with remaining peers has a negative influence on customer churn. Furthermore, the study indicates that gamified rewards as opposed to monetary rewards decrease customer churn and moderate the effects of peer influence. Specifically, gamified rewards attenuate the positive influence of exposure toward already defected peers and facilitate the negative influence of interconnectedness with remaining peers on customer churn.

Zusammenfassung

Das digitale Zeitalter hat bahnbrechende Veränderungen im Konsumentenverhalten und in der -kultur hervorgerufen. Eine der bedeutsamsten Entwicklungen ist Homo Ludens, das heißt, der Mensch als Spieler. Dies bedeutet, dass eine zunehmende Anzahl der Konsumenten von der Aktivität des Spielens fasziniert ist. Während Marketingpraktiker der Auffassung sind, dass Spiele neue und vielversprechende Möglichkeiten zum Management von Kundenbeziehungen darstellen, ist wenig über die *Evolution von Kundenbeziehungen in Spielkontexten* und ihren damit verbundenen Auswirkungen auf Unternehmen bekannt. Um diese Forschungslücke zu schließen, umfasst die vorliegende Dissertation drei Artikel, die untersuchen, wie *Gestaltungsdimensionen, Prozesse und soziale Dynamiken in groß skalierten Netzwerken* die unterschiedlichen Stufen der Kundenbeziehung beeinflussen; sprich, wie Unternehmen ihre Kundenbeziehungen initiieren (Artikel 1), intensivieren (Artikel 2) und aufrechterhalten (Artikel 3) können.

Der erste Artikel zeigt, dass nur spielerische Interaktionen, die interaktiv und optimal herausfordernd sind, Markenbindung erzeugen, indem derartige Spiele die Konsumenten mit der Marke emotional und kognitiv involvieren. Die Studie identifiziert auch Bedingungen unter denen Konsumenten mit der Marke nicht involviert werden. Dies ist der Fall, wenn Unternehmen den Konsumenten die Entscheidungskontrolle entziehen, freiwillig an einem Spiel teilzunehmen oder ein Spiel so lange zu spielen wie sie möchten. Der zweite Artikel zeigt mittels im Feld erhobener Zeitreihendaten eines Massive Multiplayer Online Games, dass Teilen von Kaufinformationen einen positiven, wenn auch zeitlich abnehmenden, Effekt auf das Kaufverhalten von Kunden in sozialen Netzwerken hat. Zudem zeigt die Studie, dass diesem Effekt die sozialen Charakteristika im lokalen und globalen Netzwerk der Kunden zu Grunde liegen. Genauer gesagt, Kunden kaufen nicht nur mehr Produkte, die von sachkundigen, vernetzten und vielen Personen geteilt wurden, sondern auch, wenn Kunden selbst als „Verteiler“ von Informationen agieren. Der dritte Artikel zeigt mittels im Feld erhobener Zeitreihendaten eines Massive Multiplayer Online Games, dass der Kontakt zu bereits abgewanderten Personen einen positiven und die Vernetzung zu noch verbleibenden Personen einen negativen Einfluss auf die Kundenabwanderung ausüben. Außerdem zeigt die Studie, dass spielerische versus monetäre Belohnungen die Kundenabwanderung verringern und den Effekt des sozialen Einflusses moderieren. Spielerische Belohnungen heben den positiven Einfluss des Kontakts zu bereits abgewanderten Personen auf, während sie den negativen Einfluss der Vernetzung zu noch bestehenden Personen verstärken.

Preface

Customer Relationships in Game Contexts: Relationship Initiation, Maintenance, and Termination

Working Paper

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Abstract The digital era has caused ground-breaking shifts in consumer behavior and culture. One of the most significant developments is homo ludens, namely man the player, implying that an increasing number of consumers has become attracted by the activity of playing games. While marketing practitioners agree that games create novel and promising opportunities for managing customer relationships, little is known about the evolution of customer relationships in game contexts as well as their associated business impact; that is, how firms can initiate relationships between their consumers and brands (i.e., self–brand connection), intensify existing customer relationships (i.e., spending), or prevent customers from terminating the relationship (i.e., churn). Addressing this dearth in literature, the current dissertation combines research from various theoretical streams, including motivational psychology (e.g., flow theory, self-determination theory), social psychology (e.g., self–expansion theory, social impact theory), and social network theory (e.g., network centrality, network closure) to establish a holistic perspective on how design dimensions, processes, and social dynamics in large-scale networks affect the different relationship stages. Results of this dissertation provide theoretical and managerial implications on how to successfully manage customer relationships in game context.

Keywords Customer Relationship Management · Game Contexts · Design Dimensions · Processes · Social Dynamics · Large-Scale Networks

Introduction

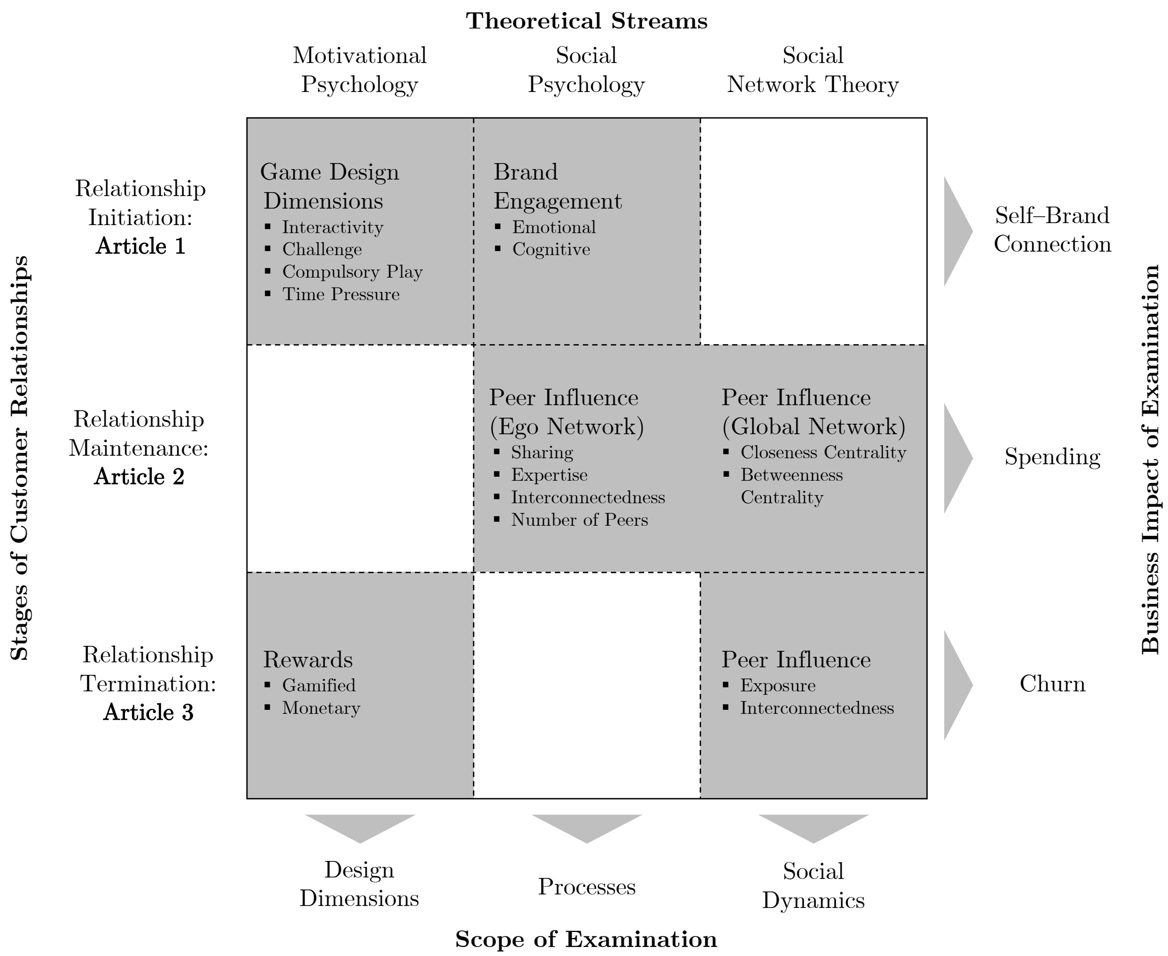
The digital era has caused ground-breaking shifts in consumer behavior and culture. One of the most significant developments is the emergence of homo ludens (Hamari 2013), namely man the player, implying that an increasing number of consumers has become attracted by the activity of playing games. According to recent studies, playing games belonged to the most frequently done activities on mobile devices in 2016, accounting for 1.1 billion hours of gameplay each month (Murdock 2017). Interestingly, traditional boundaries between age groups and genders are dissolving, leading to recent forecasts that 2.1 billion people will play online or mobile games by 2022 (Statista 2017). Noteworthy, many games are not played by a single person alone, but jointly by millions of people, creating large-scale social networks where players can interact with one another. For example, the currently largest massive multiplayer online game has approx. 100 million monthly players (Tassi 2016). Taken together, these figures demonstrate that playing games is no longer the pastime of a niche segment, but a mainstream phenomenon that has found its way in consumers' everyday lives.

The global market value of online and mobile games is predicted to reach EUR 48.1 billion by 2022, a raise of 28.3% compared to 2017 (Statista 2017), creating novel and promising opportunities to manage customer relationships (Hamari and Lehdonvirta 2010). The underlying notion is that game contexts allow firms to engage their customers into interactions that are characterized by fun and entertainment (e.g., Hamari et al. 2014; Waiguny et al. 2012). Consistently, firms are increasingly investing into marketing instruments like gamification, advergames, or in-game advertising to create engaging customer-firm interactions (Terlutter and Capella 2013). According to recent forecasts, firms' global media spending into games will reach USD 124.0 billion in 2019, which will constitute half of global media spending into TV advertisement (Bagchi et al. 2015). However, many firms that aim to create engaging interactions with their customers in game contexts are entering unknown territory. As a result, firms need to understand which factors are key to manage their customer relationships in game contexts successfully, allowing them to capitalize on the new paradigm of homo ludens.

Customer Relationships in Game Contexts

From a strategic standpoint, the management of customer relationships requires firms to create customer-centric interactions along the different stages of the customer lifecycle (Srivastava et al. 1998), namely from the initiation over the maintenance to the termination of the relationship (Payne 2005; Reinartz et al. 2004). Advancing this traditional perspective of customer relationship management, the current dissertation is the first scientific investigation that applies this framework to the domain of games. Specifically, the dissertation consists of three articles that examine the *evolution of customer relationships in game contexts* as well as their associated business impact (see Fig. 1); that is, how firms can initiate relationships between their consumers and brands (i.e., self–brand connection), intensify existing customer relationships (i.e., spending), or prevent customers from terminating the relationship (i.e., churn). To this end, the current dissertation combines research from various theoretical streams, including motivational psychology (e.g., flow theory, self-determination theory), social psychology (e.g., self–expansion theory, social impact theory), and social network theory (e.g., network centrality, network closure) to establish a holistic perspective on how *design dimensions, processes, and social dynamics in large-scale networks* affect the different relationship stages (see Fig. 1).

Fig. 1 Business Impact and Scope of Examination



In what follows, a brief summary of each article (see Table 1), including its contribution to prior marketing literature, research questions, empirical approach, and findings will be provided.

Relationship Initiation

Firms primarily use games to initiate relationships by co-creating playful experiences between their consumers and brands—a phenomenon that is referred to as gamified interactions. However, a review of existing literature indicates that there is no consensus among prior research regarding particular game design dimensions and underlying processes—whether affective (Choi and Lee 2012; Herrewijn and Poels 2013; Jeong et al. 2011; Kuo and Rice 2015; Vanwesenbeeck et al. 2015; Waiguny et al. 2013) or cognitive (Besharat et al. 2013; Cauberghe and De Pelsmacker 2010; Hussein et al. 2010; Jung et al. 2013; Lee et al. 2014; Nelson et al. 2006) in nature—that can explain the consequences of such experiences on brand responses, which is particularly true for the formation of self–brand connections. Addressing this lack in research, the first article "Gamified Interactions: Whether, When, and How Games facilitate Self–Brand Connections" (Berger, A., Schlager, T., Sprott, D. E., & Herrmann, A. (2017). accepted at *Journal of the Academy of Marketing Science*) treats games as playful experiences between a firm's consumers and brand (Holbrook et al. 1984) to examine their effects on self–brand connections. In so doing, this article intends to answer the following research questions important for the successful design and presentation of gamified interactions:

RQ_{1a}: Can gamified interactions facilitate the formation of connections between a firm's consumers and brand?

RQ_{1b}: If so, what are the key dimensions leading consumers to connect with a brand in a game?

RQ_{1c}: What are the underlying processes and boundary conditions associated therewith?

Building on flow theory (Csikszentmihalyi 1990) and self–expansion theory (Aron and Aron 1986), the authors show that only gamified interactions that are highly interactive and optimally challenging facilitate the formation of self–brand connections, because such games lead to emotional and cognitive brand engagement. A field study from a social networking site and three laboratory experiments across various product domains and game designs support this theory. The authors also identify conditions under which consumers do not become engaged with a brand, namely when firms restrict their decisional control either to voluntarily participate in the game (i.e., compulsory play) or to spend as much time as desired playing the game (i.e., time pressure). These findings advance existing knowledge about the use of games in marketing and provide important implications for how marketers can harness their potential to build self–brand connections, initiating relationships between their consumers and brands.

Relationship Maintenance

In game contexts, many firms struggle to intensify their existing customer relationships, namely converting non-paying customers to paying ones. This is particularly true when firms operate games as freemium (free + premium) business models (Kumar 2014), implying that a game's basic functionalities are offered for free, while an add-on is charged for premium features. In such cases, studies found that up to 95% of the customer base does not buy any premium features over the course of their lifetime (Anderson 2009). Interestingly, prior research revealed that many purchase decisions are affected by social interactions among customers and their peers in a social network (Godes and Mayzlin 2004); likewise peer reviews, ratings (Chevalier and Mayzlin 2006; Chintagunta et al. 2010; Ding et al. 2016; Duan et al. 2008; Godes and Mayzlin 2004; Lee et al. 2015; Liu et al. 2014; Moe and Trusov 2011; Tirunillai and Tellis 2012), or referrals (Iyengar et al. 2011, 2015; Katona et al. 2011; Trusov et al. 2009) were found to increase customer spending. By contrast, research has dedicated only little attention to the social phenomenon of sharing behavior (Aral and Nicolaides 2017) and, particularly to the question whether and how the mere dissemination of purchase information (i.e., without providing an explicit recommendation) in a social network affects other customers' spending. However, addressing this gap in research is highly relevant, since many game providers, especially those running freemium models, strongly encourage their customers to share their purchases with others (e.g., the online game Farmville allows players to notify fellow players about in-game purchases via Facebook). Consequently, the second article "Contagious Consumption: The Social Dynamics of Sharing Purchase Information on Spending in Freemium Networks" (Berger, A., Schlager, T., & Herrmann, A. (2017). submitted to *Journal of Marketing*) examines how sharing of purchase information affects spending on premium features in freemium networks, thereby intending to answer the following research questions:

$\mathbf{RQ_{2a}}$: Does information that peers share about their purchases increase customer's spending on these features and how does this effect evolve over time?

RQ$_{\mathbf{2b}}$: If so, what underlying social characteristics of a customer's ego and global network account for this effect?

RQ$_{\mathbf{2c}}$: How do interactions between ego and global network characteristics influence customer's spending in freemium networks?

Combining research on social impact theory (Latané 1981) and social network theory (e.g., Coleman 1988; Freeman 1978), this article uses longitudinal field data from a massive multiplayer online game to show that sharing of purchase information is contagious and has a positive, yet temporarily decaying effect on spending in freemium networks. The study also reveals that social characteristics of customers' ego and global network account for this effect. Specifically, customers not only spend more on premium features when they are shared by knowledgeable, interconnected, and numerous peers, but also when customers—themselves—operate as information "brokers" in the social network. These findings advance the current understanding about the dynamic effects of social interactions on spending in social networks and provide firms with implications on how to maintain profitable customer relationships.

Relationship Termination

Finally, customers' decision to terminate their relationship with a firm, also known as customer churn, is a severe threat for firms' long-term profitability (Braun and Schweidel 2011; Datta et al. 2015; Rust et al. 2004). This is especially true for online social networks, such as massive multiplayer online games that largely depend on an active and healthy online community (Karnstedt et al. 2010). While prior research highlighted the role of peer influence for examining customer churn in social networks (Backiel et al. 2016; Benedek et al. 2014; Haenlein 2013; Nitzan and Libai 2011; Richter et al. 2010), little is known about the underlying network effects accounting for this relationship and how firms can proactively prevent churn from peer influence. Filling this gap in research, the third article "Increasing the Odds of Survival: How Peer Influence and Reward Programs affect Customer Churn in Social Networks" (Berger, A. (2018). submitted to *Journal of Interactive Marketing*) examines how peer influence occurring on an individual and group level affects customer churn and to which degree reward programs can be used to prevent customers from defecting, leading to the final research questions:

RQ$_{\mathbf{3a}}$: Does peer influence on an individual and group level affect customer churn in social networks?

RQ$_{\mathbf{3b}}$: How do different types of reward programs influence customer churn, especially when it is induced by peer influence?

RQ$_{\mathbf{3c}}$: What is the impact of customer churn on firms' financial performance in consideration of different reward interventions?

Incorporating research on self-determination theory (Deci 1975; Deci and Ryan 1985; Ryan 1982) and social networks (e.g., Coleman 1988; Freeman 1978), the author examines to which degree customers' exposure toward already defected peers and interconnectedness with remaining peers affect their hazard to churn from a social network and how firms can use gamified (i.e., "earning" a reward) as opposed to monetary rewards (e.g., merely receiving a reward) to proactively prevent churn. Based on longitudinal field data from a massive multiplayer online game, the results indicate that exposure toward already defected peers has a positive influence on customer churn, whereas interconnectedness with remaining peers has a negative influence on churn. Furthermore, the author shows that gamified rewards as opposed to monetary rewards decrease customer churn and moderate the effects of peer influence. Specifically, gamified rewards attenuate the positive influence of exposure and facilitate the negative influence of interconnectedness on churn. These findings contribute to our current understanding of customer churn in social networks and provide practitioners with implications on how to decrease customers' likelihood to terminate their relationship with a firm, or put differently: increase social networks' odds of survival.

General Discussion

As a first attempt in marketing research, the current dissertation examines the evolution of customer relationships in game contexts, namely from relationship initiation (i.e., self–brand connection) over maintenance (i.e., spending) to termination (i.e., churn). To this end, the dissertation consists of three articles that incorporate various theoretical streams (i.e., motivational psychology, social psychology, and social network theory) and methodological approaches (i.e., field and laboratory experiments, econometrics, and social network modeling) to provide a holistic perspective on how design dimensions, processes, and social dynamics in large-scale networks affect the different relationship stages. By this means, the current dissertation provides several and, more importantly overarching implications for marketing scholars and practitioners that are interested in successfully managing customer relationships in game context.

Table 1 Overview of Articles: Theoretical, Conceptual, and Empirical Foundations

	Evolution of Customer Relationships in Game Contexts		
	Relationship Initiation	Relationship Maintenance	Relationship Termination
Article	Gamified Interactions: Whether, When, and How Games facilitate Self–Brand Connections	Contagious Consumption: The Social Dynamics of Sharing Purchase Information on Spending in Freemium Networks	Increasing the Odds of Survival: How Peer Influence and Reward Programs affect Customer Churn in Social Networks
Authors	Berger, A., Schlager, T., Sprott, D. E., & Herrmann, A.	Berger, A., Schlager, T., & Herrmann, A.	Berger, A.
Publication Status and Journal	Accepted at Journal of the Academy of Marketing Science	Submitted to Journal of Marketing	Submitted to Journal of Interactive Marketing
Theoretical Streams	Flow Theory (Csikszentmihalyi 1990) Self–Expansion Theory (Aron and Aron 1986) Psychological Reactance (Brehm and Brehm 1981) Cognitive Closure (Kruglanski and Webster 1996)	Social Impact Theory (Latané 1981) Social Network Theory (e.g., Freeman 1978)	Self-Determination Theory (Deci and Ryan 1985) Social Network Theory (e.g., Freeman 1978)
Dependent Variable	Self–Brand Connection	Spending	Churn
Independent and Moderating Variables	Interactivity, Challenge, Emotional Brand Engagement, Cognitive Brand Engagement, Compulsory Play, Time Pressure	Sharing Purchase Information, Expertise, Interconnectedness, Number of Peers, Closeness Centrality, Betweenness Centrality	Exposure toward already Defected Peers, Interconnectedness with Remaining Peers, Gamified Rewards, Monetary Rewards
Methods	Longitudinal Quasi-Field Experiment, Laboratory Between-Subjects Experiments	Longitudinal Field Study	Longitudinal Field Study
Study Context	69 Product and Game Domains	Massive Multiplayer Online Game	Massive Multiplayer Online Game
Observations	1,113[a]	304,080	17,902
Models	Linear Mixed Models, ANOVA, (moderated) parallel multiple mediation models	Linear Panel Models with System Generalized Methods of Moments (Arellano-Bond Estimator)	Parametric Proportional Hazard Models (Weibull-Specification)

Note. [a]Only Laboratory Experiments

Theoretical Implications

As previously noted, prior research on the evolution of customer relationships in game contexts is still in its infancy. While marketing scholars agree that game contexts provide novel and promising opportunities to foster customer-firm interactions that are characterized by fun and entertainment (e.g., Hamari et al. 2014; Waiguny et al. 2012), research lacks evidence on how design dimensions, underlying processes, and social dynamics affect the different relationship stages along the customer lifecycle.

One major finding is that games' effectiveness to initiate and prevent the termination of customer relationships (articles 1 and 3) largely depends on their design and presentation, or more specifically, on their capability to facilitate intrinsically motivating interactions. While the first article shows that games need to be highly interactive and optimally challenging to initiate relationships, there is also comprehensive evidence that customers' perception of voluntariness tends to play an important role in triggering and retaining relationships. Specifically, article 1 indicates that games will not increase consumers' brand engagement, when gameplay is perceived as compulsory or occurs under time pressure, whereas article 3 demonstrates that gamified rewards, that is, rewards supporting customers' perception of competence and autonomy decrease their hazard to churn from a social network.

A second key finding is that social dynamics among customers and their peers in a social network (i.e., peer influence) affect the lifecycle stages of relationship maintenance and termination. Specifically, article 2 provides first-of-its-kind evidence that peers' sharing of purchase information has a positive, yet temporally decaying effect on customers' spending in freemium networks. Furthermore, articles 2 and 3 indicate that the social characteristics of customers' ego network (i.e., peers that customers are directly connected with) have a significant influence on relationship maintenance and termination. The findings consistently demonstrate that the number of peers exerting influence (article 2: number of peers sharing purchase information; article 3: exposure toward already defected peers) as well as their connections with one another (article 2 and 3: interconnectedness) are key characteristics that facilitate the effects of peer influence on customer relationships in social networks.

Finally, the current dissertation contributes to preliminary research at the intersection of (social) psychology and social network research; that is, articles 2 and 3 demonstrate that social impact theory (Latané 1981) and self-determination theory (Deci 1975; Deci and Ryan 1985; Ryan 1982) are conceptual frameworks that are highly compatible with findings from social network research (e.g., Coleman 1988; Freeman

1978)—an integration of theoretical streams that is pioneering in the domain of marketing research. While article 2 shows that social impact theory's (Latané 1981) key dimensions can be operationalized by local network measures and, more importantly have significant interdependencies with customers' global network position, article 3 demonstrates that self-determination theory's (Deci 1975; Deci and Ryan 1985; Ryan 1982) basic need of relatedness is determined by customers' exposure toward already defected and interconnectedness with remaining peers in a social network.

Managerial Implications

Besides these theoretical contributions, the current dissertation also provides marketing practitioners with meaningful implications on how to successfully manage their customer relationships in game contexts. To this end, each of the three articles was motivated by and crafted in collaboration with firms (e.g., automotive manufacturer, financial services provider, massive multiplayer online games), ensuring that the dissertation addresses relevant questions from a managerial standpoint. While the dissertation provides marketers with detailed insights on how design dimensions, processes, and social dynamics affect the different stages of the customer lifecycle (see articles for detailed implications), the selected and applied study designs also increase the applicability of findings. Specifically, each article of the dissertation is either partially or entirely based on (large-scale) field data, representing real-world consumer behavior, and uses variable measurements as well as methodological approaches that can be used by firms' market research and analytics departments. In so doing, the current dissertation addresses the growing importance of data science in marketing practice, including both, behavioral lab and quantitative field research. By this means, the current dissertations intends to provide marketing practitioners with inspirational insights on how big data and advanced statistical modelling techniques (i.e., linear mixed models, panel data models, hazard models) can be used to shed light on individual consumer decision-making above and beyond the game context.

In light of these theoretical and managerial implications, the current dissertation intends to not only guide future research endeavors in the domain of games, but also fuel practitioners' growing interest in managing homo ludens—man the player—as a novel paradigm in consumer behavior and culture.

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Article 1

Gamified Interactions: Whether, When, and How Games facilitate Self–Brand Connections

Accepted at

Journal of the Academy of Marketing Science

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Abstract Firms increasingly use games to interact with their customers. Yet, surprisingly little is known about whether, when, and how such "gamified" interactions engage consumers with a firm's brand, thereby facilitating self–brand connections. Building on flow theory, we show that gamified interactions that are highly interactive and optimally challenging facilitate self–brand connections, because such games lead to emotional and cognitive brand engagement. A field study and three experiments across various product domains and game designs support our theory. We also identify conditions under which consumers do not become engaged with a brand, namely when firms restrict their decisional control either to voluntarily participate in the game (i.e., compulsory play) or to spend as much time as desired playing the game (i.e., time pressure). Our findings advance existing knowledge about the use of games in marketing and provide important implications for how marketers can harness their potential to build self–brand connections.

Keywords Games · Flow · Interactivity · Challenge · Self–Brand Connection · Brand Engagement · Compulsory Play · Time Pressure

Introduction

Firms share the common belief that creating compelling experiences is key for successful branding (e.g., Brakus et al. 2009) and achieving competitive advantage (Pine and Gilmore 1998; Prahalad and Ramaswamy 2004). Firms have increasingly used games to co-create such experiences with their customers—a phenomenon that we call *gamified interactions*. The current research originated from collaboration with a large European automotive manufacturer and a globally operating Swiss financial services provider who both wanted to break new ground in building stronger connections with customers by including games on their websites and corporate social media profiles. Our experience with these firms is not isolated in the marketplace: forecasts predict that gamified interactions will result in a USD 10.02 billion industry by 2020 (Research and Markets 2015).

Despite prior research efforts examining the commercial application of games in marketing (e.g., Jung et al. 2013; Kim et al. 2016; Müller-Stewens et al. 2017), there is no conclusive evidence whether, when, and how gamified interactions enhance brand responses, particularly the formation of self–brand connections. We believe that a major reason for this dearth of literature is that prior studies have not closely examined the experiential nature of gameplay. We address this situation by treating games as playful experiences between a firm's customers and brand (Holbrook et al. 1984); this approach allows us to focus on design dimensions, psychological processes, and situation-specific conditions of games used within marketing contexts. In so doing, we intend to answer the following questions important for the successful design and presentation of gamified interactions: Can gamified interactions facilitate self–brand connections? If so, what are the key dimensions leading consumers to connect with a brand in a game? What are the underlying processes and boundary conditions associated therewith?

Drawing on flow theory (Csikszentmihalyi 1990), we hypothesize that only highly interactive and optimally challenging gamified interactions will facilitate the formation of consumers' self–brand connections. Further, we predict that the formation of self–brand connections occurs via a process of emotional and cognitive brand engagement. However, we do not expect these predictions to hold when consumers sense a restriction on their decisional control to engage in gameplay (i.e., when gameplay is compulsory or occurs under time pressure). A combination of a field study and three experiments across various product domains and game designs provides conclusive evidence for our theory.

Our findings make three contributions to our understanding of games in marketing. First, we provide first-of-its-kind evidence that gamified interactions (characterized by high interactivity and optimal challenge) facilitate the formation of self–brand connections. This finding extends earlier work that has examined (in isolation) the effects of interactivity (Lee et al. 2014; Nelson et al. 2006) or challenge (Herrewijn and Poels 2013; Waiguny et al. 2012) of games on brand-specific outcomes, such as brand memory or attitudes. We also advance earlier studies (Herrewijn and Poels 2013; Jeong et al. 2011; Kuo and Rice 2015) that provide only limited insights into the underlying psychological processes of gamified interactions on self–brand connections by identifying emotional and cognitive brand engagement as mediators of this effect. Finally, we reveal a novel set of boundary conditions (i.e., compulsory play and time pressure) that provides marketers with insights on how to present gamified interactions to consumers successfully. Taken together, our findings show how firms can use gamified interactions as tools for creating compelling experiences that lead to favorable long-term consequences related to brand engagement and self–brand connections.

In the following, we first review prior work on games in marketing. Then, we develop our conceptual model on how gamified interactions affect self–brand connections, before we detail our empirical findings and conclude with implications for marketing theory and practice.

Games in Marketing

Games are a central part of culture, society, and the human experience, with examples ranging from childhood play to commercial gaming. Research on games goes back to Johan Huizinga's (1949, p. ix) idea of "Homo Ludens, Man the Player" that put games at the heart of civilization's development. Since that time, researchers across various disciplines have wrestled with philosophical elaborations (Wittgenstein 1953), conceptualizations (Huizinga 1949; Suits 1967), and classifications (Caillois 1961) of games. Although various definitions have been offered in the literature, scholars appear only to agree on the basic nature of games; namely, games are voluntarily-chosen, enjoyable activities that allow players to escape from ordinary routines (Caillois 1955; Huizinga 1949; for more information on games see McGonigal 2011).

Following this notion, early academic work by Holbrook et al. (1984) introduced games to the domain of marketing, laying the foundations for appreciating games as playful experiences between a firm's customers and brand. In a similar fashion, marketers have increasingly realized the potential of using games to co-create such experiences with their customers, a phenomenon that we refer to as gamified interactions. Initially, games were only seen as a part of firms' promotional strategies (Feinman et al. 1986), but their role within the marketing mix has dramatically expanded, mainly due to the proliferation of electronic devices among consumers and the associated popularity of digital games. Indeed, many firms now acknowledge gamified interactions as a major form of consumer entertainment with the objective of building relationships between consumers and brands.

Prior research on the use of gamified interactions in digital contexts is often differentiated into advergames and in-game advertising. While advergames are custom-made games designed to promote a firm's brand or products (Waiguny et al. 2012), in-game advertising refers to brand or product placement within an existing game (Schneider and Cornwell 2005). Both types of gamified interactions share the goal of providing consumers with positive experiences while interacting with a firm's brand. However, as Table 1 illustrates, there is no consensus among prior research regarding general mechanisms—whether affective or cognitive in nature—and particular game design dimensions that can explain the consequences of such experiences on brand responses.

Much of the prior research has presumed that games produce an affective spillover on the brands featured within the game. This work has shown that the positive valence of in-game stimuli (e.g., inserting firm content like a brand logo as the "good" stimuli and competitor content like a competitor's product as the "bad" stimuli, Kuo and Rice 2015; inclusion of likeable spokes-characters into the game, Choi and Lee 2012) may enhance brand responses. In contrast, violent game content can result in negative attitudes toward the featured brand (Waiguny et al. 2013), especially with increased realism of gameplay (Jeong et al. 2011). Other researchers have framed the emotional experiences associated with gameplay, using the pleasure, arousal, and dominance dimensions of Mehrabian and Russell (1974). Although research has not found evidence for these dimensions to play a significant role in mediating the effects of gameplay on brand responses (Herrewijn and Poels 2013), they do appear to increase consumers' absorption during gameplay (Vanwesenbeeck et al. 2015).

Unlike the preceding affect-based approaches, researchers have also suggested a number of cognitive mechanisms that can lead to positive experiences during gameplay. For instance, Schlosser's (2003) object interactivity model builds on interactivity and cognitive processes to explain how consumers experience brands in virtual environments. Applying this framework to online games, researchers have found that interactive gaming experiences increase consumers' brand attitudes and purchase intentions (Lee et al.

2014), particularly when they encounter such games while casually browsing and not having a specific shopping goal in mind (Jung et al. 2013). However, repeated interactions may also result in wear-out effects, with studies showing that playing multiple game rounds can lead to lower brand attitudes (Cauberghe and De Pelsmacker 2010). Finally, research has focused on the concept of telepresence and examines consumers' brand responses as a result of their feeling of being "transported" inside a virtual environment (Steuer 1992) during gameplay. While prior studies have reported varying results (Nelson et al. 2006), the predominant findings suggest that telepresence during gameplay not only increases consumers' purchase intentions (Hussein et al. 2010) but also facilitates the positive effects of virtual product experience on brand memory (Besharat et al. 2013).

A framework that can integrate affect- and cognition-based approaches to explain the effects of positive experiences during gameplay on consumers' brand responses is flow theory (Csikszentmihalyi 1990). Flow is a state of "optimal experience" (Csikszentmihalyi and LeFevre 1989, p. 816), in which people feel simultaneously happy and cognitively efficient (Moneta and Csikszentmihalyi 1996), becoming "so involved in an activity that nothing else seems to matter" (Csikszentmihalyi 1990, p. 4). Prior research has not only emphasized the importance of flow to create online experiences (Hoffman and Novak 1996; Koufaris 2002; Mathwick and Rigdon 2004; Novak et al. 2000; Skadberg and Kimmel 2004; Van Noort et al. 2012), but also highlighted its key role for game settings (Sherry 2004). Indeed, researchers contend that "games are obvious flow activities, and play is the flow experience par excellence" (Csikszentmihalyi 1975, pp. 36–37).

Reflecting this experiential lens on gameplay, the current research draws on flow theory (Csikszentmihalyi 1990) to examine the effects of gamified interactions on the formation of self–brand connections. In contrast to the rich literature on affective or cognitive mechanisms, however, Table 1 reveals that we know surprisingly little about the effects of flow-eliciting gameplay on consumers' brand responses, particularly with no evidence on the formation of self–brand connections. Specifically, earlier work has been unable to demonstrate the effects of consumers' flow experiences on brand memory (Schneider and Cornwell 2005) or attitudes (Mau et al. 2008; Waiguny et al. 2013). We believe that a major reason for these null effects is that prior studies failed to consider fully the experiential nature of gameplay, particularly in terms of effective game design dimensions and the underlying psychological process. Addressing these gaps in research, we next detail our conceptual model and research hypotheses.

Table 1 Relevant Literature on Gamified Interactions

Reference	Mechanism	Game Design Dimension	Mediator	Moderator	Consumer Response	Research Design	Key Findings
Affect-based Approaches							
Choi and Lee (2012)	Affect Transfer	Presence of Animated Spokes-Character		Product Type	Brand Attitude, Purchase	1 Experiment 1 Game 2 Products	Product type moderates the effect of spokes-characters on brand attitude and purchase intention, such that spokes-characters decrease brand attitude and purchase intention for utilitarian, but not for hedonic products.
Jeong et al. (2011)	Affect Transfer	Violence Cues	Involvement, Arousal, Realism	Trait of Aggression	Brand Memory, Attitude	1 Experiment 1 Game 20 Products	Violence cues increase brand memory via involvement, violence cues increase brand attitude via arousal; realism increases brand memory and decreases brand memory; trait of aggression moderates the effect of violence cues on arousal, such that violence cues increase arousal for non-aggressive people more than for aggressive people.
Kuo and Rice (2015)	Affect Transfer	Valence of in-Game Stimulus	Positive Affect	Difficulty	Choice	2 Experiments 1 Game N/A Product	Difficulty moderates the effect of stimulus valence on choice, such that good stimuli increase choice for difficult, but not for easy games; stimulus valence increases choice via positive effect for difficult, but not for easy games.
Waiguny et al. (2013)	Affect Transfer	Game Content, Flow	Attitude toward Game	Brand Familiarity	Brand Attitude	1 Experiment 2 Games 2 Products	Brand familiarity moderates the effect of content on brand attitude, such as violence decreases brand attitude for unfamiliar brands, but not for familiar brands; content decreases brand attitude via attitude toward the game for familiar and unfamiliar brands; flow does not increase brand attitude.
Herrewijn and Poels (2013)	PAD-Dimensions	Difficulty	Pleasure, Arousal, Dominance		Brand Memory, Attitude	1 Experiment 1 Game 5 Products	Difficulty decreases brand memory and attitude; difficulty decreases pleasure and dominance; difficulty increases arousal; no significant mediation of difficulty on brand memory or attitude via pleasure, arousal, or dominance.
Vanwesen-beeck et al. (2015)	PAD-Dimensions	Pleasure, Arousal, Dominance	Absorption		Persuasion Knowledge	1 Survey 1 Game 1 Product	Pleasure and arousal increase persuasion knowledge via absorption; dominance decreases persuasion knowledge via absorption.

Table 1 *(continued)*

Reference	Mechanism	Game Design Dimension	Mediator	Moderator	Consumer Response	Research Design	Key Findings
Cognition-based Approaches							
Jung et al. (2013)	Object Interactivity Model	Interactivity	Perceived Entertainment Value	Shopping Goal Accessibility	Brand Attitude, Purchase	1 Experiment 1 Game 1 Product	Goal accessibility moderates the effect of interactivity on brand attitude and purchase intention, such that interactivity increases brand attitude and purchase intention for consumers without a shopping goal, but not for consumers with a shopping goal; interactivity increases brand attitude and purchase intention via perceived entertainment value for consumers without a shopping goal, but not for consumers with a shopping goal.
Lee et al. (2014)	Object Interactivity Model	Interactivity			Brand Attitude, Purchase	1 Experiment 2 Games 2 Products	Interactivity increases brand attitude and purchase intention.
Cauberghe and De Pelsmacker (2010)	Wear-In/ Wear-Out Effect	Game Repetition		Product Involvement	Brand Memory, Attitude	2 Experiments 1 Game 2 Products	Product involvement moderates the effect of game repetition on brand attitude, such that game repetition decreases brand attitude more for high involvement products than for low involvement products.
Besharat et al. (2013)	Telepresence	Virtual Attribute Experience		Telepresence	Brand Memory	1 Experiment 1 Game 2 Products	Telepresence moderates the effect of virtual attribute experience on brand memory, such that virtual attribute experiences increases brand memory more when telepresence increases.
Hussein et al. (2010)	Telepresence	Telepresence			Purchase	1 Survey 1 Game N/A Product	Telepresence increases purchase intention.
Nelson et al. (2006)	Telepresence	Interactivity, Telepresence		Brand Familiarity	Brand Memory	1 Experiment 1 Game 4 Products	Brand familiarity does not moderate the effect of interactivity on brand memory, such that interactivity decreases brand memory for real and fictitious brands; telepresence does not decrease brand memory.

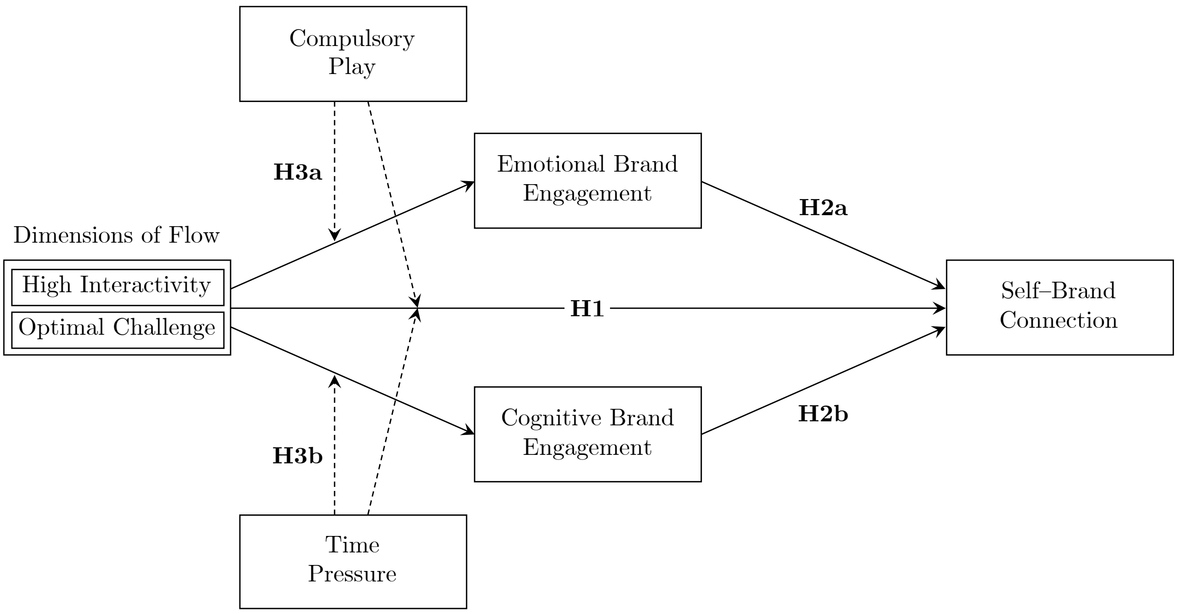
Table 1 *(continued)*

Reference	Mechanism	Game Design Dimension	Mediator	Moderator	Consumer Response	Research Design	Key Findings
Affect- and Cognition-based Approaches							
Mau et al. (2008)	Flow	Playing an Advergame, Flow		Brand Familiarity	Brand Attitude	1 Experiment 1 Game 2 Products	Brand familiarity moderates the effect of playing an advergame on brand attitude, such that playing an advergame increases brand attitude for unfamiliar brands, but decreases brand attitude for familiar brands; flow does not increase brand attitude.
Schneider and Cornwell (2005)	Flow	Brand Prominence, Flow			Brand Memory	1 Survey 1 Game N/A Product	Brand prominence increases brand memory; flow does not increase brand memory.
Waiguny et al. (2012)	Flow	Challenge		Persuasion Knowledge	Brand Attitude	1 Survey 1 Game 1 Product	Persuasion knowledge does not moderate the effects of challenge on brand attitude, such that challenge (post-hoc) increases brand attitudes for consumers with and without persuasion knowledge.
Current Research	Flow	Interactivity, Challenge	Emotional Brand Engagement, Cognitive Brand Engagement	Compulsory Play, Time Pressure	Self–Brand Connection	1 Field Study 3 Experiments 69 Games and Products	Interactivity and challenge increase self–brand connection via emotional and cognitive brand engagement; compulsory play and time pressure moderate the effect of challenge on self–brand connections, such that challenge increases self–brand connections via emotional engagement only for voluntary, but not involuntary play and cognitive engagement only when there is no time pressure, but not when there is time pressure.

Conceptual Model

In our conceptual model (see Fig. 1), we propose that the interplay of high interactivity and optimal challenge within a gamified interaction facilitates connections between consumers and the brand featured in the game and that the underlying process of this effect is based on emotional and cognitive brand engagement. We further explore boundary conditions regarding the mediating role of brand engagement, which are rooted in the basic premise of voluntary gameplay, namely, compulsory play and time pressure.

Fig. 1 Conceptual Model and Research Hypotheses



High Interactivity and Optimal Challenge

Two key dimensions of flow are high interactivity and optimal challenge (Csikszentmihalyi 1990; Nakamura and Csikszentmihalyi 2002). Regarding interactivity, people need to be able to modify their environment to experience flow (Steuer 1992) and, therefore require an active (rather than passive) role during interactions with the environment (Nakamura and Csikszentmihalyi 2002; Novak et al. 2000; Skadberg and Kimmel 2004; Van Noort et al. 2012). In addition to interactivity, the use of skills (Csikszentmihalyi 1988) is critical and sets flow apart from other enjoyable, yet passive experiences, such as watching a movie or listening to music (Privette 1983). Importantly, flow is most likely to occur in situations that neither underutilize nor surpass a person's skills, that is, when challenge is perceived as optimal. For example, people may experience anxiety if challenges are perceived to be greater than skills, or boredom if skills are perceived to be greater than challenges. Thus, flow is most likely to occur when skill and challenge are optimally balanced (i.e., an inverted U-shape pattern; Csikszentmihalyi et al. 2005; Engeser and Rheinberg 2008) and there is a high level of interactivity.

While games are clearly a flow-based experience (Csikszentmihalyi 1975), what can we expect for consumers during gamified interactions with a brand? Prior research has found that flow occurs even during short and casual online activities, such as website browsing (Koufaris 2002; Mathwick and Rigdon 2004; Novak et al. 2000; Skadberg and Kimmel 2004; Van Noort et al. 2012). Therefore, we expect that flow should also occur during gamified interactions, which are typically not designed as lengthy gameplay. In the following, we argue that high interactivity and optimal challenge within a gaming context will create consumers' engagement with a brand during gameplay thereby facilitating the formation of self–brand connections.

Mediating Role of Brand Engagement

Prior research has proposed that brand engagement—an experiential state resulting from brand interactions (Calder et al. 2009; Hollebeek 2011)—may conceptually link consumers' flow experiences to self–brand connections (Brodie et al. 2011). As previoulsy noted, flow can trigger both affective and cognitive responses to an experiential activity (Moneta and Csikszentmihalyi 1996). In a similar manner, prior research has shown that flow causes engagement (Shernoff et al. 2003) and that emotions and cognitions are important dimensions underlying the engagement process in online contexts (Calder et al. 2009; Mollen and Wilson 2010). Thus, we propose that the effect of gamified interactions on self–brand connections is mediated by emotional and cognitive brand engagement.

While not previously tested, our theorizing on the mediational role of emotional and cognitive brand engagement is supported by prior work on the effects of highly interactive and optimally challenging online experiences. In terms of emotions, studies have shown that increasing the interactive and challenging nature of consumers' browsing experiences yields greater enjoyment of websites in general (Van Noort et al. 2012) and of online shopping in particular (Koufaris 2002). Research in gaming contexts has found similar results. For example, people perceive greater enjoyment during gameplay when they can interact (versus not interact) with brands (Jung et al. 2013) or feel optimally challenged by the gaming environment (Abuhamdeh and Csikszentmihalyi 2012). Similarly, research has emphasized the role of interactivity and optimal challenge in triggering cognitive responses. Specifically, studies on website browsing have found that interactivity increases consumers' attention toward the content (McMillan and Hwang 2002) and leads to more thorough information processing (Silicia et al. 2005), whereas challenge promotes higher levels of attention (Novak et al. 2000), concentration (Koufaris 2002), and learning (Skadberg and Kimmel 2004). Likewise, research on the effects of gameplay shows that highly interactive encounters with a brand enhance brand recall (Schneider and Cornwell 2005), while optimal challenge leads to higher levels of concentration (Keller and Blomann 2008).

Consistent with the branding literature and self–expansion theory (Aron and Aron 1986), we expect that emotional and cognitive brand engagement facilitate self–brand connections. For example, Hollebeek et al. (2014) showed that consumers' affective and cognitive brand engagement with a social networking service predicts self–brand connections. Additionally, research has demonstrated that not only positive affect (Batra et al. 2012), but also cognitive brand evaluations (Park et al. 2010), result in stronger connections with a brand. Taken together, the extant literature on flow, experiential online activities, and branding supports our proposition that gamified interactions characterized only by high interactivity (a positive relationship) and optimal challenge (an inverted U-shape pattern) will facilitate the formation of self–brand connections, which is mediated by emotional and cognitive brand engagement. We hypothesize:

H1: Gamified interactions that are highly interactive and optimally challenging have a positive influence on consumers' self–brand connections. Specifically, only optimal (but not low or high) levels of challenge increase consumers' self–brand connections (inverted U-shape).

H2: The influence of gamified interactions that are highly interactive and optimally challenging on consumers' self–brand connections is mediated by (a) emotional and (b) cognitive brand engagement.

Moderating Role of Decisional Control

Flow theory suggests that the ability to enter and maintain a state of flow largely depends on people's perception of control over their actions and environment (Csikszentmihalyi 1990), which is supported by research on decisional control in the domain of online experiences (Mathwick and Rigdon 2004). We posit that decisional control (i.e., perception of choice among alternative courses of action; Averill 1973) may also be critical for gamified interactions, since games are inherently voluntary activities (Caillois 1955). Specifically, prior research showed that control is particularly relevant for increasing enjoyment and concentration for optimally, but less so for under- and over-challenging games (Keller and Blomann 2008). We explore two forms of decisional control—compulsory play and time pressure—that we expect to attenuate the effects of gamified interactions on brand engagement, ultimately diminishing self–brand connections.

Compulsory play refers to the perception that consumers' choice to play a game was forced upon them (Benita et al. 2014), whereas time pressure is the perception that there is insufficient time available to play the game (Iyer 1989). A look to the market reveals that firms often impinge upon these forms of control when launching online games. For example, in 2011 Google News rewarded consumers' reading behavior by gamifying their Google accounts (i.e., adding badges) without permission (Wauters 2011). Forcing consumers to engage in this form of gameplay led to heavy criticism, which resulted in the program's termination. In contrast, in 2001 the travel services provider Orbitz integrated games within pop-up banners in an attempt to increase online advertising efficiency. Unfortunately, consumers did not have time for gameplay as they were already engaged in browsing (Elliott 2005). We expect compulsory play and time pressure to have different effects on emotional and cognitive brand engagement.

We propose that compulsory play mainly moderates the effect of gamified interactions on emotional (but not cognitive) brand engagement. Specifically, when people are required to engage in an activity, they typically respond with affect in the form of reactance (Brehm and Brehm 1981). As a result, people form opposing attitudes toward the source from which the coercion results from (Clee and Wicklund 1980) and perceive the outcome of the associated activity to be less valuable (Cooper and Fazio 1984). For example, Botti and McGill (2011) found that forcing people to engage in an activity decreases their evaluation of the latter when the goal is to have fun compared to learn. This is especially true for challenging activities (Benita et al. 2014), such as gamified interactions. For instance, Cauberghe and De Pelsmacker (2010) showed that for high-involvement products, forcing consumers to repeat a game numerous times has a negative effect on affective, but not cognitive, brand responses. We hypothesize:

H3a: Compulsory play attenuates the positive influence of highly interactive and optimally challenging gamified interactions on emotional (but not cognitive) brand engagement, ultimately not facilitating consumers' self–brand connections.

In contrast, we expect time pressure primarily to attenuate the effect of games on cognitive (but not emotional) brand engagement. Research often views time pressure as a cost of information processing (Kruglanski and Webster 1996), which in moderate (i.e., not extremely high) levels triggers cognitive but not affective responses (Dhar and Nowlis 1999; Svenson and Edland 1987). Studies have also shown that time pressure reduces thorough information processing (Kruglanski and Freund 1983), as well as increases the tendency to use early information in judgments (Heaton and Kruglanski 1991). We predict similar consequences for gameplay, such that when consumers experience time pressure to complete the game, their cognitive elaboration about the brand will be diminished. Initial evidence supporting this expectation finds that people who need to meet deadlines during puzzle tasks are cognitively less interested in completing the activity than those without such a deadline (Amabile et al. 1976; Zuckerman et al. 1978). We propose:

H3b: Time pressure attenuates the positive influence of highly interactive and optimally challenging gamified interactions on cognitive (but not emotional) brand engagement, ultimately not facilitating consumers' self–brand connections.

In the following, we present four studies that test our hypotheses. Study 1 is a quasi-field experiment that examines whether highly interactive and optimally challenging gamified interactions in a social media setting facilitate self–brand connections (H1). Study 2 uses an experiment to assess the causality of this effect and to examine the mediation process via emotional (H2a) and cognitive (H2b) brand engagement. Study 3 and Study 4 test the boundary conditions for our proposed effects (H3a, H3b), providing additional evidence for the conceptual model and highlighting common pitfalls related to brand building in gamified interactions.

Study 1: Field Evidence from a Social Network

Study 1 provides field evidence as to whether highly interactive and optimally challenging gamified interactions facilitate self–brand connections (H1). To this end, we examined gamified interactions that firms had launched on a major social networking site and used consumers' likes of brand profiles as a behavioral measure for self–brand connections.

Design and Sample

To examine the effects of gamified interactions on self–brand connections, we used a longitudinal quasi-experimental design (Cook and Campbell 1979) and collected data on a social network. Such networks are a primary touchpoint for firms to introduce gamified interactions (Gupta 2014). Three research assistants blind to our hypotheses identified 67 brands from various industries (see Table 2 for further details) that had posted a gamified interaction on their social network profile between December 2009 and May 2016. Using software that enabled us to automatically crawl data from this social network, we obtained data for each gamified interaction over a four-week period (starting 14 days before and ending 14 days after its launch), resulting in 29 observations per gamified interaction and a total of 1,943 observations.

Measures

Dependent and Independent Variables. Consistent with prior work (e.g., Naylor et al. 2012) we used the number of daily likes of a brand's network profile as a behavioral measure of self–brand connections. Launch, interactivity, and challenge of the gamified interaction served as independent variables. To examine the effect of launching a gamified interaction, we used a binary variable comparing self–brand connections (operationalized by brand likes) on the day of the launch (1 = treatment group) with the 14 days prior and after this event (0 = pre-/post-treatment groups). To assess interactivity and challenge, we conducted a pretest on Amazon Mechanical Turk (MTurk; $N = 71$; $M_{Age} = 32.49$, $SD_{Age} = 10.06$; 42.3% female). Participants received screenshots and detailed descriptions of all 67 games in randomized order. After indicating brand familiarity and understanding of the description, participants rated the gamified interactions in terms of interactivity and challenge. Interactivity ("I felt ..."; 1 = "Reactive" to 7 = "Interactive"; Nelson et al. 2006) and challenge ("The current demands were ..." −3 = "Too high" to 0 = "Just right" to 3 = "Too low"; Engeser and Rheinberg 2008) were both measured with single, seven-point scale items.

Control Variables. We included several control variables to assess the robustness of our findings. First, we included the day of the week (0 = Monday to 6 = Sunday) when the game was launched to account for the possibility that consumers might have visited brand profiles more frequently on the weekend than on weekdays (De Vries et al. 2012). Second, we captured each brand's daily media presence since a stronger prominence may have also affected the frequency consumers called up a brand's profile (McCombs and Guo 2014). To this end, we collected the number of daily news articles about each brand via a major online search engine, resulting in 2,827 articles. Third, we controlled for other marketing activities on a brand's social media profile (e.g., announcing price promotion) since such initiatives could have increased brand likes as well. For a closer examination of these marketing activities, we collected all posts (2,536 posts) and assigned two research assistants (blind to our hypotheses) to code these posts using a content analysis protocol (Krippendorff 2004). Following accepted practice of textual coding (Corbin and Strauss 2008), the assistants first openly coded a 10% random sample to create descriptive codes which were then classified by a different set of independent coders, reflecting the four marketing-mix dimensions: product-, price-, communication-, and distribution-related posts. Applying this coding scheme to the remaining posts yielded a Cohen's Kappa of .65 ($p < .001$), representing substantial inter-coder reliability (Cohen 1960) and agreement of 80.28%. We only used the posts that coders commonly agreed upon for our analyses (2,036 posts).

Estimated Models

We chose a linear mixed model that accounts for interdependence in the data structure. Specifically, days h were nested in brands j, resulting in a two-level data structure. We computed three models to examine whether highly interactive and optimally challenging gamified interactions enhanced the number of daily brand likes ($Likes_{hj}$), including the intercept θ, fixed effects β (standardized beta coefficients), random effect δ_j, and residuals ε_{hj}. To test the baseline effect, Model 1 only accounted for the launch ($Launch_{hj}$) of the gamified interactions (see Eq. 1):

$$Likes_{hj} = \theta_1 + \beta_1 \times Launch_{hj} + \delta_{1j} + \varepsilon_{hj}. \tag{1}$$

Model 2 tested whether gamified interactions characterized by high interactivity and optimal challenge increased the number of likes on a brand's website. In line with H1, we expected that the effect of challenge on the number of likes has a tipping point at an optimum value of zero and is only present when the game is highly interactive. To account for this effect, we included the games' interactivity ($Interactivity_j$), challenge ($Challenge_j$), squared challenge ($Challenge_j^2$), and their interaction terms (see Eq. 2):

$$\begin{aligned} Likes_{hj} = \theta_2 &+ \beta_2 \times Launch_{hj} \\ &+ \beta_3 \times Interactivity_j + \beta_4 \times Challenge_j + \beta_5 \times Challenge_j^2 \\ &+ \beta_6 \times Interactivity_j \times Challenge_j \\ &+ \beta_7 \times Interactivity_j \times Challenge_j^2 + \delta_{2j} + \varepsilon_{hj}. \end{aligned} \tag{2}$$

Model 3 tested for robustness by adding controls to Model 2, including the day the games were launched ($Weekday_j$), the brands' media presence ($News_{hj}$), and other marketing activities ($Product_{hj}$, $Price_{hj}$, $Communication_{hj}$, $Distribution_{hj}$) on the network profile (see Eq. 3):

$$Likes_{hj} = \theta_3 + \beta_8 \times Launch_{hj}$$

$$
\begin{aligned}
&+ \beta_9 \times Interactivity_j + \beta_{10} \times Challenge_j + \beta_{11} \times Challenge_j^2 \\
&+ \beta_{12} \times Interactivity_j \times Challenge_j \\
&+ \beta_{13} \times Interactivity_j \times Challenge_j^2 \\
&+ \beta_{14} \times Weekday_j + \beta_{15} \times News_{hj} \\
&+ \beta_{16} \times Product_{hj} + \beta_{17} \times Price_{hj} \\
&+ \beta_{18} \times Communication_{hj} + \beta_{19} \times Distribution_{hj} + \delta_{3j} + \varepsilon_{hj}. \qquad (3)
\end{aligned}
$$

Results

Per Model 1, gamified interactions facilitated self–brand connections as measured by the number of likes (β_1 = .372, z = 2.53, p < .011) in contrast to the pre-/post-treatment groups. Model 2 indicates that this was especially true for highly interactive and optimally challenging gamified interactions. As Fig. 2 illustrates, interactivity increased the number of likes (β_3 = .244, z = 3.14, p < .002), whereas squared challenge (β_5 = −.305, z = −2.56, p < .011) and the interaction between both measures (β_7 = −.087, z = −2.65, p < .008) had negative effects on likes, that is, interactivity in combination with an increasing challenge drives liking behavior. However, when an optimum level of challenge is exceeded, consumers' liking behavior of a brand's network profile decreases. As shown in Table 2, a likelihood ratio test shows that Model 2 significantly outperformed Model 1 ($\chi^2(5)$ = 63.98, p < .001). Overall, these results offer initial evidence for H1. Finally, Model 3 supports the robustness of our findings by showing that the gamified interactions' interactivity (β_9 = .231, z = 3.11, p < .002), squared challenge (β_{11} = −.304, z = −2.80, p < .005), and their interaction (β_{13} = −.086, z = −2.86, p < .004) remained significant predictors of consumers' likes even when accounting for all controls.

Discussion

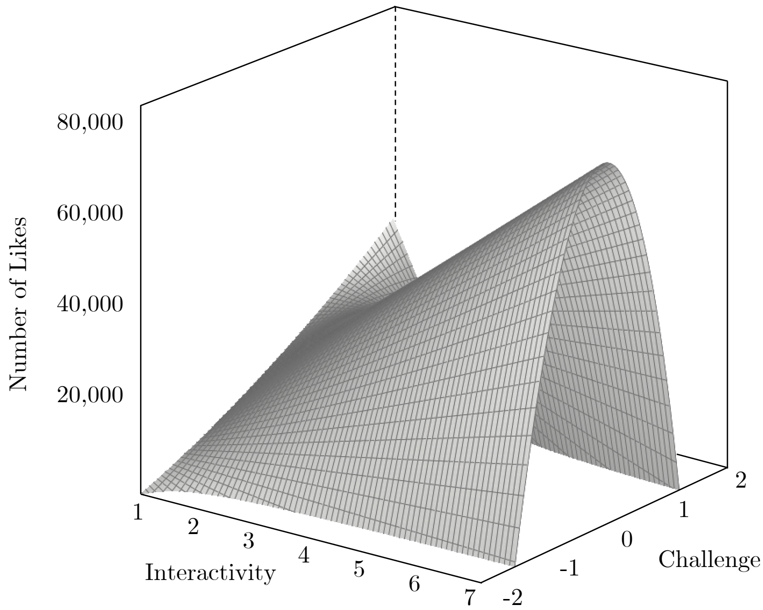
The results of Study 1 show that gamified interactions, particularly those that are highly interactive and optimally challenging, facilitate self–brand connections (H1). Importantly, this study is based on 67 games and brands from a major social networking site, thereby indicating that our basic effect is supported in a field setting and across numerous industries. While our approach avoids some methodological pitfalls, such as common method variance (Mackenzie and Podsakoff 2012), quasi-experiments also come with drawbacks (e.g., the lack of causal conclusions and insights into the underlying psychological process; Cook and Campbell 1979). We address these issues in the following three experiments.

Table 2 Launching Gamified Interactions (Model 1) with High Interactivity and Optimal Challenge (Model 2) increases Number of Likes, even when controlling for Weekdays, Media Presence, and other Marketing Initiatives (Model 3) of a brand (Study 1)

	Number of Likes ($Likes_{hj}$)																				
	Model 1							Model 2							Model 3						
		β	*se*	*z*	*p*	CI_{95}			β	*se*	*z*	*p*	CI_{95}			β	*se*	*z*	*p*	CI_{95}	
Gamified Interactions																					
$Launch_{hj}$	β_1	.372*	.147	2.53	.011	.084	.660	β_2	.723**	.264	2.74	.006	.206	1.240	β_8	.570*	.252	2.26	.024	.075	1.064
Game Design Dimensions																					
$Interactivity_j$								β_3	.244**	.078	3.14	.002	.092	.396	β_9	.231**	.074	3.11	.002	.085	.376
$Challenge_j$								β_4	1.043***	.275	3.80	.000	.504	1.582	β_{10}	1.017***	.269	3.78	.000	.490	1.544
$Challenge_j^2$								β_5	−.305*	.119	−2.56	.011	−.538	−.071	β_{11}	−.304**	.109	−2.80	.005	−.517	−.091
$Interactivity_j \times Challenge_j$								β_6	.321***	.087	3.70	.000	.151	.491	β_{12}	.303***	.086	3.53	.000	.135	.471
$Interactivity_j \times Challenge_j^2$								β_7	−.087**	.033	−2.65	.008	−.151	−.023	β_{13}	−.086**	.030	−2.86	.004	−.146	−.027
Controls																					
$Weekday_j$															β_{14}	−.009	.007	−1.29	.196	−.023	.005
$News_{hj}$															β_{15}	.067*	.032	2.10	.036	.004	.129
$Product_{hj}$															β_{16}	.012	.019	.61	.539	−.026	.049
$Price_{hj}$															β_{17}	.159***	.036	4.44	.000	.089	.229
$Communication_{hj}$															β_{18}	.276***	.072	3.83	.000	.135	.418
$Distribution_{hj}$															β_{19}	.115**	.044	2.61	.009	.029	.202
Brand																					
Random Effect (δ_j)	δ_{1j}	.308	.133			.132	.716	δ_{2j}	.288	.123			.125	.666	δ_{3j}	.208	.110			.074	.586
Model Fit Indexes																					
Waldχ^2				6.40 ($p < .011$)							19.02 ($p < .004$)							64.73 ($p < .001$)			
Log Likelihood				−2,493.54							−2,461.56							−2,387.41			
AIC				4,995.09							4,941.11							4,804.82			
BIC				5,017.36							4,991.22							4,888.34			
Model Improvement																					
Log Likelihood Ratio Test											Model 1 → Model 2 ($p < .001$)							Model 2 → Model 3 ($p < .001$)			

Note. *$p < .050$; **$p < .010$; ***$p < .001$; Robust Parameter Estimates; $N = 1{,}943$ nested in $N = 67$ Brands; Food/Beverage: 37%; Entertainment/Media/Event: 27%; Retail/Stationaries/Toys: 10%; Automotive: 7%; Financial Services/Insurance: 4%; Internet Services/Electronics: 4%; Airlines/Travel: 3%; Fashion: 3%; Others: 3%

Fig. 2 Gamified Interactions with High Interactivity and Optimal Challenge increase Number of Likes (Study 1; Estimation of Model 2 with Unstandardized Coefficients)



Study 2: Mediating Role of Brand Engagement

Study 2 was designed to test experimentally whether highly interactive and optimally challenging gamified interactions cause stronger self–brand connections (H1) and whether emotional (H2a) and cognitive (H2b) brand engagement mediate this effect.

Design and Participants

The study employed a 2 (interactivity: low, high) × 3 (challenge: low, optimal, high) between-subjects experimental design. A total of 431 (M_{Age} = 36.30, SD_{Age} = 12.13; 59.9% female) U.S. participants were recruited from MTurk. For this study's setting, we cooperated with a European automotive manufacturer that did not sell its brands in the U.S., thus providing a context that reduced the risk of brand familiarity potentially confounding our results.

Procedure and Stimuli

We first presented participants the brand name and logo of the car manufacturer. Next, participants read a short introduction about the brand and were randomly assigned to one of six experimental conditions (each based on the same car-racing game). We manipulated interactivity by allowing participants to either view a video of the game (i.e., low interactivity) or play the game (i.e., high interactivity; Nelson et al. 2006). Thus, all participants were exposed to the same visual impressions of the game for the same amount of time (i.e., 20 s). We manipulated challenge by varying game difficulty (Keller and Blomann 2008). In the low challenge conditions, the car drove at low speed on a straight and traffic-free circuit. In the optimal challenge conditions, the car drove at moderate speed on a curvy racing circuit with minor traffic. In the high challenge conditions, the car drove at higher speed and the circuit had lots of traffic. After that, participants were redirected to the same social network as in Study 1, where they could like the car manufacturer's actual brand website. Finally, they filled out manipulation checks, as well as questions assessing other dependent, mediating, and demographic variables.

Measures

Dependent and Independent Variables. The dependent variable(s) were consumers' self–brand connections, assessed by liking of the brand's profile (0 = No Like, 1 = Like) and Escalas and Bettman's (2003; α = .97) self–brand connection scale, using seven items on a seven-point scale. The manipulations of interactivity and challenge served as independent variables.

Mediating Variables. We assessed emotional brand engagement with four seven-point scale items (α = .96) and cognitive brand engagement with three seven-point scale items (α = .92) from Hollebeek et al. (2014) and adapted them to fit the game context (see Appendix 1 for details of the measures).

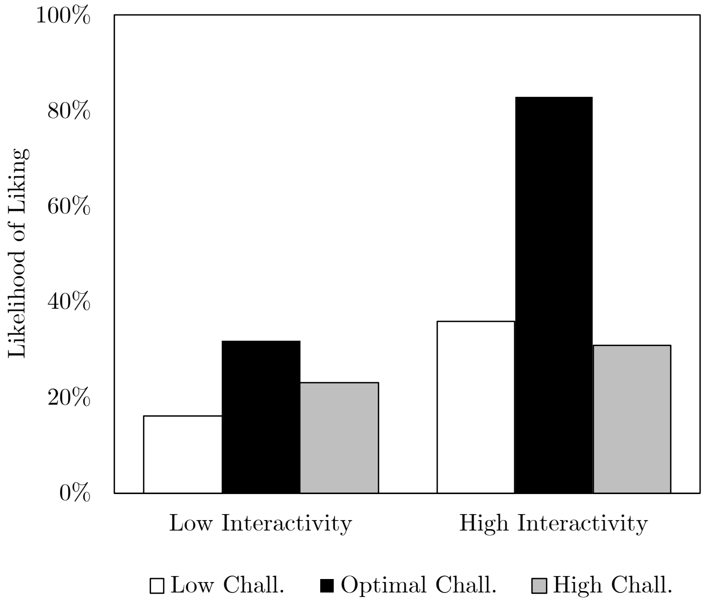
Manipulation Checks. We tested the manipulation of interactivity and challenge as in Study 1. In addition, we measured participants' experience of flow with ten seven-point scale items (Engeser and Rheinberg 2008; α = .84).

Measurement Model. Confirmatory factor analyses yielded good fit indexes for the measurement model (Hu and Bentler 1999) and found that each factor's composite reliability (Bagozzi and Yi 1988; CR $\geq$ .84) and Cronbach's α (Nunnally 1978; CA $\geq$ .84) exceeded recommended thresholds (see Appendix 1). Further, the measurement model was characterized by convergent and discriminant validity (see Appendix 2) since each factor's average variance extracted surpassed not only recommended thresholds (Bagozzi and Yi 1988; AVE $\geq$ .51) but also the highest squared correlations of each construct (Fornell and Larcker 1981).

Results

Manipulation Checks. Three 2 $\times$ 3 ANOVAs confirmed that our manipulations were successful. In terms of interactivity (F(1, 425) = 150.656, p < .001), the high interactive conditions were rated as more interactive (M = 5.81) than the low interactive conditions ($M = 3.89$; $t = -12.242$, $p < .001$). Regarding challenge ($F(2,\ 425) = 51.154$, $p < .001$), participants in the optimal challenge conditions rated the challenge to more closely match their skills ($M = -.03$) than those in the low ($M = .84$; $t = 5.337$, $p < .001$) and high challenge conditions ($M = -.78$; $t = -4.561$, $p < .001$). A one-sample t-test showed that the optimal challenge conditions did not significantly differ from a zero mean (i.e., an optimal challenge; $t(1,\ 136) = -.254$, $p > .80$). Finally, interactivity ($F(1,\ 425) = 42.710$, $p < .001$) and challenge ($F(2,\ 425) = 28.612$, $p < .001$), as well as their interaction ($F(2,\ 425) = 3.650$, $p < .027$), predicted the experience of flow. Specifically, participants in the highly interactive and optimally challenging condition rated flow significantly higher ($M = 5.76$; ps $< .001$) than those in all other conditions. Importantly, beyond the results reported, no other main or interaction effects were significant for any manipulation.

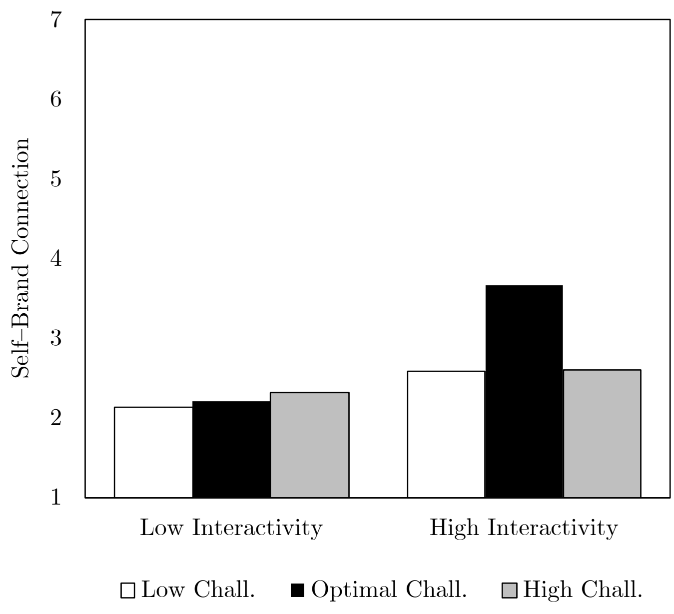
Fig. 3 Gamified Interactions with High Interactivity and Optimal Challenge increase Likelihood of Liking (Study 2)



Liking of Brand Website. A logistic regression model (Nagelkerke $R^2 = .234$, Waldχ^2 (5, 425) $= 80.396$, $p < .001$) with indicator coding (i.e., optimal challenge conditions were defined as the reference categories) showed a positive main effect of interactivity ($\beta = 2.287$, Wald$\chi^2(1,\ 429) = 30.452$, $p < .001$) and negative main effects of the low ($\beta = -2.124$, Wald$\chi^2(1,\ 429) = 26.482$, $p < .001$) and high ($\beta = -2.369$, Wald$\chi^2(1,\ 429) = 32.471$, $p < .001$) challenge conditions on participants' tendency to like the brand's profile. More importantly, we found two positive interaction effects between interactivity and both, the low (β = 1.184, Waldχ^2(1, 429) = 4.235, p < .040) and high (β = 1.868, Waldχ^2(1, 429) = 11.074, p < .001) challenge conditions on liking behavior. As shown in Fig. 3, participants in the highly interactive and optimally challenging condition were significantly more likely to like the brand's social network profile (83%; p < .001) than those in all other conditions. These results support H1.

Self–Brand Connection. The self-reported measure of self–brand connections correlated significantly with the liking of the brand's social network profile (r = .831, p < .001). A 2 × 3 ANOVA found interactivity (F(1, 425) = 24.734, p < .001), challenge (F(2, 425) = 5.668, p < .004), and their interaction (F(2, 425) = 6.053, p < .003; see Fig. 4) to facilitate self–brand connections. Participants in the highly interactive and optimally challenging condition reported stronger self–brand connections (M = 3.66; ps < .001) than those in all other conditions, also confirming H1. The other groups did not significantly differ between each other (ps > .07).

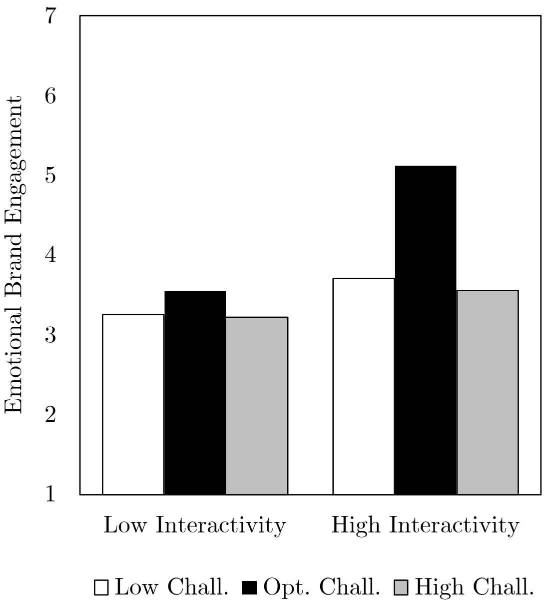
Fig. 4 Gamified Interactions with High Interactivity and Optimal Challenge increase Self–Brand Connection (Study 2)

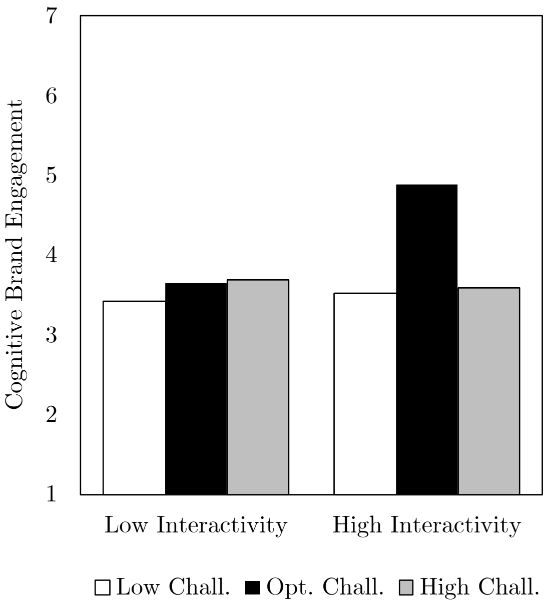


Brand Engagement. Employing two 2 × 3 ANOVAs showed that interactivity (emotional: F(1, 425) = 28.063, p < .001; cognitive: F(1, 425) = 6.768, p < .010), challenge (emotional: F(2, 425) = 16.100, p < .001; cognitive: F(2, 425) = 9.254, p < .001), and their interaction created brand engagement (emotional: F(2, 425) = 6.840, p < .001; cognitive: F(2, 425) = 6.902, p < .001; see Fig. 5). Participants in the highly interactive and optimally challenging condition were more emotionally (M = 5.12; ps

$< .001$) and cognitively ($M = 4.89$; $ps < .001$) engaged with the brand than those in all other conditions. The latter conditions did not significantly differ from each other in terms of emotional ($ps > .07$) or cognitive ($ps > .33$) brand engagement.

Fig. 5 Gamified Interactions with High Interactivity and Optimal Challenge increase Emotional and Cognitive Brand Engagement (Study 2)





Mediation Analysis. We estimated two parallel multiple mediation models (Hayes 2013; SPSS Macro PROCESS, Model 4; bootstrap samples = 5,000) to examine whether emotional and cognitive brand engagement mediated the effect of highly interactive and optimally challenging gamified interactions on participants' likes of the brand's profile and self–brand connections. Both mediation models compared the highly interactive and optimally challenging condition with all other pooled conditions. As expected, the highly interactive and optimally challenging condition increased emotional ($\beta = 1.663$, $t = 7.920$, $p < .001$; $R^2 = .128$, $F(1, 429) = 62.724$, $p < .001$) and cognitive ($\beta = 1.317$, $t = 5.932$, $p < .001$; $R^2 = .076$, $F(1, 429) = 35.189$, $p < .001$) brand engagement, which predicted liking of the brand ($\beta_{Emotional} = .747$, Wald$\chi^2(1, 429) = 34.510$, $p < .001$; $\beta_{Cognitive} = .703$, Wald$\chi^2(1, 429) = 35.080$, $p < .001$; Nagelkerke $R^2 = .533$, $p < .001$) and self–brand connections ($\beta_{Emotional} = .342$, $t = 7.697$, $p < .001$; $\beta_{Cognitive} = .412$, $t = 9.543$, $p < .001$; $R^2 = .536$, $F(2, 428) = 247.477$, $p < .001$). Next, we used the highly interactive and optimally challenging condition, as well as emotional and cognitive brand engagement, as predictors of the dependent variables. The condition and both mediators predicted liking behavior ($\beta_{HighInter\ \times\ OptimalChall} =$

1.826, $z = 4.359$, $p < .001$; $\beta_{Emotional} = .633$, $z = 4.737$, $p < .001$; $\beta_{Cognitive} = .726$, $z = 5.832$, $p < .001$; Nagelkerke $R^2 = .575$, $p < .001$), whereas only emotional and cognitive engagement predicted self–brand connections ($\beta_{HighInter \times OptimalChall} = .207$, $t = 1.307$, $p > .19$; $\beta_{Emotional} = .327$, $t = 7.166$, $p < .001$; $\beta_{Cognitive} = .410$, $t = 9.494$, $p < .001$; $R^2 = .538$, $F(3, 427) = 165.827$, $p < .001$). The indirect effects were significant for both models (liking: $\beta_{Emotional} = 1.053$, $CI_{95} = [.642, 1.609]$; $\beta_{Cognitive} = .957$, $CI_{95} = [.584, 1.493]$; self–brand connection: $\beta_{Emotional} = .544$, $CI_{95} = [.376, .754]$; $\beta_{Cognitive} = .540$, $CI_{95} = [.371, .745]$), indicating that emotional and cognitive brand engagement mediated the effect of the highly interactive and optimally challenging gamified interaction on liking behavior and self–brand connections. Rerunning mediation analyses without pooling conditions yielded similar results, supporting H2a and H2b.

Discussion

Study 2 provides causal evidence for the effect of highly interactive and optimally challenging gamified interactions on self–brand connections (H1), assessed by behavioral and self-reported measures. Study 2 also sheds light on the processes underlying our observed effect and supports our proposition that emotional (H2a) and cognitive (H2b) brand engagement mediate this effect of gamified interactions on self–brand connections.

Study 3: Moderating Role of Compulsory Play

Study 3 was designed to test whether compulsory play attenuates the effect of highly interactive and optimally challenging gamified interactions on emotional (but not cognitive) brand engagement (H3a). In comparison to Study 2, we focus exclusively on highly interactive games (i.e., we do not manipulate interactivity in this study). We manipulated challenge similarly to Study 2, yet, we chose to focus on the low and optimally challenging conditions, since the highly challenging conditions are less prevalent in practice (as shown by our field data).

Design and Participants

Study 3 employed a 2 (challenge: low, optimal) × 2 (compulsory play: voluntary, involuntary) between-subjects experimental design. We recruited a total of 329 U.S. participants from MTurk ($M_{Age} = 35.14$, $SD_{Age} = 11.74$; 53.5% female) and randomly assigned them to one of the four experimental conditions. Study 3 used a fictional brand to control for participants' prior familiarity (see Cauberghe and De Pelsmacker 2010 for similar approach).

Procedure and Stimuli

The procedure was similar to the one in Study 2, except that we used a fictional tennis ball brand and an online tennis game for the gamified interaction. Participants were first shown the brand's name and logo. Next, participants played the gamified interaction. We again manipulated challenge by varying the game's difficulty. In the low challenge conditions, the tennis ball moved at moderate speed and controlling the racket was less sensitive. In the optimal challenge conditions, the tennis ball moved at higher speed and controlling the racket was more sensitive. We manipulated compulsory play by framing the game as either voluntary or involuntary (Benita et al. 2014). In the voluntary conditions, we told participants that they could play the game to receive payment, whereas we told those in the involuntary conditions that they had to play the game to receive payment. To ensure similar amounts of time, all participants were told that they could stop playing after 20 s. All manipulations were pretested. Then, participants answered manipulation checks, dependent, mediating, and demographic variables.

Measures

We used the same measures for self–brand connection (α = .98), emotional brand engagement (α = .98), and cognitive brand engagement (α = .93) as in Study 2. We also applied the same manipulation checks for challenge and flow (α = .89). The manipulation of compulsory play was assessed with five items on a 12-point scale (Unger and Kernan 1983; α = .92). As in Study 2, the measurement model had good fit indexes and exceeded thresholds (CR $\geq$ .89; CA $\geq$ .89; AVE $\geq$ .53), confirming reliability, convergent, and discriminant validity (see Appendix 1 and 2).

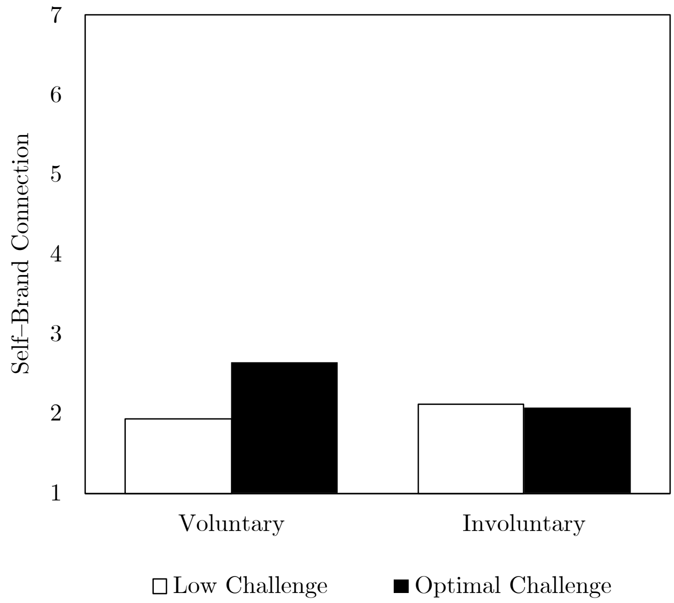
Results

Manipulation Checks. Three 2 $\times$ 2 ANOVAs supported both of our manipulations. In particular, participants in the optimal challenge conditions rated challenge to more closely match their skills (M = .10; F(1, 325) = 123.623, p < .001) than those in the low challenge conditions (M = 1.83; t = 11.148, p < .001). As in Study 2, the optimally challenging conditions did not significantly differ from a zero mean (t(1, 157) = .988, p > .32), indicating that participants in those conditions perceived an optimal challenge. Further, participants in the optimal challenge conditions also experienced significantly more flow (M = 5.22; F(1, 325) = 143.685, p < .001) than participants in the low challenge conditions (M = 3.73; t = −12.032, p < .001). Finally, participants in the involuntary play conditions perceived greater compulsion to play the game (M

= 4.69; $F(1, 325) = 46.988$, $p < .001$) than those in the voluntary conditions (M = 2.90; $t = -6.851$, $p < .001$). No other main or interaction effects were significant for all manipulation checks.

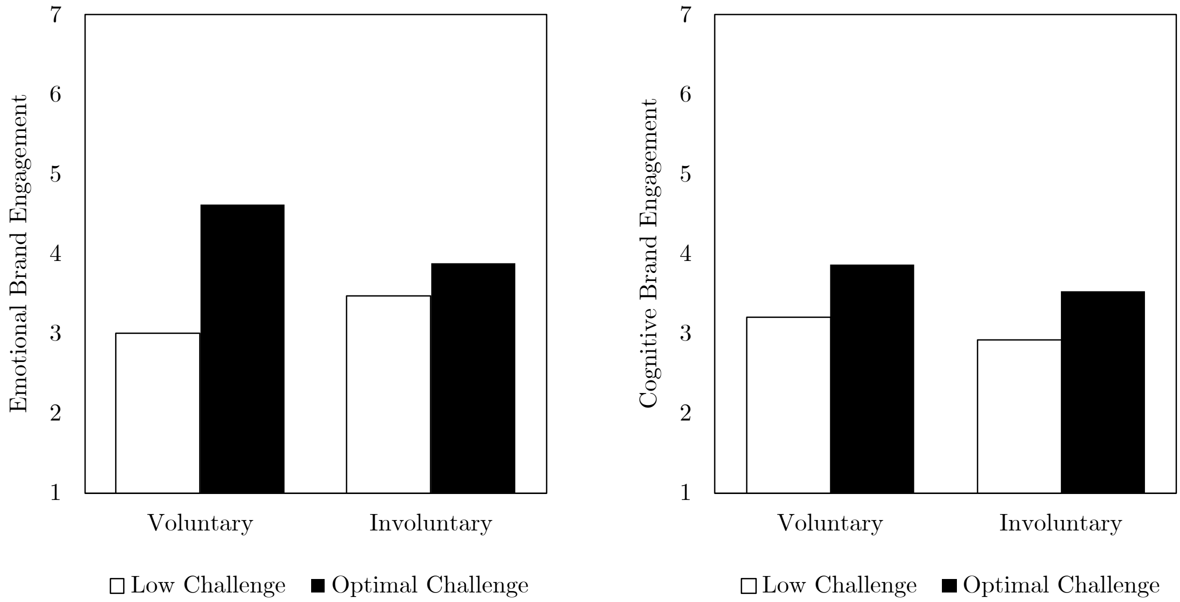
Self–Brand Connection. A 2 × 2 ANOVA showed that compulsory play had no significant effect on self–brand connections ($F(1, 325) = 1.584$, $p > .21$), whereas optimal challenge ($M_{LowChall} = 2.03$, $M_{OptimalChall} = 2.36$; $t = 2.069$, $p < .039$; $F(1, 325) = 4.296$, $p < .039$) and the interaction between both factors facilitated self–brand connections ($F(1, 325) = 5.575$, $p < .019$). Optimally challenging gamified interactions only facilitated self–brand connections when participants initiated them voluntarily ($M_{LowChall} = 1.94$, $M_{OptimalChall} = 2.65$; $t = 3.171$, $p < .002$) but not when they did so involuntarily ($M_{LowChall} = 2.12$, $M_{OptimalChall} = 2.07$; $t = .203$, $p > .84$; see Fig. 6).

Fig. 6 Compulsory Play moderates the Effect of Optimal Challenge on Self–Brand Connection (Study 3)



Brand Engagement. Two 2 × 2 ANOVAs revealed that optimally challenging gamified interactions created emotional ($M_{LowChall} = 3.24$, $M_{OptimalChall} = 4.25$; $t = 4.851$, $p < .001$; $F(1, 325) = 23.561$, $p < .001$) and cognitive ($M_{LowChall} = 3.07$, $M_{OptimalChall} = 3.70$; $t = 3.234$, $p < .001$; $F(1, 325) = 10.495$, $p < .001$) brand engagement. Compulsory play had no effect on either type of engagement (ps > .13). The interaction between optimal challenge and compulsory play was only significant for emotional ($F(1, 325) = 8.400$; $p < .004$), but not cognitive ($F(1, 325) = .037$; $p > .85$; see Fig. 7) brand engagement. Specifically, optimal challenge only created emotional brand engagement when gameplay was voluntary ($M_{LowChall} = 3.01$, $M_{OptimalChall} = 4.62$; $t = 5.540$, $p < .001$) but not involuntary ($M_{LowChall} = 3.48$, $M_{OptimalChall} = 3.88$; $t = 1.370$, $p > .17$).

Fig. 7 Compulsory Play moderates the Effect of Optimal Challenge on Emotional Brand Engagement, but not on Cognitive Brand Engagement (Study 3)



Moderated Mediation Analysis. We estimated a moderated parallel multiple mediation model (Hayes 2015; SPSS Macro PROCESS, Model 8; bootstrap samples = 5,000) to test whether compulsory play moderates the underlying process via emotional (but not cognitive) brand engagement. The model used challenge as the independent variable, emotional and cognitive engagement as mediators, and compulsory play as the moderator. The interaction between challenge and compulsory play was only significant for emotional ($\beta = -1.205$, $t = -2.898$, $p < .004$; $R^2 = .092$, $F(3, 325) = 11.030$, $p < .001$) but not for cognitive brand engagement ($\beta = -.076$, $t = -.194$, $p > .85$; $R^2 = .039$, $F(3, 325) = 4.388$, $p < .005$). Emotional and cognitive brand engagement, in turn, facilitated self–brand connections ($\beta_{Emotional} = .235$, $t = 6.146$, $p < .001$; $\beta_{Cognitive} = .335$, $t = 8.038$, $p < .001$; $R^2 = .428$, $F(2, 326) = 121.791$, $p < .001$). Compulsory play moderated the indirect effect of optimal challenge on self–brand connections only via emotional (CI_{95} of the index of moderated mediation = [$-.513$, $-.105$]) but not cognitive engagement (CI_{95} of the index of moderated mediation = [$-.300$, .233]). The indirect effect of optimal challenge on self–brand connections via emotional brand engagement was only significant for the voluntary ($\beta = .370$, CI_{95} = [.222, .579]) but not for the involuntary conditions ($\beta = .093$, CI_{95} = [$-.045$, .272]), confirming H3a.

Discussion

Study 3 shows that requiring consumers to engage in gamified interactions (i.e., compulsory play) only attenuates their positive effect on emotional (not cognitive) brand engagement, ultimately decreasing consumers' self–brand connections (H3a). These results not only support our theorizing but are also relevant to marketing practitioners. In particular, firms should design gamified interactions such that consumers won't perceive them as compulsory; otherwise, they will fail to facilitate self–brand connections.

Study 4: Moderating Role of Time Pressure

In contrast to the previous study, Study 4 tests whether time pressure to participate in gameplay attenuates the effect of highly interactive and optimally challenging gamified interactions on cognitive (but not emotional) brand engagement (H3b).

Design and Participants

Study 4 used a 2 (challenge: low, optimal) $\times$ 2 (time pressure: low, high) between-subjects experimental design. We recruited a total of 353 U.S. participants from MTurk ($M_{Age} = 36.02$, $SD_{Age} = 11.30$; 57.5% female) and randomly assigned them to one of the four conditions. Study 4 used the same brand and game as Study 3.

Procedure and Stimuli

Challenge was manipulated as in Study 3. The time pressure manipulation was based on telling participants that the game was followed by a choice task (Kruglanski and Freund 1983). In the low time pressure conditions, participants were told that they had enough time to complete the task and, hence, for gameplay. In the high time pressure conditions, participants were told that they may lack time to complete the task and had to quickly finish the game. A pretest supported this approach. Next, participants played the game (varying by challenge) and completed manipulation checks, dependent, mediating, and demographic variables and were redirected to the choice task.

Measures

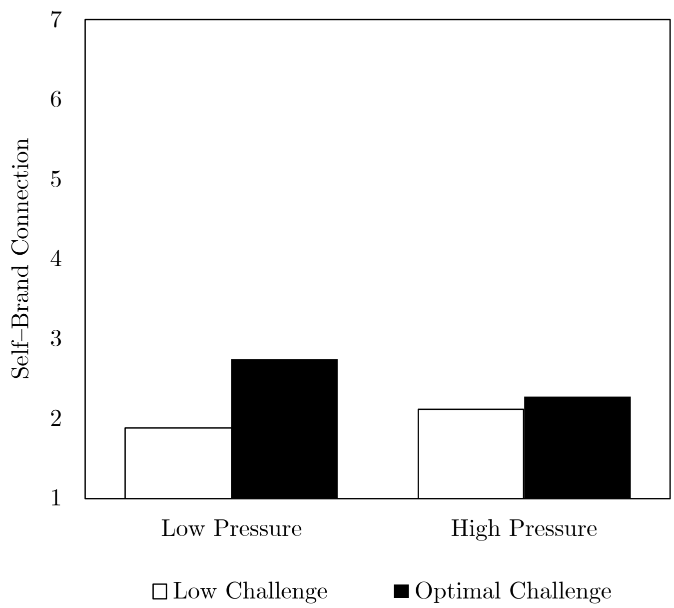
Self–brand connections ($\alpha = .98$), emotional brand engagement ($\alpha = .97$), cognitive brand engagement ($\alpha = .95$), challenge, and flow experience ($\alpha = .89$) were measured as in Study 2 and 3. We used three 12-point scale items as a manipulation check for time pressure (De Dreu 2003; $\alpha = .86$). Again, the measurement model had good fit and met appropriate thresholds (CR $\geq .86$; CA $\geq .86$; AVE $\geq .50$), demonstrating reliability, convergent, and discriminant validity regarding our constructs (see Appendix 1 and 2).

Results

Manipulation Checks. Three 2 × 2 ANOVAs assessed our manipulations. Participants in the optimal challenge conditions perceived the challenge to more closely match their skills ($M = .13$; $F(1, 349) = 86.344$, $p < .001$) than those in the low challenge conditions ($M = 1.58$; $t = 9.301$, $p < .001$). The optimally challenging conditions did not differ from an optimal challenge, namely a zero mean ($t(1, 168) = 1.233$, $p > .22$). The optimal challenge conditions also experienced more flow ($M = 4.79$; $F(1, 349) = 89.158$, $p < .001$) than the low challenge conditions ($M = 3.53$; $t = -9.451$, $p < .001$). Participants in the high time pressure conditions felt a greater urge to complete the game ($M = 7.58$; $F(1, 349) = 196.708$, $p < .001$) than those in the low time pressure conditions ($M = 4.01$; $t = -14.000$, $p < .001$). No other effects were significant.

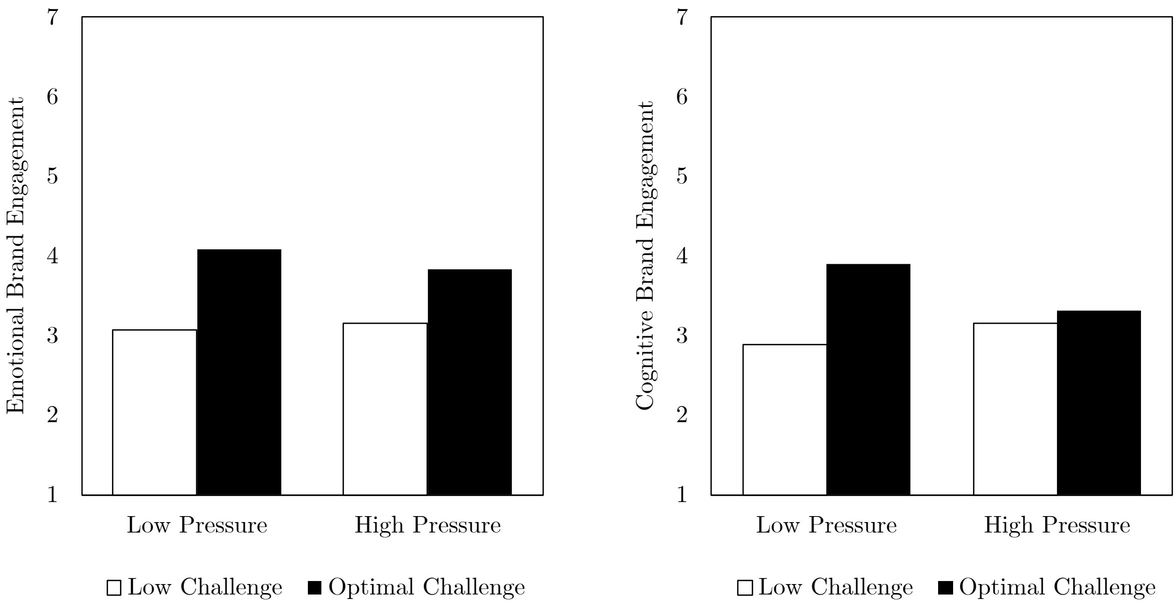
Self–Brand Connection. A 2 × 2 ANOVA showed that time pressure had no significant effect on self–brand connections ($F(1, 349) = .531$, $p > .47$), whereas optimal challenge ($M_{LowChall} = 2.00$, $M_{OptimalChall} = 2.51$; $t = 3.172$, $p < .002$; $F(1, 349) = 10.000$, $p < .002$) and the interaction between challenge and time pressure significantly influenced self–brand connections ($F(1, 349) = 4.720$, $p < .030$). Optimally challenging gamified interactions only facilitated self–brand connections, when participants perceived low ($M_{LowChall} = 1.88$, $M_{OptimalChall} = 2.75$; $t = 3.841$, $p < .001$), but not high time pressure ($M_{LowChall} = 2.12$, $M_{OptimalChall} = 2.28$; $t = .689$, $p > .49$; Fig. 8).

Fig. 8 Time Pressure moderates the Effect of Optimal Challenge on Self–Brand Connection (Study 4)



Brand Engagement. Results of two 2 × 2 ANOVAs showed that optimal challenge created emotional ($M_{LowChall}$ = 3.12, $M_{OptimalChall}$ = 3.96; t = 4.466, p < .001; F(1, 349) = 19.892, p < .001) and cognitive ($M_{LowChall}$ = 3.02, $M_{OptimalChall}$ = 3.60; t = 2.985, p < .003; F(1, 349) = 8.957, p < .003) brand engagement. Time pressure had no significant effect on either type of engagement (ps > .41). Consistent with our theorizing, the interaction between time pressure and optimal challenge only attenuated cognitive (F(1, 349) = 4.886, p < .028) but not emotional (F(1, 349) = .793, p > .37; see Fig. 9) brand engagement. That is, optimal challenge only created cognitive brand engagement when time pressure was low ($M_{LowChall}$ = 2.89, $M_{OptimalChall}$ = 3.90; t = 3.748, p < .001), but not when it was high ($M_{LowChall}$ = 3.16, $M_{OptimalChall}$ = 3.31; t = .543, p > .59).

Fig. 9 Time Pressure moderates the Effect of Optimal Challenge on Cognitive Brand Engagement, but not on Emotional Brand Engagement (Study 4)



Moderated Mediation Analysis. We again employed a moderated parallel multiple mediation model (Hayes 2015; SPSS Macro PROCESS, Model 8; bootstrap samples = 5,000) to test the moderating effects of time pressure on the underlying process via cognitive (but not emotional) brand engagement. The model used challenge as the independent variable, emotional and cognitive engagement as mediators, and time pressure as the moderator. As expected, the interaction between optimal challenge and time pressure was only significant for cognitive ($\beta = -.860$, $t = -2.210$, p < .028; R^2 = .041, F(3, 349) = 5.002, p < .002), but not for emotional ($\beta = -.337$, $t = -.891$,

$p > .37$; $R^2 = .057$, $F(3, 349) = 7.085$, $p < .001$) brand engagement. Emotional and cognitive brand engagement facilitated self–brand connections ($\beta_{Emotional} = .359$, $t = 8.464$, $p < .001$; $\beta_{Cognitive} = .326$, $t = 7.828$, $p < .001$; $R^2 = .550$, $F(2, 350) = 213.541$, $p < .001$). As hypothesized, time pressure moderated the effect of optimal challenge on self–brand connections only via cognitive (CI_{95} of the index of moderated mediation = $[-.566, -.035]$) but not emotional (CI_{95} of the index of moderated mediation = $[-.415, .141]$) brand engagement. Specifically, the indirect effect of an optimal challenge on self–brand connections via cognitive brand engagement was only significant for low ($\beta = .323$, $CI_{95} = [.152, .548]$) but not high ($\beta = .049$, $CI_{95} = [-.135, .222]$) time pressure. Thus, H3b is supported.

Discussion

Study 4 shows that time pressure only attenuates the effect of optimally challenging gamified interactions on cognitive but not emotional brand engagement, ultimately decreasing self–brand connections (H3b). Again, these findings not only support our theorizing, but also marketers in presenting gamified interactions, showing that firms should avoid using gamified interactions when consumers are likely to be under time pressure.

General Discussion

In this article, we explore whether, when, and how gamified interactions (games used by firms to co-create experiences with their customers) facilitate self–brand connections. Results of a field study and three experiments show that only gamified interactions, which are highly interactive and optimally challenging, facilitate self–brand connections via emotional and cognitive brand engagement. We also identified conditions under which consumers do not become engaged with a brand, namely when firms restrict their decisional control either to participate in the game voluntarily (compulsory play attenuates emotional brand engagement) or to spend as much time as desired to play the game (time pressure diminishes cognitive brand engagement). Our findings have several implications for marketing research and practice.

Theoretical Implications

First, our research has implications for the literature examining the effects of games on brand outcomes. We present first-of-its-kind evidence that gamified interactions can facilitate behavioral and psychological measures of self–brand connections across numerous industries and game designs. In so doing, this article not only advances prior studies on brand-related outcomes, such as product choice (Kuo and Rice 2015) or innovation adoption (Müller-Stewens et al. 2017) but also contrasts work on brand-specific outcomes. For example, prior work has been unable to find positive effects of flow-eliciting gameplay on brand memory (Schneider and Cornwell 2005) and brand attitudes (Mau et al. 2008; Waiguny et al. 2013). Our research suggests that a possible reason for such null effects is that these studies have not (sufficiently) adopted an experiential lens for gamified interactions and thereby have neglected the dimensions of interactivity and challenge. Specifically, prior research has only regarded these dimensions in isolation, which has produced mixed results. For example, interactivity was found to increase brand attitudes (Lee et al. 2014) but also to decrease brand recall (Nelson et al. 2006). Likewise, gamified interactions were found to improve brand attitudes when they imposed an either particularly low (Herrewijn and Poels 2013) or high (Waiguny et al. 2012) challenge. The unique contribution of our research is that we show gamified interactions need to be both highly interactive and optimally challenging to create experiential touchpoints with consumers, ultimately facilitating the formation of self–brand connections. This finding has implications for research on experiential customer-firm interactions, which has found transcendent consumer experiences can strengthen brand communities (Schouten et al. 2007) or conceptualized experiential branding (Brakus et al. 2009; Schmitt 1999).

Second, our findings have implications for research on the influence of games on consumer engagement. Prior literature has offered only inconsistent and limited insights into the psychology that underlies the effects of gameplay on such brand responses. Specifically, prior work has shown that positive affect may (Kuo and Rice 2015) or may not (Herrewijn and Poels 2013) mediate the effects of gameplay on brand choice or attitudes, whereas other studies have focused solely on cognitive involvement to account for this relationship (Jeong et al. 2011). We advance these preliminary findings by providing considerable evidence that high interactivity and optimal challenge are causal antecedents of emotional and cognitive brand engagement, ultimately facilitating the formation of self–brand connections. In so doing, we provide empirical support for the experiential and multidimensional nature of gameplay and corroborate suggestions that engagement conceptually links flow-eliciting experiences with self–brand connections (Brodie et al. 2011).

Third, this article has implications for research exploring boundary conditions of games. Drawing from research on decisional control (Mathwick and Rigdon 2004), we show that compulsory play and time pressure can undermine games' potential to trigger flow, ultimately failing to create brand engagement and self–brand connections. These findings detail recent evidence suggesting that consumers' perceived autonomy may affect their responses to gameplay (Kim et al. 2016). Furthermore, both of our moderators are situation-specific and represent circumstances under which consumers may encounter a firm's gamified interaction. Apart from a study by Jung et al. (2013) regarding shopping goals, prior research has neglected such situation-specific boundary conditions regarding the outcomes of gamified interactions. Specifically, this type of research has mainly focused on boundary conditions related to consumer characteristics, such as brand familiarity (Mau et al. 2008; Nelson et al. 2006; Waiguny et al. 2013) or product characteristics, such as hedonic versus utilitarian (Choi and Lee 2012) or low versus high involvement goods (Cauberghe and De Pelsmacker 2010). In contrast, our research highlights the voluntary nature of gameplay as a situation-specific precondition for gamified interactions. Our findings regarding compulsory play and time pressure not only provide additional process evidence for our conceptual model, but also enrich the managerial implications of our research.

Managerial Implications

Our research provides firms with valuable insights on how to design (via high interactivity and optimal challenge) and present (via compulsory play and time pressure) gamified interactions, also highlighting the importance for managers to get the right partners on board for implementation. We explore these implications with a real world example, namely a mobile game application that was launched by the Swiss financial services provider who collaborated with us on this research. The game's objective was to promote the raffle of a vacation trip among the bank's customers. Although customers did not have to play the game to be part of the raffle, game participation increased the likelihood of winning the trip. In the game, customers took on the role of pilots who had to accumulate as many points as possible by, either collecting items via an airplane or answering quiz questions about the bank. According to a short proprietary survey by the firm, customers playing the game were more engaged and felt stronger connections with the brand.

Game Design. Our findings highlight the critical importance of designing gamified interactions that are highly interactive and optimally challenging. To this end, marketers should integrate interactive elements into gameplay, as did the Swiss financial firm. As noted previously, the game design allowed customers to engage not only with the brand via a game-based quiz (a rather passive brand experience), but also via a flight simulation that involved highly interactive game experiences between the customers and brand. Besides interactivity, firms should also design games that provide an optimal level of challenge. Given that the perception of challenge depends on a person's skill level, firms should design games that either have several levels (i.e., from easy to difficult) or dynamically align challenge with a person's skills. In the service provider game, customers entered more difficult game levels as they exceeded a threshold of collected points, thereby allowing for the creation of optimal challenge.

Game Presentation. Firms should also be aware that even well-designed gamified interactions may fail to create engagement and connections with the brand when consumers feel "controlled" in their decision to participate in gameplay. Alternately, firms can offer consumers the option to start playing the game, while highlighting the option to stop gameplay at any time. In our bank example, customers could create an individual game account that did not require customers to complete the game all at once, but included the option to exit and return to the game at any point in time without losing earned points. Finally, firms should promote gamified interactions in situations where consumers are (typically) less time pressured. In today's world of massive online data, firms can use customer analytics to identify and target consumers who are less time pressured. For instance, customer browsing behavior (such as click patterns and time spent on specific websites) can serve as a reasonable indicator of time pressure. Based on these insights, firms could dynamically adjust which consumers would be exposed to gamified interactions. Returning to our example, advertising the mobile game on the bank's own website or social media profiles (e.g., Facebook, Twitter) is probably more advantageous than, for example, on news websites, since consumers normally spend more time at the former touchpoints than at the latter (Experian 2013) and thus sense less time pressure.

Collaboration with External and Internal Partners. We propose that gamified interactions are a way to create experiences that sustainably contribute to firm performance (Brakus et al. 2009; Pine and Gilmore 1998; Prahalad and Ramaswamy 2004; Schmitt 1999). To do so, however, we encourage firms to rely upon external and internal expertise to design and present gamified interactions to their customers. As noted by Müller-Stewens et al. (2017), the successful launch of games will require firms to collaborate with professional game designers. Returning to our bank example, the gamified interaction was designed in collaboration with an external game development company who helped to ensure that the game would be highly interactive and optimally challenging and result in compelling experiences during gameplay. Furthermore, the firm relied upon internal expertise to avoid attenuating effects from compulsory play and time pressure. Specifically, the branding team worked with the IT department (who had prior experience with the deployment of customer mobile accounts) and the market research department (who provided analytics in terms of customer behavior regarding website and social media channels). Thus, firms need to collaborate with both external and internal partners to design and launch gamified interactions successfully, making them drivers of competitive advantage. In such cases, firms benefit from the behavioral and attitudinal consequences of gamified interactions (Studies 1–4).

Limitations and Future Research

While our research provides consistent support for our model (based on multiple methods, games, and various product categories), this article has also some limitations that provide opportunities for future research. First, our experiments focused on games of skill, which naturally may be more effective in facilitating challenge (thereby enhancing brand engagement and self–brand connections) than games of chance. Research has found that games of chance might also induce flow under certain circumstances, for instance among intense gamblers (Csikszentmihalyi 1990); thus, it would be potentially interesting to examine whether our model also applies to these games. Along these lines, prior research has also identified further mechanisms of flow, such as clear goals or immediate feedback (Nakamura and Csikszentmihalyi 2002). Therefore, future studies may also investigate to which degree other game design dimensions (or combinations of them) trigger consumers' experiences of flow during gameplay. Second, flow theory makes a strong argument for a dual process of emotional and cognitive brand engagement. However, prior research has identified a behavioral dimension of brand engagement (Hollebeek et al. 2014). While we addressed behavioral dimensions of self–brand connections (via likes in social media in Studies 1 and 2), we did not examine behavioral brand engagement as a possible mediator. Future research may test whether and how highly interactive and optimally challenging gamified interactions affect the behavioral (in addition to emotional and cognitive) dimension of brand engagement. Finally, prior research suggests that engagement may dynamically evolve from repeated interactions with a brand (Hollebeek et al. 2016). While examining the dynamics of engagement was beyond the scope of the current article, future research may test the development of brand engagement over time.

Summary

In this article, we presented gamified interactions with a brand as a means of influencing consumers' brand engagement and self–brand connections. Our work was motivated by and crafted in collaboration with two globally-operating firms (i.e., automotive manufacturer, financial services) who wanted to impact their brand by employing games at their online customer touchpoints. Through our work, we demonstrate in a multitude of settings that games which are highly interactive and optimally challenging lead to increased emotional and cognitive engagement, in turn resulting in stronger connections with the brand. While the application of gamified interactions is highly practical, we believe that it is important for marketing scholars to reflect this growing interest and continue efforts to expand our understanding of this unique means by which to create compelling experiences. Our results regarding context-specific boundary conditions (along with our results on effective game design dimensions) provide marketers with actionable recommendations to introduce gamified interactions for their own brands. We are hopeful that our work guides additional research efforts to examine other design factors and consequences of using games in marketing above and beyond the branding context.

Appendix

Appendix 1 Measurement Models: Items, Reliabilities, and Model Fits

Constructs and Items	Study 2		Study 3		Study 4	
	CR	CA	CR	CA	CR	CA
Self–Brand Connection (*not at all/extremely well*)	.97	.97	.98	.98	.98	.98
[Brand] reflects who I am.						
I can identify with [Brand].						
I feel a personal connection to [Brand]. (*not at all/very much so*)						
I can use [Brand] to communicate who I am to other people.						
I think [Brand] (could) help me become the type of person I want to be.						
I consider [Brand] to be me. (not me/me)						
[Brand] suits me well.						
Emotional Brand Engagement (*strongly disagree/strongly agree*)	.96	.96	.98	.98	.97	.97
I felt very positive when I was dealing with [Brand] through the game.						
Dealing with [Brand] through the game made me happy.						
I felt good when I was dealing with [Brand] through the game.						
I was proud to deal with [Brand] through the game.						
Cognitive Brand Engagement (*strongly disagree/strongly agree*)	.92	.92	.93	.93	.95	.95
Dealing with [Brand] through the game got me to think about [Brand].						
I thought about [Brand] a lot when I was dealing with it through the game.						
Dealing with [Brand] in the game arose my interest to learn more about it.						
Flow Experience (*not at all/very much*)	.84	. 84	.89	.89	.89	.89
I feel just the right amount of challenge.						
My thoughts/activities run fluidly and smoothly.						
I don't notice time passing.						
I have no difficulty concentrating.						
My mind is completely clear.						
I am totally absorbed in what I am doing.						
The right thoughts/movements occur of their own accord.						
I know what I have to do each step of the way.						
I feel that I have everything under control.						
I am completely lost in thought.						
Compulsory Play (*strongly disagree/strongly agree*)			.92	.92		
I did feel forced to play the game.						
To play the game was completely involuntary.						
I did feel obligated to play the game.						
Others did have to talk me into playing the game.						
Not because I want to, but because I have to did characterize it.						
Time Pressure (*strongly disagree/strongly agree*)					.86	.86
I felt that I had not sufficient time to play the game to proceed to task 2.						
I felt time pressure during the game in order to begin with task 2.						
Time left was an issue while playing the game to start with task 2.						
Model Fit Indexes						
Comparative Fit Index	.977		.978		.972	
Tucker-Lewis Index	.968		.973		.965	
Root Mean Square Error of Approximation	.059		.049		.058	
Standardized Root Mean Squared Residual	.060		.058		.075	

Appendix 2 Average Variances Extracted and Squared Correlations

Constructs				Squared Correlations				
			AVE	1	2	3	4	5
1	Self–Brand Connection	Study 2	(.83)					
		Study 3	(.86)					
		Study 4	(.89)					
2	Emotional Brand Engagement	Study 2	(.85)	.44				
		Study 3	(.91)	.31				
		Study 4	(.89)	.47				
3	Cognitive Brand Engagement	Study 2	(.79)	.47	.49			
		Study 3	(.82)	.36	.34			
		Study 4	(.86)	.46	.47			
4	Flow Experience	Study 2	(.51)	.05	.10	.07		
		Study 3	(.53)	.05	.18	.11		
		Study 4	(.50)	.11	.16	.15		
5	Compulsory Play	Study 3	(.69)	.02	.08	.04	.01	
6	Time Pressure	Study 4	(.68)	.00	.00	.00	.00	–[a]

Note. [a]Not included in Study

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Article 2

Contagious Consumption: The Social Dynamics of Sharing Purchase Information on Spending in Freemium Networks

Submitted to
Journal of Marketing

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Abstract Social networks that offer the basic functionalities of a product for free, but charge a premium for additional features ("freemium networks") have become a prevalent business model in today's digital economy. In these networks, firms often encourage their customers to share information about their purchases of premium features with other customers. Drawing on social impact theory and social network theory, this article examines whether and how sharing of purchase information affects other customers' spending on premium features. Results of a large-scale longitudinal field study show that sharing is contagious and has a positive, yet temporarily decaying effect on spending. The study also reveals that social characteristics of customers' ego and global network account for this effect. Specifically, customers not only spend more on premium features when they are shared by knowledgeable, interconnected, and numerous peers, but also when customers—themselves—operate as information "brokers" in the network. These findings advance the current understanding about the dynamic effects of social interactions on spending in social networks and provide implications for firms running freemium models.

Keywords Freemium · Social Networks · Sharing · Network Characteristics · Dynamic Panel Model

Introduction

In today's digital economy, an increasing number of firms host social networks that use "freemium" models (Liu et al. 2014; Wang and Chin 2011) to offer the basic functionalities of a product for free, while charging an add-on for premium features (Kumar 2014). However, many firms fail to capitalize on freemium networks (Enders et al. 2008; Kumar 2014), mainly because up to 95% of customers do not buy premium features (Anderson 2009).

Prior research found that social interactions among customers influence purchase decisions in social networks (Godes and Mayzlin 2004); likewise peer reviews, ratings (e.g., Chevalier and Mayzlin 2006; Moe and Trusov 2011), or referrals (e.g., Trusov et al. 2009) were found to increase spending. By contrast, research has dedicated little attention to sharing behavior (Aral and Nicolaides 2017), and particularly to the question whether and how the mere dissemination of purchase information—without providing an explicit recommendation—affects other customers' spending. However, addressing this gap in research is highly relevant, since firms, especially those operating freemium networks, strongly encourage their customers to share their purchases with others. For instance, the online music provider Spotify enables customers to share the songs they purchased with others, or the online game Farmville allows players to notify fellow players about in-game purchases via Facebook.

Combining research on social impact theory (SIT; Latané 1981) and social networks (e.g., Freeman 1978), we propose that information that peers share about purchasing premium features increases other customers' spending on those features in freemium networks, a phenomenon we call *contagious consumption*. We conjecture that this effect decays quickly over time and is largely determined by social characteristics of customers' ego and global network. Specifically, we predict that customers not only spend more on premium features when they are shared by knowledgeable (i.e., source strength), interconnected (i.e., spatial proximity), and numerous (i.e., number of sources) peers, but also when customers' own embeddedness in the global network is high, that is, when their access to (i.e., closeness centrality) and brokerage of (i.e., betweenness centrality) purchase information increases. Based on longitudinal field data from a large-scale freemium network, we specify a set of dynamic panel models with the system generalized method of moments (Arellano and Bover 1995; Blundell and Bond 1998) to test our theorizing.

This article advances our current understanding about the dynamic effects of social interactions on spending in two ways. First, we examine sharing behavior as a novel type of social interaction. By showing that sharing purchase information dynamically affects spending in social networks, we contribute to prior research on related phenomena, such as product reviews, ratings, and referrals (e.g., Chevalier and Mayzlin 2006; Moe and Trusov 2011; Trusov et al. 2009) that provide more explicit recommendations. Second, we contribute to SIT (Latané 1981) and thereby advance existing knowledge about social mechanisms underlying peer influence. Specifically, we provide first-of-its-kind evidence for a multiplicative effect between expertise, interconnectedness, and number of peers on spending, extending prior studies that examined one- or two- dimensional models only (Argo et al. 2005; Daunt and Greer 2015; Ding et al. 2016; Hui et al. 2009; Zhang et al. 2014). Moreover, by conceptualizing and showing that the effect of sharing purchase information is stronger when customers themselves act as active brokers of information in the global network (i.e., high betweenness centrality), we further advance SIT in the context of social networks. This finding also adds to work at the intersection of social psychology and network research (Iyengar et al. 2011, 2015; Katona et al. 2011) that has not examined interdependencies between ego and global network characteristics.

In what follows, we review prior work on the effects of social interactions on spending in social networks, before we detail our conceptual model and research hypotheses. We then report our empirical findings from a large-scale field study to conclude with implications for marketing research and practice.

Sharing in Freemium Networks

"Freemium" has become a prevalent business model in today's digital economy (Kumar 2014). Much of the prior research has examined how firms should design freemium models to maximize profits, including the fit between the free and premium offer (e.g., Cheng and Liu 2012; Wagner et al. 2014) or the choice of bundling strategies (Zhang et al. 2016). As freemium models are often integrated into social networks, marketing scholars have increasingly examined the degree to which the social value of the underlying network affects spending decisions (Vock et al. 2013). While initial evidence has found that the number of paying users among one's friends increases willingness to pay for premium features (Wang and Chin 2011), the role of sharing purchase information as a novel phenomenon of social interactions in freemium networks remains unclear.

In general, social interactions are a form of "informal communications directed at other consumers about the ownership, usage, or characteristics of particular goods and services and/or their sellers" (Westbrook 1987, p. 261). As Table 1 depicts, prior work on the effects of social interactions can be classified into literature on (a) reviews and ratings, (b) referrals, and (c) sharing.

Most research has focused on the first category, reviews and ratings, showing that they improve products' sales ranks on websites (Chevalier and Mayzlin 2006), subsequent ratings (Godes and Mayzlin 2004; Lee et al. 2015), offline (Chintagunta et al. 2010; Ding et al. 2016; Duan et al. 2008) and online (Liu et al. 2014; Moe and Trusov 2011) sales, or even firms' stock market performance (Tirunillai and Tellis 2012). Furthermore, research on referrals found that they have a positive effect on customers' product adoption (Iyengar et al. 2011, 2015) and their likelihood to sign up on social networking sites (Katona et al. 2011; Trusov et al. 2009). As opposed to ratings, reviews, and referrals that explicitly recommend the purchase of a product, sharing purchase information refers to the mere dissemination of purchase information in a social network and is, therefore, much more implicit in nature. Specifically, when people share purchase information they merely mention (e.g., "I purchased this product") rather than assess (e.g., "You'd love/hate this product") their purchase of a product (Berger 2014). Since sharing of purchase information lacks positive/negative elements, its effects on customers' subsequent behaviors may thus be driven by much subtler cues, such as the social characteristics of their ego and global network. So far, the only article on the effects of information sharing has found that peers who share their running behaviors (e.g., distance, pace, duration, and burned calories) in a social network positively affect other peoples' workout behaviors (Aral and Nicolaides 2017). Yet, there is no evidence as to whether and how sharing of purchase information also affects spending, particularly on premium features in freemium networks.

Addressing these gaps in marketing research, we establish a theory-based model that captures the (dynamic) effects of sharing purchase information and underlying network effects on customers' spending in freemium networks.

Conceptual Model

Integrating research on SIT (Latané 1981) and social networks (e.g., Freeman 1978), Fig. 1 depicts our conceptual model and research hypotheses on the social dynamics of sharing purchase information on customers' spending. Specifically, we propose that customers not only spend more on premium features that knowledgeable, interconnected, and numerous peers purchased and shared with them, but also when customers' embeddedness in the global network, that is, their access to and brokerage of purchase information, is high (i.e., closeness centrality and betweenness centrality).

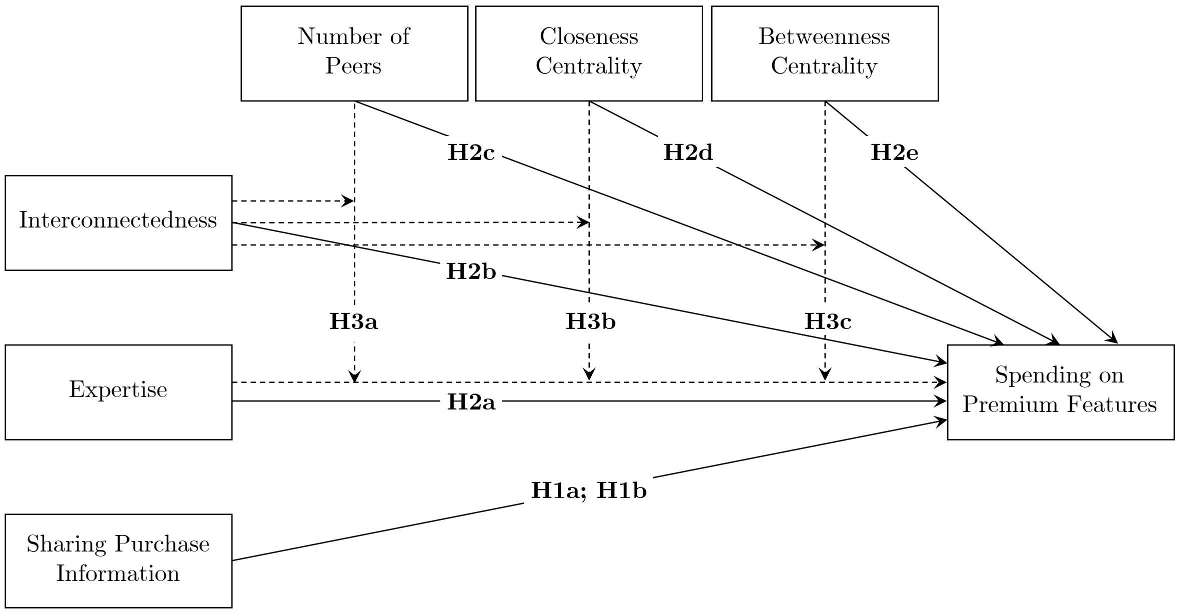
Table 1 Relevant Literature on Social Interactions

Reference	Independent Variable	Dependent Variable	Ego Network	Global Network	Study Context	Estimation Approach	Key Findings
Reviews and Ratings							
Chevalier and Mayzlin (2006)	Number of Reviews, Valence of Ratings	Sales Rank on Website			Book Retailing Website	Mixed Model	Number of reviews and positive ratings increase sales rank of books.
Chintagunta et al. (2010)	Number of Reviews, Variance and Valence of Ratings	Box Office Sales			Movie Website	Mixed Model	Valence of ratings increase box office sales, whereas number of reviews and variance of ratings have no effect.
Ding et al. (2016)	Number of Likes	Box Office Sales			Movie Website	Dynamic Panel Model	Number of pre-release likes of movies increase box office sales.
Duan et al. (2008)	Number of Reviews and Rating	Box Office Sales			Movie Website	3SLS Regression Model	Number of reviews increase box office sales (effect declines quickly), whereas rating of movie has no effect.
Godes and Mayzlin (2004)	Number and Dispersion of Reviews	Rating of TV Show			Movie Website	Mixed Model	Dispersion of reviews increase rating of TV show, whereas number of reviews have no effect.
Lee et al. (2015)	Number and Average Ratings	Rating of Movies	✓		Movie Website	Probit Model	Number of friends that rated a movie and their average prior rating increase rating of movie.
Liu et al. (2014)	Valence of Ratings	Sales of Premium Features			App Store	GLS Regression Model	Valence of ratings increase sales of premium features.
Moe and Trusov (2011)	Number, Variance, and Valence of Ratings	Sales on Website			Cosmetics Retailing Website	Hazard/ Rating Model	Number, variance, and valence of ratings increase sales of cosmetics.

Table 1 *(continued)*

Reference	Independent Variable	Dependent Variable	Ego Network	Global Network	Study Context	Estimation Approach	Key Findings
Tirunillai and Tellis (2012)	Number and Valence of Reviews	Stock Market Performance			Websites/ Forums	VAR Model	Number of reviews increase abnormal returns; negative reviews decrease abnormal returns; number of reviews and negative reviews increase trading volume.
Referrals							
Iyengar et al. (2011)	Number of Referrals	Adoption and Usage of Drug	✓		Physician Referral Network	Hazard Model	Number of referrals increase adoption and usage of drug, whereas opinion leadership only increases usage of drug.
Iyengar et al. (2015)	Number of Referrals	Adoption and Repeated Usage of Drug	✓		Physician Referral Network	Hazard/ Probit Model	Number of referrals increase adoption and repeated usage of drug, whereas opinion leadership only increases adoption, but not repeated usage of drug.
Katona et al. (2011)	Number of Referrals	Sign-up on Social Network	✓	✓	Social Networking Site	Hazard Model	Number of referrals, number of already adopted friends, clustering, and betweenness centrality decrease time to sign up on a social network.
Trusov et al. (2009)	Number of Referrals	Sign-up on Social Network			Social Networking Site	VAR Model	Number of referrals increase sign-ups on a social network.
Sharing							
Aral and Nicolaides (2017)	Sharing of Workout Information	Exercising Behaviors	✓		Social Networking Site	IV Framework	Sharing workout information increases exercising behavior (effect declines quickly).
Current Research	Sharing of Purchase Information	Spending on Premium Features	✓	✓	Massive Multiplayer Online Game	System GMM	Sharing purchase information increases spending (effect declines quickly); expertise, interconnectedness, exposure, betweenness centrality increase spending; three-way interaction between expertise, interconnectedness, and exposure and betweenness centrality; closeness centrality no effect.

Fig. 1 Conceptual Model and Research Hypotheses



Dynamics of Sharing Purchase Information

SIT refers to "the great variety of changes in [...] behavior, that occur in an individual [...] as a result of the [...] actions of other individuals" (Latané 1981, p. 343). Consistently, evidence from marketing has shown that online reviews and ratings increase product sales (Chintagunta et al. 2010; Ding et al. 2016; Duan et al. 2008; Moe and Trusov 2011), that referrals of prescription drugs increase these drugs' adoption and (repeated) usage (Iyengar et al. 2011, 2015), and that positively rated premium features in an app store are more frequently sold (Liu et al. 2014). In a similar vein, we propose that information that peers share with customers about their purchase of premium features increases customers' subsequent spending on those premium features. To our knowledge, the only empirical evidence for this assertion concerns workout behaviors, and showed that sharing them increases the magnitude of other peoples' exercising behaviors (Aral and Nicolaides 2017). Thus, we hypothesize:

H1a: Purchase information that is shared by peers has a positive influence on customers' spending on premium features.

Consistent with prior findings on the dynamics of social interactions (e.g., Moe and Trusov 2011), we suspect that the impact of sharing purchase information will mainly be temporary. For example, research on box office sales found that a 1% increase in online movie ratings four days before the actual release date increases ticket sales by 39.8%, whereas a 1% increase on the same day of the movie release boosts sales by

45.2% (Ding et al. 2016). Likewise, a 10% increase in the volume of movie reviews results in an increase of same-day box office sales of 6.3%, next-day box office sales of 1.7%, and third-day box office sales of only 1% (Duan et al. 2008). Similar effects are evident in the domain of online product ratings, whose effects are commonly short-term (Moe and Trusov 2011), with the largest effects being on the subsequent day (Tirunillai and Tellis 2012). Consistent with this work, SIT predicts that peers have a stronger impact on other peoples' behaviors the more recently the influence was exerted (Latané 1981). Therefore, we expect that sharing purchase information has a greater effect on spending the more recently customers received shares from their peers.

H1b: The influence of sharing purchase information on customers' spending on premium features decays over time.

Ego Network Characteristics

We integrate work on SIT and social networks to propose that the social characteristics of customers' ego network, namely, of those peers that customers receive shares from, is key to explaining the magnitude of the effect of information sharing. SIT predicts that the strength (i.e., expertise), spatial proximity (i.e., interconnectedness), and number (i.e., number of peers) of sources sharing purchase information positively affect customers' spending on premium features (Latané 1981).

Expertise. We conjecture that customers rely more heavily on information that is shared by peers with greater social power (Latané 1981). According to French and Raven (1959), social power can be rooted in multiple factors, such as reward, coercion, legitimacy, reference, and expertise. Among these factors, expertise was found to be most influential in predicting peoples' responses to peer influence (Wilson and Sherrell 1993). For example, Harmon and Kenneth (1982) found that customers form more positive product attitudes and higher purchase intentions when they receive information from sales representatives with high rather than moderate product expertise. Likewise, Iyengar et al. (2011) showed that peoples' subsequent adoption behaviors of a drug are increased when peers referring this drug have a high expertise with pharmaceuticals. Therefore, we propose that customers should spend more on premium features when they are shared by more knowledgeable peers.

H2a: Expertise of peers sharing purchase information has a positive influence on customers' spending on premium features.

Interconnectedness. We propose that the interconnectedness between a customer and his/her peers, a dimension termed spatial proximity, also determines the magnitude of the effect of information sharing. According to SIT (Latané 1996), peers should have a stronger impact on customers when they belong to the same cluster, that is, when the density of connections between a customer and his/her peers increases. The idea of cluster-specific contagion is supported by research on network closure (Coleman 1988), that is, if two people are connected to the same person and are, additionally, connected to each other (i.e., triplets), they have a greater impact on that person than if they were not connected. Thus, when peers share purchase information with both, the customer and among each other, densely connected clusters are formed and shares should have a stronger effect on customers' spending. Prior work showed that highly interconnected customers bid more in auctions (Hinz and Spann 2008) and sign up earlier on social networking sites (Katona et al. 2011). We conjecture that customers spend more on premium features that are shared by highly interconnected peers.

H2b: Interconnectedness of peers sharing purchase information has a positive influence on customers' spending on premium features.

Number of Peers. Furthermore, we propose that the number of peers who share information about their purchase of premium features increases customers' spending on the latter. The underlying rationale is that customers receiving shares from an increasing number of peers will have a higher exposure to purchase information (Freeman 1978; Valente et al. 2008), eventually facilitating their spending. In line with this, SIT posits that influence arising from numerous peers follows a power function and, hence, has a positive, yet marginally decreasing effect on spending (Latané 1981). Consistently, research showed that receiving referrals from a greater number of peers has a positive, yet declining effect on peoples' likelihood to adopt a new drug (Iyengar et al. 2015) or join a social networking site (Katona et al. 2011). Thus, we propose that the number of peers sharing purchase information has a positive, but marginally decreasing effect on customers' spending on premium features.

H2c: Number of peers sharing purchase information has a positive, but marginally decreasing influence on customers' spending on premium features.

Global Network Characteristics

Besides customers' ego network, we draw on social network research to propose that customers' own embeddedness in the global network also determines to which degree sharing purchase information affects their purchases (Krackhardt 1998). The underlying rationale is that even information that originates in distant parts of a network may affect spending, exerting an indirect influence via the diffusion of information (Freeman

1978). Prior work has found that information is more likely to affect customers when the number of intermediaries conveying information declines (Katona et al. 2011), that is, when their embeddedness in the global network is high. Consistent with prior work in the domain of social networks, we focus on closeness and betweenness centrality as two important network characteristics to characterize peoples' embeddedness in social networks (Freeman 1978; Wasserman and Faust 1994).

Closeness Centrality. Closeness centrality refers to the number of shortest paths (i.e., geodesics) connecting a person to all other people in a network (Freeman 1978). Prior research found that information spreads more efficiently, or at lower costs and in shorter time, to members in a social network when it requires fewer transmissions (Sabidussi 1966). Accordingly, we expect a customer's closeness centrality to facilitate the efficiency by which they receive purchase information shared by indirectly connected peers in the global network, ultimately increasing their spending on premium features. Initial evidence for this prediction stems from Gao et al. (2014) who showed that content shared in micro-blogging networks is more likely to affect people with high closeness centrality as they cover information in the global network more efficiently. Therefore, we presume that customers' closeness centrality also facilitates their spending on premium features.

H2d: Customers' closeness centrality has a positive influence on their spending on premium features.

Betweenness Centrality. Betweenness centrality is the frequency by which people fall on the geodesics that connect pairs of others. In a social network, people with a high betweenness centrality are also referred to as "brokers", as they bridge different parts of a network and control the spread of information (Freeman 1978). We presume that customers with a high betweenness centrality have more controlled access to purchase information that is shared by indirectly related peers, and that this increases their own spending on premium features. Consistent evidence showed that betweenness centrality has a positive influence on purchase and adoption behaviors. For example, Hinz and Spann (2008) found that customers' betweenness centrality optimizes their bidding in online auctions. Moreover, Katona et al. (2011) showed that betweenness centrality reduces the time until customers sign up on a social networking site. We propose that customers' spending is positively affected by their betweenness centrality.

H2e: Customers' betweenness centrality has a positive influence on their spending on premium features.

Interactions between Ego and Global Network Characteristics

The next set of hypotheses concerns the interdependencies between customers' ego and global network characteristics and their influence on customers' spending on premium features in freemium networks.

Ego Network Characteristics. SIT predicts that peer influence is a multiplicative function of the strength, spatial proximity, and number of sources (Latané 1981). Thus, sharing purchase information should have the strongest impact on customers' spending when it is shared by knowledgeable, interconnected, and numerous peers. Hitherto, research has only examined one- or two-dimensional models of social impact, primarily in offline retail environments, and therefore lacks evidence as to whether this multiplicative influence indeed affects consumer behavior, especially in the online context. For example, people are less likely to commit theft in retail stores when they are surrounded by familiar (i.e., source strength) and numerous people (Daunt and Greer 2015). Moreover, customers are more likely to visit certain store zones (Hui et al. 2009), touch products (Zhang et al. 2014) and buy more expensive brands (Argo et al. 2005) when the spatial proximity and number of other people present in these areas increases. Advancing these findings, we assert that expertise, interconnectedness, and number of peers intensify each other's influence on customers' spending on premium features in freemium networks.

H3a: Expertise, interconnectedness, and number of peers have a multiplicative influence on customers' spending on premium features, such that the largest (smallest) influence exists when expertise, interconnectedness, and number of peers are high (low).

Ego and Global Network Characteristics. Besides the interplay between the social characteristics of customers' ego network, we further propose that the effects of expertise and interconnectedness are also intensified by customers' embeddedness in the global network, namely their closeness and betweenness centrality. While this proposition is novel to SIT and prior marketing research, such an interaction is likely to occur, as peoples' ego and global network positions are often (although not always) highly correlated (Kiss and Bichler 2008; Valente et al. 2008); that is, when people have many directly connected peers in their ego network, they also tend to have a high (closeness and betweenness) centrality in the global network. Thus, we assume that customers' closeness and betweenness centrality should intensify the effect of expertise and interconnectedness on customers' spending on premium features.

H3b: Expertise, interconnectedness, and closeness centrality have a multiplicative influence on customers' spending on premium features, such that the largest (smallest) influence exists when expertise, interconnectedness, and closeness centrality are high (low).

H3c: Expertise, interconnectedness, and betweenness centrality have a multiplicative influence on customers' spending on premium features, such that the largest (smallest) influence exists when expertise, interconnectedness, and betweenness centrality are high (low).

Data

Next, we present the results of a longitudinal field study that uses data from a freemium network to test our hypotheses. Specifically, we estimate a set of dynamic panel models (Arellano and Bover 1995; Blundell and Bond 1998) to examine whether and how sharing purchase information affects spending on premium features.

Empirical Setting

For the empirical application, we chose a massive multiplayer online game (MMOG) that was launched in March 2011 and currently has over 1.2 million registered accounts. Online games present a particularly suitable research context to test our hypotheses. First, most MMOGs use a freemium business model allowing customers to buy premium features (i.e., in-game purchases) while signing up and playing the basic functionalities of the game is free of charges. In the case of our collaborating MMOG, customers could, for example, buy additional equipment and resources that facilitated their gameplay. Second, many MMOGs encourage their customers to share in-game purchases with other customers. In our case, customers could select purchased premium features from an inventory list and send out a notification to other customers they wanted to share their purchases with. The notification not only contained a description of the premium feature but also additional information regarding the peer's gaming profile.

Sample and Measures

To avoid issues from panel mortality, the MMOG provided us with daily data of a random sample of 5,068 customers that had played the game over a period of 60 days (September–October 2016), resulting in a total number of 304,080 observations.

Spending. We used transactional data on customers' payments to assess their spending on premium features. We measured customer v's spending as the total amount of money (in EUR) they spent on day t on premium features that got shared by peers ($Spending_{vt}$). Consequently, this measure does not include spending on premium features for which customers did not receive shares from peers.

Sharing Purchase Information. The primary independent variable is sharing. We assessed which peers shared purchase information with which customers, leading to a unidirectional network graph $\mathbb{G}_t(\mathbb{V}_t, \mathbb{E}_t)$, where $\mathbb{V}_t = \{v_{1t}, ..., v_{nt}\}$ are customers and $\mathbb{E}_t = \{e_{1t}, ..., e_{nt}\}$ denotes whether a customer shared the purchase of a premium feature with another customer. The result is a set of asymmetric binary relationships among a customer v and his/her directly connected peers $\mathbb{D}_t = \{d_{1t}, ..., d_{nt}\}$ on day t, where $\mathbb{D}_t(v) = \{d \mid d \in \mathbb{V}_t \wedge (v, d) \in \mathbb{E}_t\}$. For purchase information shared by d with v, then

$$e_t(v,d) = \begin{cases} 1 & \text{if } (v,d) \in \mathbb{E}_t \\ 0 & \text{otherwise.} \end{cases}$$

To assess the effects of sharing purchase information on spending, we measured the total number of shares ($Shares_{vt}$) that customer v received from his/her peers $\mathbb{D}_t(v)$, formally defined as

$$Shares_{vt} = \sum_{d=1}^{\mathbb{D}} Shares_{vdt}. \tag{1}$$

Notably, for computing customers' ego and global network characteristics we weighted the unidirectional relationships with the number of shares $\sum_{d=1}^{\mathbb{D}} Shares_{vdt}$ that were sent from $\mathbb{D}_t(v)$, captured by the weighting factor w_{vdt}. The adjacency matrix thus has entries equal to the number of shares from $\mathbb{D}_t(v)$.

Ego Network Characteristics. The second set of independent variables describes the characteristics of a customer v's ego network and, hence, only refers to $\mathbb{D}_t(v)$; that is, peers that directly shared information about their purchases with customer v. As noted, when customers received shares on premium features, they could see peers' gaming profiles, including their current badge in the game (e.g., rookie), which served as a measure for their expertise. This ordinal variable had twenty different levels. Since customer v could receive shares from multiple peers per day, we measured expertise (Exp_{vt}) by computing the median badge of peers $\mathbb{D}_t(v)$ as depicted in Eq. 2, where $\mathbb{X}_{vt} = \{Exp(d,t) \mid d \in \mathbb{D}_t(v)\}$ and $\overrightarrow{Exp_{vt}}$ is the sorted vector of peers' badges; that is,

$$Exp_{vt} = \begin{cases} \overrightarrow{Exp_{vt}}_{\frac{|\mathbb{X}_{vt}|+1}{2}} & \text{if } \mid \mathbb{X}_{vt} \mid \text{ is odd} \\ \frac{1}{2}\left(\overrightarrow{Exp_{vt}}_{\frac{|\mathbb{X}_{vt}|}{2}} + \overrightarrow{Exp_{vt}}_{\frac{|\mathbb{X}_{vt}|}{2}+1}\right) & \text{otherwise.} \end{cases} \tag{2}$$

Interconnectedness refers to the extent to which customer v's ego network forms spatial clusters (Latané 1996) and, thus, describes the density of connections between customer v and his/her peers $\mathbb{D}_t(v)$ as well as their connections among each other. Consequently, we measured interconnectedness ($Inter^w_{vt}$) as customer v's clustering coefficient. Following Barrat et al. (2004), the clustering coefficient for directed and weighted networks is computed as

$$Inter^w_{vt} = \frac{1}{s_{vt}(k_{vt}-1)} \sum_{d=1}^{\mathbb{D}} \frac{(w_{vd_1t} + w_{vd_2t})}{2} a_{vd_1t} a_{vd_2t} a_{d_1d_2t}, \tag{3}$$

where $s_{vt}(k_{vt}-1)$ is a normalization factor that accounts for the weight of each connection times the maximum possible number of triplets in which it may participate, a_{vd_1t}, a_{vd_2t}, and $a_{d_1d_2t}$ are elements of the weighted adjacency matrix, and w_{vd_1t} and w_{vd_2t} are the number of shares that customer v received from peer d_1 and d_2 on day t. Thus, the clustering coefficient assesses the density of weighted connections (by number of shares) among customer v and peers d_1 and d_2, thus ranging from 0 (no connections between actors) to 1 (all actors are connected with one another). Next, we measured the number of peers (Num^w_{vt}) that shared purchase information with customer v. Like Opsahl et al. (2010), we computed customer v's in-degree centrality in weighted networks as

$$Num^w_{vt} = \sum_{d=1}^{\mathbb{D}} e_{vdt} \left(\frac{w_{vdt}}{\sum_{d=1}^{\mathbb{D}} e_{vdt}} \right)^{\alpha}, \tag{4}$$

where w_{vdt} equals, as previously noted, the number of shares that customer v received from his/her peers (i.e., weighting factor), $\sum_{d=1}^{\mathbb{D}} e_{vdt}$ the number of peers sharing purchase information on day t, and α a tuning parameter. When $\alpha = 1$ this measure represents node strength and when $\alpha = 0$ it represents in-degree centrality in non-weighted networks. To assign the number of shares and number of peers an equal importance, we chose a tuning parameter of $\alpha = .5$ (Opsahl et al. 2010).

Global Network Characteristics. The third set of independent variables refers to customer v's embeddedness into the global network. As noted, influence is not only exerted by peers $\mathbb{D}_t(v)$ that are directly connected with customer v, that is, $(v, d) \in \mathbb{E}_t$ but also spreads from peers $\mathbb{I}_t = \{i_{1t}, ..., i_{nt}\}$ that are indirectly connected with customer v through intermediaries, or in other words $(v, i) \notin \mathbb{E}_t$. We denote this network as $\mathbb{I}_t(v) = \{i \mid i \in \mathbb{V}_t \wedge \exists (i_{1t}, ..., i_{nt}) : (i_t, i_{1t}) \in \mathbb{E}_t, (i_{1t}, i_{2t}) \in \mathbb{E}_t, ..., (i_{n-1t}, i_{nt}) \in \mathbb{E}_t, (i_{nt}, v_t) \in \mathbb{E}_t\}$. To measure closeness centrality ($Close^w_{vt}$), we compute the inverse of the sum of the geodesic distances between all peers $\mathbb{I}_t(v)$ in the network that are indirectly connected to customer v. In weighted networks, closeness centrality (Opsahl et al. 2010) is denoted as

$$Close^w_{vt} = \left(\sum_{i=1}^{\mathbb{I}} sd_t^{w\alpha}(v, i) \right)^{-1}, \tag{5}$$

where $\sum_{i=1}^{\mathbb{I}} sd_t^{w\alpha}(v,i)$ is the sum of weighted geodesic connections between customer v and any peer $\mathbb{I}_t(v)$ that can be reached from v, while the tuning parameter α is assigned using Dijkstra's algorithm (1959). Customer v has a high closeness centrality, when he/she has many short connections to peers of $\mathbb{I}_t(v)$. Moreover, betweenness centrality (Bet_{vt}^w) tests whether customer v lies on the geodesics between other pairs of peers i_1 and i_2. Betweenness centrality (Opsahl et al. 2010) in weighted networks is

$$Bet_{vt}^w = \sum_{v \neq i_1 \neq i_2}^{\mathbb{I}} \frac{sd_{i_1 i_2 t}^{w\alpha}(v)}{sd_{i_1 i_2 t}^{w\alpha}}, \tag{6}$$

where $sd_{i_1 i_2 t}^{w\alpha}(v)$ is the number of shortest paths linking peers i_1 and i_2 containing customer v and $sd_{i_1 i_2 t}^{w\alpha}$ the number of shortest paths linking peers i_1 and i_2. The tuning parameter α is again based on Dijkstra's algorithm (1959). Customer v has a high betweenness centrality when he/she falls on the geodesics between many peers of $\mathbb{I}_t(v)$.

Control Variables. Finally, we included various controls to test for the robustness of our findings, including customers' lagged spending, tenure, homophily, firm's promotional activities, and graph properties. We included customers' lagged spending ($Spending_{vt-1}$) to control for state dependency, unobserved heterogeneity, and to account for endogeneity arising from customers adapting their spending based on prior purchases (Iyengar et al. 2015). We also controlled for customer tenure ($Tenure_{vt}$) with the MMOG (measured in days), which may be correlated with higher spending in freemium networks (Lee et al. 2013). As homophily, or customers' similarity to peers, may enhance peer influence (Rogers 1983), we constructed a measure of homophily ($Homophily_{vt}$) based on the share of joint membership in clans (0 = no peer belonged to a customer's clan, 1 = all peers belonged to a customer's clan); this reflects the notion that homophily is often measured by people's membership in the same social subgroups (Brown and Reingen 1987). To account for marketing activities, we also incorporated a binary variable denoting as to whether the MMOG launched promotions on premium features ($Promotion_t$) that were intended to increase spending (0 = "No", 1 = "Yes"). Finally, we measured the MMOGs overall network transitivity and centralization to account for properties of the graph. Transitivity ($Transitivity_t$) indicates the likelihood of dense triplets between the customers. According to Opsahl and Panzarasa (2006), we computed the weighted transitivity of the network graph as

$$Transitivity_t = \frac{\sum_{\tau_\Delta} \varpi}{\sum_{\tau} \varpi}, \tag{7}$$

where $\sum_{\tau} \varpi$ is the total number of weighted triplets and $\sum_{\tau_\Delta} \varpi$ is the subset of these triplets that may be completed by adding a third connection. This measure can take values from 0 to 1. Measures of centralization refer to the extent to which the connectivity of a network is centered around a few people. Following Freeman (1978) we assessed the different graph centralizations as follows: Degree centralization ($DegCentral_t$) is computed as

$$DegCentral_t = \frac{\sum_{v=1}^{\mathbb{V}}[C_{D_t}(v^*) - C_{D_t}(v_n)]}{[(\mathbb{V}_t - 1)(\mathbb{V}_t - 2)]}, \tag{8}$$

where $\sum_{v=1}^{\mathbb{V}}[C_{D_t}(v^*) - C_{D_t}(v_n)]$ is the sum of customers' degree centralities subtracted from the highest degree centrality of customer v^* divided by the maximum possible value of degree centrality in a network $[(\mathbb{V}_t - 1)(\mathbb{V}_t - 2)]$, where $\mathbb{V}$ equals, as previously noted, the number of customers. Closeness centralization ($CloseCentral_t$) is based on the standardized closeness centrality

$$CloseCentral_t = \frac{\sum_{v=1}^{\mathbb{V}}[C'_{C_t}(v^*) - C'_{C_t}(v_n)]}{[(\mathbb{V}_t - 1)(\mathbb{V}_t - 2)]/(2\mathbb{V}_t - 3)}, \tag{9}$$

where $\sum_{v=1}^{\mathbb{V}}[C'_{C_t}(v^*) - C'_{C_t}(v_n)]$ is the sum of differences between the closeness centrality of the most central customer v^* and the closeness centralities of all other customers, divided by the maximum value of closeness centrality in a network $[(\mathbb{V}_t - 1)(\mathbb{V}_t - 2)]/(2\mathbb{V}_t - 3)$. Finally, betweenness centralization ($BetCentral_t$) is computed as

$$BetCentral_t = \frac{2\sum_{v=1}^{\mathbb{V}}[C_{B_t}(v^*) - C_{B_t}(v_n)]}{[(\mathbb{V}_t - 1)^2(\mathbb{V}_t - 2)]}, \tag{10}$$

where $\sum_{v=1}^{\mathbb{V}}[C_{B_t}(v^*) - C_{B_t}(v_n)]$ is the sum of the differences between the largest betweenness centrality of customer v^* and the betweenness centralities of all other customers, divided by $[(\mathbb{V}_t - 1)^2(\mathbb{V}_t - 2)]$, which is the maximum possible value for betweenness centrality in a social network. Table 2 depicts the descriptive statistics and correlations among the variables.

Model Estimation

We computed a set of dynamic panel models that adopt the system generalized method of moments (GMM) to predict spending as a function of the variables capturing the social dynamics of sharing purchase information. Model 1A computes the effects of sharing purchase information on spending over time and Model 2A examines to which degree ego and global network characteristics account for this effect. We reran each of the models with additional controls to test for the robustness of our findings (Model 1B; Model 2B). We also tested the predictive power of our models by using the parameters estimated with data of the first 30 days (i.e., calibration sample) and applied these to the last 30 days (i.e., hold-out sample) of our study period.

Table 2 Descriptive Statistics and Correlations

		Descriptive Statistics				Correlations													
		M	*SD*	*Min*	*Max*	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Spending	.48	5.69	.00	501.94	1.00													
2	Shares	8.87	20.71	.00	397.00	.05	1.00												
3	Expertise	9.17	4.47	1.00	20.00	.08	.12	1.00											
4	Interconnectedness	.15	.21	.00	1.00	.00	−.06	.05	1.00										
5	Number of Peers	8.13	12.11	.00	314.53	.04	.76	.19	−.11	1.00									
6	Closeness Centrality[a]	.13	.04	.00	.25	.00	.21	−.21	−.04	.34	1.00								
7	Betweenness Centrality[b]	8.50	22.31	.00	379.81	.00	.45	.19	−.14	.71	.09	1.00							
8	Tenure	147.12	81.88	7.00	565.00	.02	−.10	.43	.02	−.16	−.37	.04	1.00						
9	Homophily	.77	.42	.00	1.00	.03	.06	.30	.05	.10	−.07	.08	.13	1.00					
10	Promotion	.13	.34	.00	1.00	−.02	−.02	−.00	−.00	−.01	−.00	−.00	−.00	.01	1.00				
11	Transitivity	.06	.00	.06	.07	−.01	−.01	.01	.00	.00	.00	.00	.01	.02	−.02	1.00			
12	Degree Centralization[b]	3,947.58	254.74	3,565.77	4,366.66	−.00	.01	−.01	.01	.01	.01	.00	.02	.03	−.01	.26	1.00		
13	Closeness Centralization[a]	.13	.00	.13	.14	.01	.00	.01	.00	.00	.00	.00	.01	.08	.08	.20	.21	1.00	
14	Betweenness Centralization[b]	8,495.74	848.39	7,651.54	9,874.76	−.00	.01	−.01	.00	.01	.01	.00	.02	.01	−.04	.07	.95	.01	1.00

Note. [a]Multiplied by Factor 1,000; [b]Divided by Factor 1,000

Dynamic Panel Data

Our data has several important characteristics: Spending is a highly endogenous variable as it depends on its own past realizations. Moreover, this variable was skewed since many customers, as in most freemium contexts (Anderson 2009), did not buy any premium features. Spending also depends on the extent to which shared purchase information and characteristics of the ego as well as global network has helped customers to progress in gameplay. Thus, our regressors are not strictly exogenous (e.g., Trusov et al. 2009). We also found evidence for seasonality as spending followed weekly patterns. Finally, our data consisted of many individuals (i.e., 5,068 customers) compared to few time periods (i.e., 30 days in the calibration sample).

We adopted the system GMM approach as proposed by Arellano and Bover (1995) and Blundell and Bond (1998) to resolve endogeneity and autocorrelation concerns in "small T, large N" data structures; this model is also insensitive to variables' distribution (Hansen and West 2002). As discussed next, the system GMM is based on two sets of moments conditions, including the difference GMM (Arellano and Bond 1991) and additional levels models (Arellano and Bover 1995; Blundell and Bond 1998) to improve econometric efficiency.

Difference GMM

In general, GMM can address dynamic panel data by generating sample moments from the data (Hansen 1982) and start with the following baseline model

$$y_{vt} = \theta y_{vt-1} + \boldsymbol{x'_{vt}\beta} + \varepsilon_{vt}, \tag{11}$$

where y_{vt} is the dependent variable of observation v at day t, θ an autoregressive parameter, $\boldsymbol{x'_{vt}\beta}$ a vector of independent variables, and ε_{vt} the error term. The error term has two orthogonal components

$$\varepsilon_{vt} = \mu_v + \delta_{vt} \tag{12.1}$$

$$E(\mu_v) = E(\delta_{vt}) = E(\mu_v \delta_{vt}) = 0, \tag{12.2}$$

where μ_v are the fixed effects and δ_{vt} the observation-specific zero-mean random-error. To resolve concerns that the error term and regressor distributions are correlated, the difference GMM applies first differencing to Eq. (11) to purge the fixed effects, which gives

$$\Delta y_{vt} = \theta \Delta y_{vt-1} + \boldsymbol{\Delta x'_{vt}\beta} + \Delta\delta_{vt}, \tag{13}$$

and then adopts forward orthogonal deviations to create two-period lagged levels as instrumental variables, alleviating simultaneity and dynamic endogeneity (Arellano and Bover 1995; Blundell and Bond 1998), which results in

$$\Delta y_{vt+1} = \theta \Delta y_{vt} + \boldsymbol{\Delta x'_{vt}} \boldsymbol{\beta} + \Delta \delta_{vt+1}. \tag{14}$$

Applying this procedure to Model 1A and Model 1B, we instrument the variables in the first differencing equation using two-period lagged levels (Roodman 2009). To examine the dynamic effects of sharing, we included additional lags of shares. Specifically, we added three- to eight-day lagged levels of sharing behavior, that is, $K = 6$, since spending, as previously noted, heavily followed a weekly pattern. Thus, Model 1A is expressed by

$$\begin{aligned} &\Delta Spending_{vt+1} \\ &= \theta_1 \Delta Spending_{vt} + \beta_1 \Delta Shares_{vt} + \underbrace{\sum_{k=1}^{K} \beta_{1,k} \Delta Shares_{vt-k}}_{Lags\ Sharing:\ K=\{1,...,6\}} + \Delta \delta_{1,vt+1}. \end{aligned} \tag{15}$$

In Model 2A and 2B we also instrument the variables in the first differencing equation using two-period lagged levels (Roodman 2009). To account for the marginally decreasing effect of number of peers, we tested different exponents for the power function. An exponent of $\psi = 0.6$ resulted in the best model fit (Mullen 1985). Model 2A is thus given by

$$\begin{aligned} &\Delta Spending_{vt+1} \\ &= \theta_2 \Delta Spending_{vt} + \beta_2 \Delta Shares_{vt} \\ &+ \underbrace{\beta_{2,1} \Delta Exp_{vt} + \beta_{2,2} \Delta Inter^{w}_{vt} + \beta_{2,3} \Delta Num^{w}_{vt} + \beta_{2,4} \Delta Num^{w^{\psi}}_{vt}}_{Ego\ Network\ Characteristics} \\ &+ \underbrace{\beta_{2,5} \Delta Close^{w}_{vt} + \beta_{2,6} \Delta Bet^{w}_{vt}}_{Global\ Network\ Characteristics} + \beta_{2,7} \Delta Exp_{vt} \times \Delta Inter^{w}_{vt} \\ &+ \beta_{2,8} \Delta Exp_{vt} \times \Delta Num^{w}_{vt} + \beta_{2,9} \Delta Inter^{w}_{vt} \times \Delta Num^{w}_{vt} \\ &+ \beta_{2,10} \Delta Exp_{vt} \times \Delta Num^{w^{\psi}}_{vt} + \beta_{2,11} \Delta Inter^{w}_{vt} \times \Delta Num^{w^{\psi}}_{vt} \\ &+ \beta_{2,12} \Delta Exp_{vt} \times \Delta Close^{w}_{vt} + \beta_{2,13} \Delta Inter^{w}_{vt} \times \Delta Close^{w}_{vt} \\ &+ \beta_{2,14} \Delta Exp_{vt} \times \Delta Bet^{w}_{vt} + \beta_{2,15} \Delta Inter^{w}_{vt} \times \Delta Bet^{w}_{vt} \\ &+ \underbrace{\beta_{2,16} \Delta Exp_{vt} \times \Delta Inter^{w}_{vt} \times \Delta Num^{w}_{vt}}_{Ego\ Network:\ 3-Way\ Linear\ Interaction} + \underbrace{\beta_{2,17} \Delta Exp_{vt} \times \Delta Inter^{w}_{vt} \times \Delta Num^{w^{\psi}}_{vt}}_{Ego\ Network:\ 3-Way\ Power\ Interaction} \\ &+ \underbrace{\beta_{2,18} \Delta Exp_{vt} \times \Delta Inter^{w}_{vt} \times \Delta Close^{w}_{vt} + \beta_{2,19} \Delta Exp_{vt} \times \Delta Inter^{w}_{vt} \times \Delta Bet^{w}_{vt}}_{Ego\ and\ Global\ Network:\ 3-Way\ Linear\ Interaction} \\ &+ \Delta \delta_{2,vt+1}. \end{aligned} \tag{16}$$

Models 1B and 2B also controlled for $\Delta Spending_{vt-1}$, $\Delta Tenure_{vt}$, $\Delta Homophily_{vt}$, $\Delta Promotion_t$, $\Delta Transitivity_t$, $\Delta DegCentral_t$, $\Delta CloseCentral_t$, and $\Delta BetCentral_t$.

System GMM

As lagged levels of the difference GMM may be weak instruments for first differenced variables, especially if they are close to a random walk (Arellano and Bover 1995; Blundell and Bond 1998), and the first differencing of variables may lead to inefficient estimations (Arellano and Bover 1995), we use a system GMM estimator (Arellano and Bover 1995; Blundell and Bond 1998). As previously noted, this estimator augments the difference GMM by simultaneously estimating two sets of moments conditions; that is, using lagged differences as instruments for equations in levels, in addition to applying lagged levels as instruments for equations in first differences. We instrument the variables in the levels equation for all models using their own one-day lagged first difference (Roodman 2009). Models 1A is expressed by

$$\begin{aligned} &Spending_{vt+1} \\ &= \alpha_{1\alpha} + \theta_3 Spending_{vt} + \alpha_1 Shares_{vt} + \underbrace{\sum_{k=1}^{K} \alpha_{1,k} Shares_{vt-k}}_{Lags\ Sharing:\ K=\{1,\ldots,6\}} + \eta_{1v} + \delta_{1,vt+1} \end{aligned} \tag{17}$$

and Model 2A is denoted by

$$\begin{aligned} &Spending_{vt+1} \\ &= \alpha_{2\alpha} + \theta_4 Spending_{vt} + \alpha_2 Shares_{vt} \\ &+ \underbrace{\alpha_{2,1} Exp_{vt} + \alpha_{2,2} Inter^{w}_{vt} + \alpha_{2,3} Num^{w}_{vt} + \alpha_{2,4} Num^{w^{\psi}}_{vt}}_{Ego\ Network\ Characteristics} \\ &+ \underbrace{\alpha_{2,5} Close^{w}_{vt} + \alpha_{2,6} Bet^{w}_{vt}}_{Global\ Network\ Characteristics} + \alpha_{2,7} Exp_{vt} \times Inter^{w}_{vt} \\ &+ \alpha_{2,8} Exp_{vt} \times Num^{w}_{vt} + \alpha_{2,9} Inter^{w}_{vt} \times Num^{w}_{vt} \\ &+ \alpha_{2,10} Exp_{vt} \times Num^{w^{\psi}}_{vt} + \alpha_{2,11} Inter^{w}_{vt} \times Num^{w^{\psi}}_{vt} \\ &+ \alpha_{2,12} Exp_{vt} \times Close^{w}_{vt} + \alpha_{2,13} Inter^{w}_{vt} \times Close^{w}_{vt} \\ &+ \alpha_{2,14} Exp_{vt} \times Bet^{w}_{vt} + \alpha_{2,15} Inter^{w}_{vt} \times Bet^{w}_{vt} \\ &+ \underbrace{\alpha_{2,16} Exp_{vt} \times Inter^{w}_{vt} \times Num^{w}_{vt}}_{Ego\ Network:\ 3-Way\ Linear\ Interaction} + \underbrace{\alpha_{2,17} Exp_{vt} \times Inter^{w}_{vt} \times Num^{w^{\psi}}_{vt}}_{Ego\ Network:\ 3-Way\ Power\ Interaction} \\ &+ \underbrace{\alpha_{2,18} Exp_{vt} \times Inter^{w}_{vt} \times Close^{w}_{vt} + \alpha_{2,19} Exp_{vt} \times Inter^{w}_{vt} \times Bet^{w}_{vt}}_{Ego\ and\ Global\ Network:\ 3-Way\ Linear\ Interaction} \\ &+ \eta_{2v} + \delta_{2,vt+1}, \end{aligned} \tag{18}$$

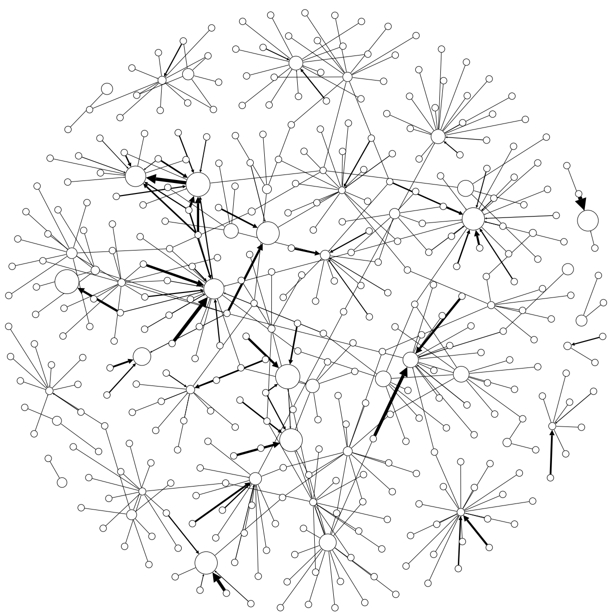
whereas Models 1B and 2B included additional control variables, that is, $Spending_{vt-1}$, $Tenure_{vt}$, $Homophily_{vt}$, $Promotion_t$, $Transitivity_t$, $DegCentral_t$, $CloseCentral_t$, and $BetCentral_t$ as well as weekday ($Weekday_t$; 0 = "Monday" to 6 = "Sunday") and date ($Date_t$) dummies. Applying the system GMM procedure, we simultaneously computed Eq. (15) and (17) together and Eq. (16) and (18). We assessed the instruments' validity using Hansen's (1982) test of over-identifying restrictions. The non-significant J-statistic for all models showed that our specifications are valid (see Tables 3 and 4).

Results

Graphical Exploration

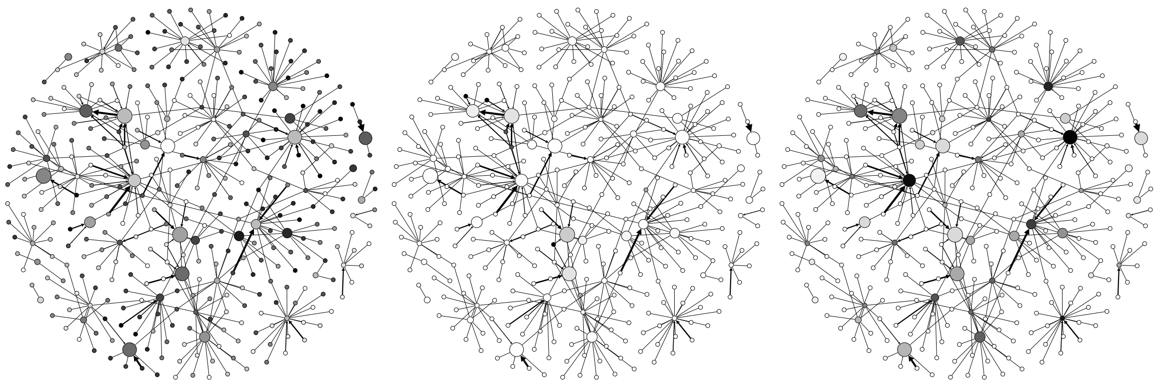
We start by discussing the graphs depicted in Fig. 2 to Fig. 4 that are based on a random sample of 50 customers and show their first differences of spending on day 30 and two-day lagged first differences regarding number of received shares and network characteristics. Nodes are customers (or peers), node size characterizes their spending (large: high amount spent), width of the edges denotes the number of shares that customers received from peers (wide: many shares received), and the shading of a node represents ego and global network characteristics (dark: high value). The pattern in Fig. 2 indicates that customers' spending on premium features tends to be positively associated with the number of shares they received prior to the purchase date, as wider edges are generally connected to larger nodes, providing tentative evidence for H1a.

Fig. 2 Graph showing Effects of Sharing Purchase Information on Spending



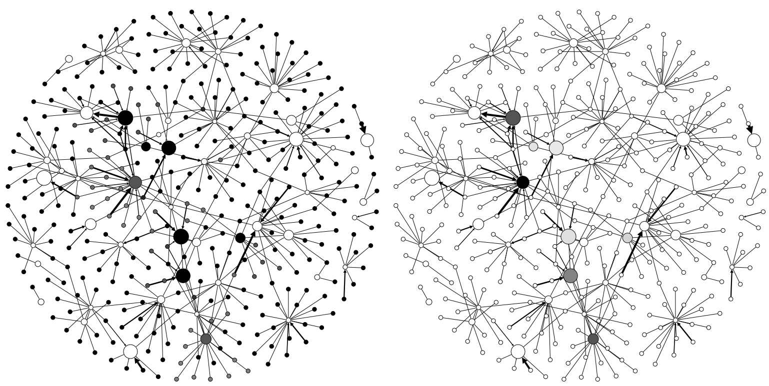
In terms of customers' ego network, Fig. 3 indicates that customers seem to buy more premium features that were shared by highly knowledgeable (H2a; left panel), interconnected (H2b; middle panel), and numerous (H2c; right panel) peers.

Fig. 3 Graphs showing Effects of Expertise *(left panel)*, Interconnectedness *(middle panel)*, and Number of Peers *(right panel)* on Spending



Contrary to our prediction H2d, the left panel of Fig. 4 shows that closeness centrality may not be associated with higher spending, as many of the larger nodes have lighter fillings and many of the smaller nodes have darker fillings. However, the right panel of Fig. 4 illustrates that customers with a high betweenness centrality tend to spend more on premium features in the freemium network, which would support H2e.

Fig. 4 Graphs showing Effects of Closeness Centrality *(left panel)* and Betweenness Centrality *(right panel)* on Spending



While the graphical exploration of the random graph provides preliminary insights into the effects of sharing purchase information as well as (ego and global) network characteristics on spending, we will proceed to the estimation results of Models 1A and 1B and Models 2A and 2B to provide a statistical test for our hypotheses.

Model-Based Results

Table 3 and Table 4 depict our model results (standardized and robust parameter estimates) based on the calibration sample. For all models, the Waldχ^2 statistics are highly significant and the symmetric mean absolute percentage errors considerably low (SMAPE, Goodwin and Lawton 1999; Model 1A: 21.76%; Model 1B: 17.03%; Model 2A: 15.61%; Model 2B: 11.29%), showing that our models fit the calibration data well. We also examined first- and second- order autoregressive statistics as the system GMM assumes that first-order serial correlation is present while second-order serial correlation is not (Arellano and Bond 1991). The results reject AR(1) but fail to reject AR(2), providing further support of the model specifications. Finally, we performed the Harris and Tzavalis (1999) unit-root test to test the null hypothesis that our variables are non-stationary. The presence of unit roots was rejected for all variables, confirming that they are stationary and fulfill the requirements of our chosen estimation approach.

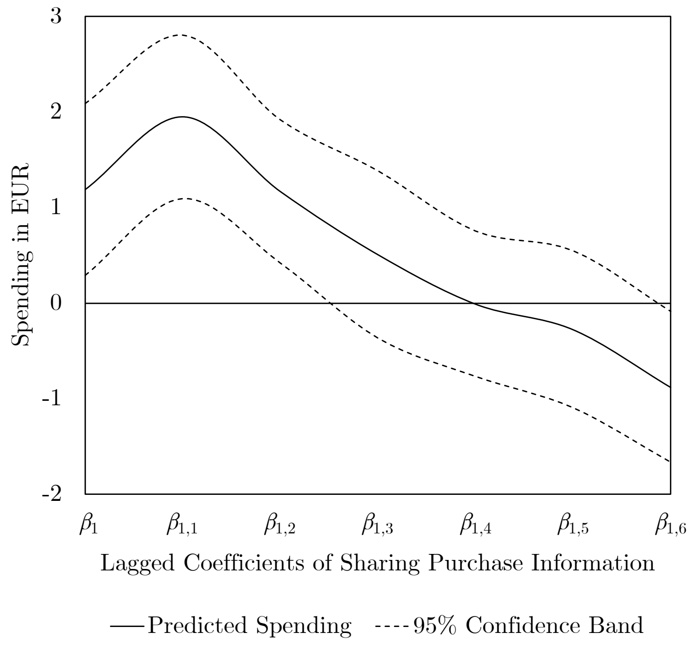
Table 3 Estimation Results of Model 1A and Model 1B

			Spending on Premium Features (Spending_{vt+1})					
			Model 1A			Model 1B		
			β	t	p	β	t	p
Sharing Behavior								
Shares_{vt}	H1a	β_1	$.326^{***}$	4.56	.001	$.425^{***}$	3.84	.001
$\text{Shares}_{vt\text{-}1}$	H1b	$\beta_{1,1}$	$.620^{***}$	9.23	.001	$.798^{***}$	7.08	.001
$\text{Shares}_{vt\text{-}2}$		$\beta_{1,2}$	$.311^{**}$	4.21	.002	$.406^{***}$	3.48	.001
$\text{Shares}_{vt\text{-}3}$		$\beta_{1,3}$	$.150^{*}$	2.19	.029	$.259^{**}$	2.75	.006
$\text{Shares}_{vt\text{-}4}$		$\beta_{1,4}$	−.003	−.29	.775	$-.024^{**}$	−2.60	.009
$\text{Shares}_{vt\text{-}5}$		$\beta_{1,5}$	−.018	−.52	.603	$-.341^{***}$	−3.19	.001
$\text{Shares}_{vt\text{-}6}$		$\beta_{1,6}$	$-.301^{**}$	−3.88	.003	$-.422^{***}$	−3.73	.001
Controls								
$\text{Spending}_{vt\text{-}1}$		$\beta_{1,7}$	$-.248^{***}$	−11.15	.001	$-.207^{***}$	−6.38	.001
Tenure_{vt}		$\beta_{1,8}$				2.916^{**}	2.78	.005
Homophily_{vt}		$\beta_{1,9}$				11.436^{***}	3.73	.001
Promotion_{t}		$\beta_{1,10}$				2.789^{***}	13.83	.001
Transitivity_{t}		$\beta_{1,11}$				.163	1.29	.197
Degree $\text{Centralization}_{t}$		$\beta_{1,12}$				$.767^{*}$	2.21	.027
Closeness $\text{Centralization}_{t}$		$\beta_{1,13}$				.124	.34	.732
Betweenness $\text{Centralization}_{t}$		$\beta_{1,14}$				$-.467^{**}$	−3.03	.002
Weekday_{t}		$\beta_{1,15}$	$.451^{***}$	24.81	.001	.046	1.04	.297
Date_{t}		$\beta_{1,16}$	$-.000^{***}$	−24.50	.001	$-.000^{***}$	−3.87	.001
Model Fit Indexes								
Waldχ^2			395.63			515.22		
AR(1)			−4.13***			−4.37***		
AR(2)			1.22			1.28		
Hansen's overidentification test (J-test)			$p > .17$			$p > .13$		

Note. $^*p < .050$; $^{**}p < .010$; $^{***}p < .001$; Standardized and Robust Parameter Estimates; $N = 152{,}040$

Sharing Purchase Information. Model 1A tested as to whether sharing purchase information has a positive, yet decreasing influence on spending over time. We found that the number of shares increased spending on premium features (β_1 = .326, t = 4.56, p < .001), supporting H1a. An examination of the lagged coefficients revealed that $Shares_{vt-1}$ had the strongest effect on spending ($\beta_{1,1}$ = .620, t = 9.23, p < .001), whereas the effect then decayed quickly (e.g., $\beta_{1,6}$ = −.301, t = −3.88, p < .003), confirming H1b. Fig. 5 depicts the unstandardized dynamic effects of sharing purchase information on spending. Specifically, if customers received a single share one day prior to the purchase date, they spent EUR 1.19, while they spent up to EUR 1.95 if they received a single share two days prior to the purchase date. However, this effect declined for day three (M = EUR 1.17) and more lagged differences, demonstrating the only-temporary nature of sharing.

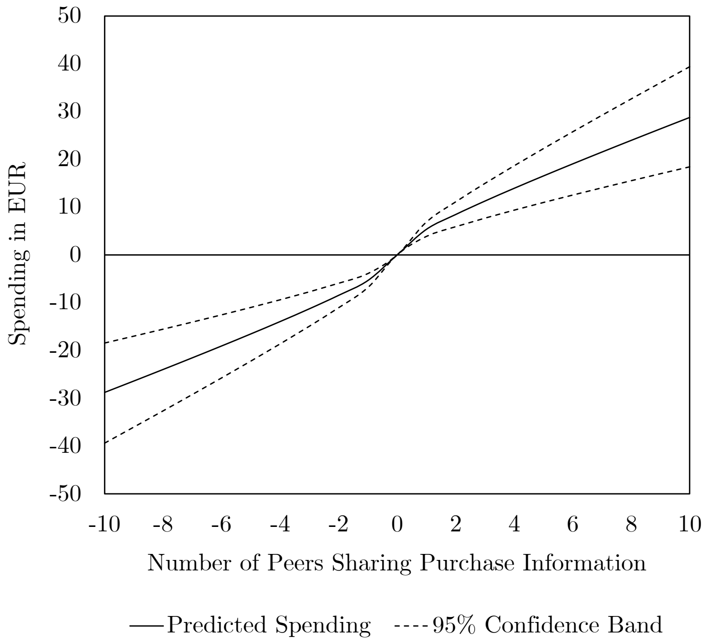
Fig. 5 Dynamic Effects of Sharing Purchase Information on Spending



Ego and Global Network Characteristics. We computed Model 2A to examine how the social characteristics of customers' ego and global network account for the effect of sharing purchase information on spending. As expected, the effect of number of shares on spending dropped to non-significance ($\beta_2 = .351$, $t = 1.46$, $p > .14$) when controlling for ego and global network characteristics. Furthermore, we found that expertise ($\beta_{2,1}$ = 4.683, t = 6.89, p < .001) and interconnectedness ($\beta_{2,2}$ = 5.199, t = 7.15, p < .001) increased spending, showing that customers purchased more when information was shared by more knowledgeable and interconnected peers, confirming H2a und H2b.

The results showed that number of peers had a positive ($\beta_{2,3} = 3.318$, $t = 2.33$, $p <$ .029), yet marginally decreasing ($\beta_{2,4} = 6.080$, $t = 3.38$, $p < .001$) effect on spending (due to the power coefficient ψ in $Num_{vt}^{w^{\psi}}$), supporting H2c. For illustration purposes, we computed the unstandardized marginal means of spending for different numbers of peers that shared purchase information (Fig. 6). The slope shows that the effect of the first peer sharing information had the largest impact on spending (M = EUR 5.29), whereas receiving shares from additional peers was increasingly less effective.

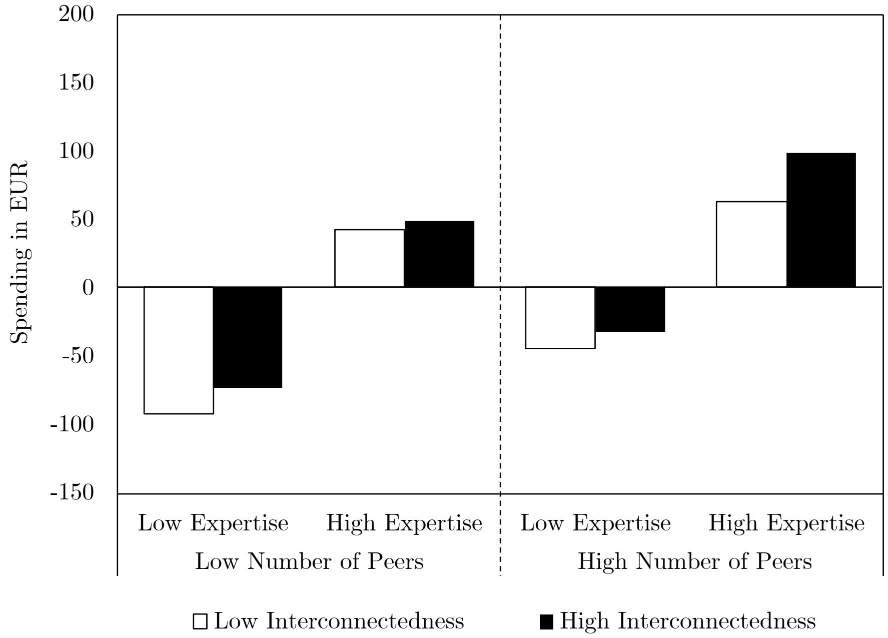
Fig. 6 Marginal Effect of Number of Peers Sharing Purchase Information on Spending



Contrary to our prediction, we did not find a significant effect of closeness centrality on spending ($\beta_{2,5} = -.203$, $t = -.77$, $p > .44$), which corresponds to the results of our graphical exploration depicted in Fig. 4. However, betweenness centrality positively affected spending on premium features ($\beta_{2,6} = 11.439$, $t = 10.07$, $p < .001$). In other words, customers spent more on premium features when they bridged the dissemination of purchase information in the network, but not when they had a more efficient access to purchase information in the network. The results reject H2d and confirm H2e.

Consistent with the premise of SIT (Latané 1981), we found a positive ($\beta_{2,16}$ = 18.017, $t = 3.21$, $p < .001$), yet marginally decreasing ($\beta_{2,17} = 16.402$, $t = 3.43$, p $< .001$), three-way interaction between expertise, interconnectedness, and number of peers on customers' spending on premium features (again due to ψ in $Num_{vt}^{w^{\psi}}$). We predicted the unstandardized values at plus and minus two standard deviations of the predictors, resulting in eight configurations of customers' ego network characteristics. As Fig. 7 depicts, the interaction between high expertise and interconnectedness was stronger when the number of peers was high ($M_{HighExp\ \times\ HighInter\ \times\ HighNum}$ = EUR 98.77) than when it was low ($M_{HighExp\ \times\ HighInter \times\ LowNum}$ = EUR 48.99; $t = -2.74$, $p < .006$). Besides, we found that for customers who received shares from a high number of peers, high expertise and interconnectedness significantly increased spending ($M_{LowExp\ \times\ LowInter\ \times\ HighNum}$ = EUR −44.73, $M_{LowExp\ \times\ HighInter\ \times\ HighNum}$ = EUR −32.28, $M_{HighExp\ \times\ LowInter\ \times\ HighNum}$ = EUR 63.12; ps < .005). This suggests that the number of peers sharing purchase information facilitates the influence of expertise and interconnectedness on spending, supporting H3a.

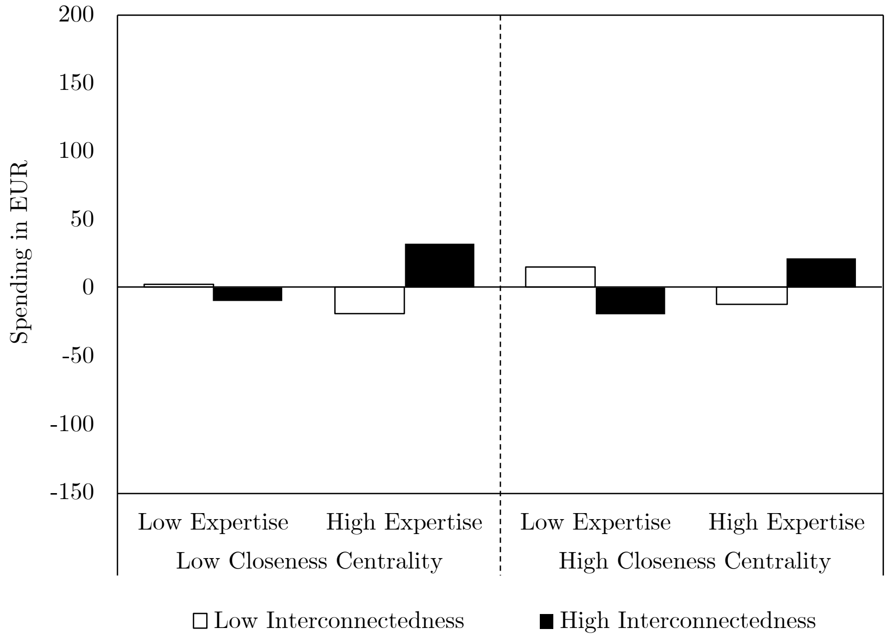
Fig. 7 Effects of the Three-Way Interaction between Expertise, Interconnectedness, and Number of Peers on Spending



Contrary to our prediction, we found that the three-way interaction between expertise, interconnectedness, and closeness centrality was not significant ($\beta_{2,18} = .194$, $t = .54$, $p > .59$). Again we used unstandardized predictions to clarify the nature of this interaction, with results showing that high expertise and interconnectedness had a greater effect on spending when closeness centrality was low ($M_{HighExp\ \times\ HighInter\ \times\ LowClose}$ = EUR 32.30) than when closeness centrality was high ($M_{HighExp\ \times\ HighInter\ \times\ HighClose}$ = EUR 21.73; $t = -3.04$, $p < .002$; Fig. 8). Specifically, for customers with a low closeness centrality, high expertise and interconnectedness significantly increased spending ($M_{LowExp\ \times\ LowInter\ \times\ LowClose}$ = EUR 1.99, $M_{LowExp\ \times\ HighInter\ \times\ LowClose}$ = EUR

-9.69, $M_{HighExp \times LowInter \times LowClose}$ = EUR -18.76; ps $< .001$). These results underscore that customers' closeness centrality does not facilitate the influence of expertise and interconnectedness on spending on premium features, rejecting H3b.

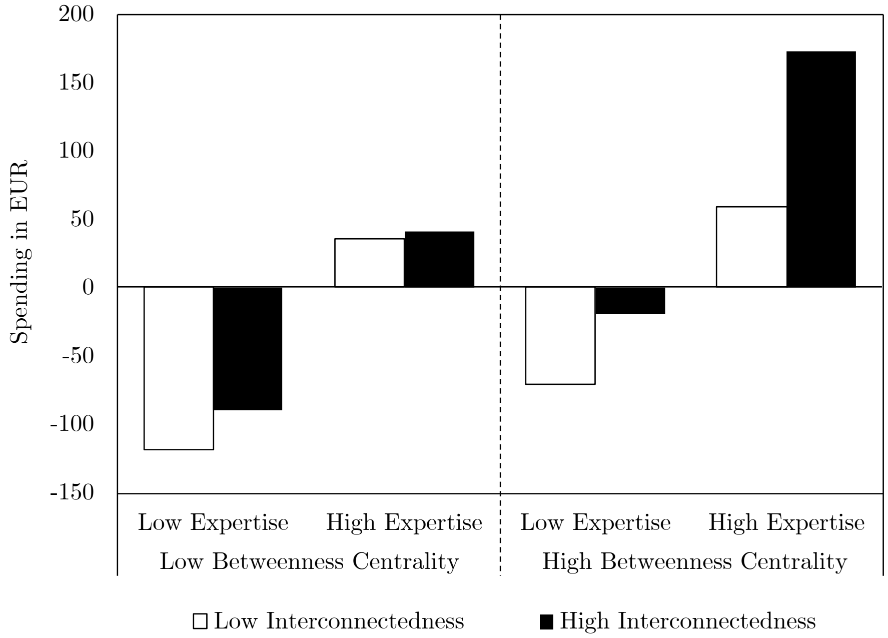
Fig. 8 Effects of the Three-Way Interaction between Expertise, Interconnectedness, and Closeness Centrality on Spending



However, we found a positive three-way interaction between expertise, interconnectedness, and betweenness centrality ($\beta_{2,19} = 20.149$, $t = 5.05$, $p < .001$). Again, unstandardized predictions showed that the interaction between high expertise and interconnectedness had a particularly marked impact when betweenness centrality was high ($M_{HighExp \times HighInter \times HighBet}$ = EUR 173.24) compared to when it was low ($M_{HighExp \times HighInter \times LowBet}$ = EUR 41.37, $t = -8.71$, $p < .001$; Fig. 9). For customers with high betweenness centrality, high expertise and interconnectedness had the greatest impact on spending on premium features ($M_{LowExp \times LowInter \times HighBet}$ = EUR -70.69, $M_{LowExp \times HighInter \times HighBet}$ = EUR -19.17, $M_{HighExp \times LowInter \times HighBet}$ = EUR 58.90; ps $< .001$). The results suggest that betweenness centrality intensifies the positive effects of expertise and interconnectedness on customers' spending on premium features, confirming H3c.

Our results broadly support our hypotheses on the social dynamics of sharing purchase information. While (recently) shared purchase information increased spending (H1a, H1b), we also found that not only information shared by knowledgeable, interconnected, and numerous peers had a positive effect (H2a-H2c, H3a) but also when customers themselves operated as brokers in the network (H2e, H3c). Contrary to our predictions, we found that closeness centrality did not foster spending (H2d, H3b).

Fig. 9 Effects of the Three-Way Interaction between Expertise, Interconnectedness, and Betweenness Centrality on Spending



Validation Analyses and Forecasting. To validate the results of Model 1A and 2A, we included additional control variables (Model 1B and 2B), yet the coefficients remained robust in both significance and direction (Tables 3 and 4). We further validated our findings by computing (1) alternative time windows for the calibration sample (one and two weeks after the start of the study period), (2) different weighting factors for the centrality measures, (3) different exponents for number of peers, and (4) non-linear panel data models that assume more heavily skewed distribution (i.e., poisson). In general, none of the alternative model specifications affected the reported conclusions, indicating that our results are robust.

Finally, we used Models 1B and 2B to forecast customers' average daily spending for the hold-out sample; Fig. 10 depicts the (unstandardized) predicted and actual spending (left panel for Model 1B; right panel for Model 2B). The small deviations indicated that our models were highly accurate in predicting spending. Specifically, customers actually spent EUR .42 per day, and EUR 25.24 over the complete study period. Model 1B slightly underestimated actual spending (daily: EUR .42, cumulative: EUR 25.17), while Model 2B slightly overestimated spending (daily: EUR .43, cumulative: EUR 25.66), with low SMAPEs (Models 1B: 22.13%; Model 2B: 13.01%)

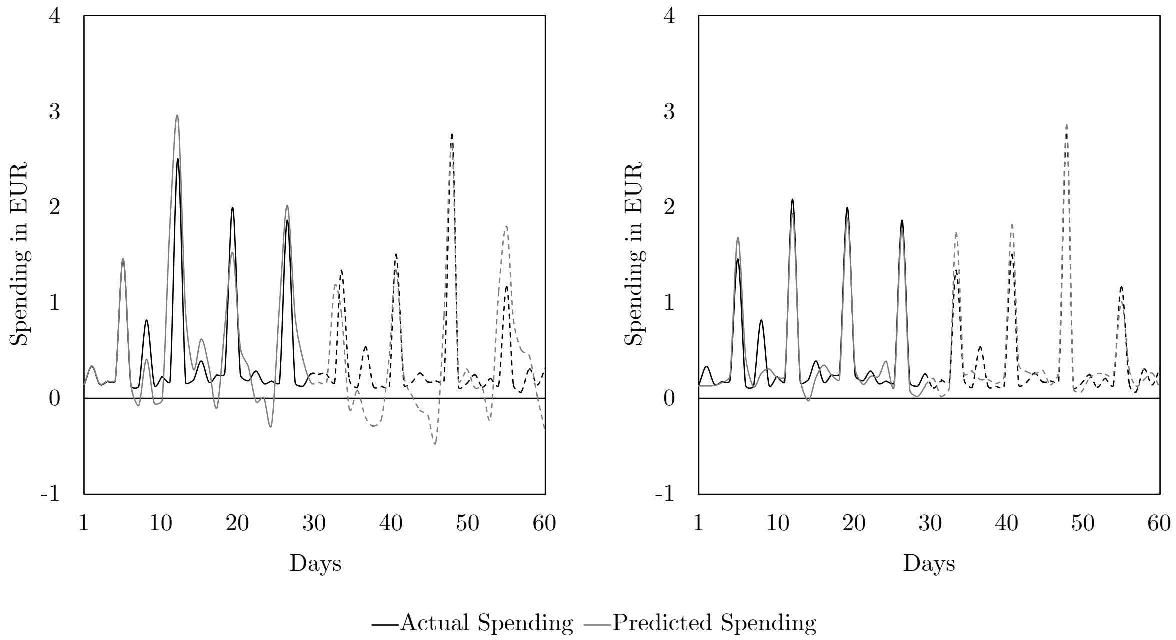
supporting the models' accuracies. Considering a customers' ego as well as global network characteristics, thus, increased the predictive accuracy by 9.12 percentage points.

Table 4 Estimation Results of Model 2A and Model 2B

			Spending on Premium Features ($Spending_{vt+1}$)					
			Model 2A			Model 2B		
			β	t	p	β	t	p
Sharing Behavior								
$Shares_{vt}$		β_2	.351	1.46	.144	.251	1.61	.117
Ego and Global Network Characteristics								
$Expertise_{vt}$	H2a	$\beta_{2,1}$	4.683***	6.89	.001	5.029***	5.40	.001
$Interconnect^{w}_{vt}$	H2b	$\beta_{2,2}$	5.199***	7.15	.001	3.947***	3.44	.001
$Number^{w}_{vt}$	H2c	$\beta_{2,3}$	3.318*	2.33	.029	5.768**	2.43	.015
$Number^{w\psi}_{vt}$		$\beta_{2,4}$	6.080***	3.38	.001	9.344***	3.88	.001
$Closeness^{w}_{vt}$	H2d	$\beta_{2,5}$	−.203	−.77	.443	−.449	−.83	.407
$Betweenness^{w}_{vt}$	H2e	$\beta_{2,6}$	11.439***	10.07	.001	11.033***	6.58	.001
Two-Way Interactions								
$Expertise_{vt} \times Interconnect^{w}_{vt}$		$\beta_{2,7}$	8.694***	5.44	.001	9.499***	4.51	.001
$Expertise_{vt} \times Number^{w}_{vt}$		$\beta_{2,8}$	7.572	1.66	.098	2.569	.47	.637
$Interconnect^{w}_{vt} \times Number^{w}_{vt}$		$\beta_{2,9}$	3.231	1.26	.209	2.391	.75	.452
$Expertise_{vt} \times Number^{w\psi}_{vt}$		$\beta_{2,10}$	6.799	1.56	.118	1.422	.27	.784
$Interconnect^{w}_{vt} \times Number^{w\psi}_{vt}$		$\beta_{2,11}$	1.443	.62	.537	1.151	.41	.683
$Expertise_{vt} \times Closeness^{w}_{vt}$		$\beta_{2,12}$	−.472	−1.54	.123	.181	.48	.629
$Interconnect^{w}_{vt} \times Closeness^{w}_{vt}$		$\beta_{2,13}$	−2.614***	−3.84	.001	−3.261***	−3.71	.001
$Expertise_{vt} \times Betweenness^{w}_{vt}$		$\beta_{2,14}$	13.271***	5.72	.001	15.355***	4.90	.001
$Interconnect^{w}_{vt} \times Betweenness^{w}_{vt}$		$\beta_{2,15}$	18.170***	8.65	.001	15.826***	4.72	.001
Three-Way Interactions								
$Expertise_{vt} \times Interconnect^{w}_{vt} \times Number^{w}_{vt}$	H3a	$\beta_{2,16}$	18.017***	3.21	.001	16.538*	2.51	.012
$Expertise_{vt} \times Interconnect^{w}_{vt} \times Number^{w\psi}_{vt}$		$\beta_{2,17}$	16.402***	3.43	.001	15.089**	2.70	.007
$Expertise_{vt} \times Interconnect^{w}_{vt} \times Closeness^{w}_{vt}$	H3b	$\beta_{2,18}$	.194	.54	.588	1.263**	2.67	.008
$Expertise_{vt} \times Interconnect^{w}_{vt} \times Betweenness^{w}_{vt}$	H3c	$\beta_{2,19}$	20.149***	5.05	.001	23.931***	4.40	.001
Controls								
$Spending_{vt-1}$		$\beta_{2,20}$	−.343***	−13.17	.001	−.341***	−10.91	.001
$Tenure_{vt}$		$\beta_{2,21}$				−.093	−.11	.913
$Homophily_{vt}$		$\beta_{2,22}$				1.668	1.61	.106
$Promotion_{t}$		$\beta_{2,23}$				1.417***	8.67	.001
$Transitivity_{t}$		$\beta_{2,24}$				.318*	2.49	.013
Degree $Centralization_{t}$		$\beta_{2,25}$				−.452	−1.14	.254
Closeness $Centralization_{t}$		$\beta_{2,26}$				.705***	3.61	.001
Betweenness $Centralization_{t}$		$\beta_{2,27}$				−.693***	−4.00	.001
$Weekday_{t}$		$\beta_{2,28}$	.115***	8.74	.001	.061	1.61	.107
$Date_{t}$		$\beta_{2,29}$	−.000***	−8.04	.001	−.000***	−4.15	.001
Model Fit Indexes								
Waldχ^2			1247.22			1602.13		
AR(1)			−3.83***			−4.15***		
AR(2)			1.16			1.18		
Hansen's overidentification test (J-test)			$p > .14$			$p > .11$		

Note. *$p < .050$; **$p < .010$; ***$p < .001$; Standardized and Robust Parameter Estimates; $N = 152{,}040$

Fig. 10 Forecasts based on Sharing Purchase Information *(left panel)* and Social Characteristics of Ego and Global Network *(right panel)*



General Discussion

The current article draws from research on SIT (Latané 1981) and social networks (e.g., Freeman 1978) to examine whether and how sharing of purchase information in freemium networks increases customers' spending on premium features—a novel phenomenon that we term contagious consumption. Using field data from a large-scale freemium network, we found that sharing information about a purchase has a positive, yet quickly declining effect on spending on premium features over time. Furthermore, our results showed that social characteristics of customers' ego and global network account for this relationship, namely, spending is not only facilitated when purchase information is shared by knowledgeable, interconnected, and numerous peers, but also when customers have a high betweenness centrality in the global network. This article makes two substantial contributions to marketing research and practice.

Theoretical Implications

First, we contribute to literature on the effects of social interactions on spending in social networks. Prior research has primarily examined whether explicit recommendations, such as reviews, ratings (e.g., Chevalier and Mayzlin 2006; Moe and Trusov 2011), or referrals (e.g., Trusov et al. 2009) affect spending decisions. Less attention has been dedicated to merely sharing purchase information, which refers to the dissemination of information about a purchase without providing an explicit recommendation. Following recent work on sharing information (Aral and Nicolaides 2017), our key hypothesis is that sharing information about a purchase is contagious, namely, that customers spend more on features in freemium networks that their peers purchased and shared with them. Our findings not only indicate that sharing positively affects spending on premium features, but also the underlying temporal dynamics (i.e., the effect decays after two days), which aligns with prior work on related phenomena (e.g., Ding et al. 2016; Duan et al. 2008).

Second, our contribution to SIT (Latané 1981) is two-fold, advancing the current understanding of social mechanisms underlying peer influence. On the one hand, we provide empirical evidence on the theory's so far unproven key assertion (Latané 1981; multiplicative effect between the dimensions of social impact), showing that customers spend more on premium features that are purchased and shared by knowledgeable (i.e., source strength), interconnected (i.e., spatial proximity), and numerous (i.e., number of sources) peers. In so doing, we advance prior work that has examined one- or two-dimensional models only (Daunt and Greer 2015; Ding et al. 2016; Hui et al. 2009; Zhang et al. 2014) and corroborate prior findings on the decaying effect of number of peers (the first peer sharing purchase information has the largest impact) on purchase decisions (Argo et al. 2005).

On the other hand, our results also advance SIT by integrating a social network perspective. While SIT has traditionally been used to explain peer influence in offline contexts, we extend the theory's area of application by using measures originating from online contexts, such as badges, clustering coefficient, and in-degree centrality, to model the multiplicative effects in freemium networks. This approach provides us with the opportunity to address the hypotheses of SIT in a network setting that is particularly relevant nowadays. Notably, this approach also allows us to reveal interdependencies between the social characteristics of customers' ego and global network. In particular, customers who operate as active brokers of information (i.e., high betweenness centrality) spend even more on premium features than customers who receive information from more peers. Thus, sharing purchase information is more contagious for customers who have more controlled access to dispersed information between different parts of the global network than being exposed to more contacts from their local network. Despite acknowledging each of these factors' importance (Iyengar et al. 2011, 2015; Katona et al. 2011), prior work did not examine their interaction. Contrary to our predictions, the interaction between expertise, interconnectedness, and closeness centrality had no effect on spending, alluding to the idea that the quantity and brokerage of shared purchase information are more contagious than the efficiency of access.

Taken together, this article sheds light on the intersection between social psychology, which has largely been dominated by theoretical concepts, and social networks, which—by means of its empirical focus—can advance our understanding of social phenomena in today's increasingly connected digital sphere.

Managerial Implications

This article has several implications for marketing practitioners, especially for those that have struggled or even failed to capitalize on freemium networks (Enders et al. 2008; Kumar 2014). Since up to 95% of customers do not buy premium features (Anderson 2009), revealing factors that promote spending is paramount for the success of firms that operate freemium networks. Our results show whether and how firms can harness the dynamics of sharing product information to facilitate customers' spending and boost the profitability of freemium networks.

Dynamics of Sharing Purchase Information. Our findings indicate that sharing information about a purchase increases customers' spending on premium features. Thus, firms running freemium models should implement services that allow their customers to share purchase information with other customers in the same network. Best practices are the online music provider Spotify, that enables customers to share the songs they purchased with other members or the online game Farmville that allows players to share in-game purchases with other players via Facebook. While we believe that the positive effects of sharing purchase information are also applicable to non-freemium contexts, such as online retailers like Amazon or eBay, our results also reveal that the phenomenon of sharing is transient in nature. Thus, firms should also consider making shares from peers even more visible to customers, for instance, by triggering an automated email notification when a peer shared a purchase with them. Moreover, firms should follow up on customers who did not purchase a premium feature that has been previously shared with them, for example, by sending out reminders and eventually asking about the reasons why a shared feature had not been bought. By this means, the temporally decaying effects of sharing purchase information may be toned down, resulting in more sustainable profits.

Ego and Global Network Characteristics. We also show that the magnitude to which sharing purchase information affects spending is determined by interdependencies between the social characteristics of customers' ego as well as global network. These findings highlight several strategies that firms can employ to render sharing behavior and make their community management more effective. First, we show that peers' expertise is positively associated with spending on premium features. In the MMOG, peers' expertise was assessed by badges they received over the course of gameplay. While "badgification" is a popular way to manifest peers' knowledge and achievement (e.g., Huffington Post Social News Community), we believe that the same logic also applies to other common instruments, such as ranking systems (e.g., Quora Knowledge Community) or different kinds of memberships (e.g., LinkedIn Career Portal). Moreover, we show that customers' interconnectedness with their peers is an important factor that drives spending. Firms should consider making shares among members of the same cluster even more visible. For example, when customers receive shares on premium features, firms could indicate which other peers have purchased this product to facilitate the formation of denser connections among customers and their peers. Third, according to our results, popularity and brokerage strongly facilitate the impact of sharing purchase information. While firms can use these insights to improve targeting and product offers, they could also incentivize peers to share their purchase information, boosting overall contagion in the network.

Limitations and Future Research

Our research also has some limitations that provoke further thought. First, our study was conducted in collaboration with a MMOG. While online games are suitable research context to examine social dynamics within freemium networks (Vock et al. 2013), the applicability of our results should be replicated in other freemium contexts, such as news or career networks. Second, spending is a highly endogenous variable. While we addressed endogeneity by our modeling approach (i.e., system GMM), customers might inherently be more or less responsive to shares from their peers. One way to address this data issue are randomized field experiments to examine whether the positive effects of sharing could be actively influenced, e.g., showing vs. not showing the expertise of a peer who shares information. Finally, we did not have any additional information on the premium features, for instance including how well other peers in the freemium social network rated them (Liu et al. 2014). Thus, future research could examine how the premium features' additional characteristics, such as their popularity and proliferation in a network, affect spending decisions. We hope that this article provides meaningful insights on the social dynamics of sharing purchase information on spending, guiding future research endeavors above and beyond the freemium contexts.

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Article 3

Increasing the Odds of Survival: How Peer Influence and Reward Programs affect Customer Churn in Social Networks

Submitted to
Journal of Interactive Marketing

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Abstract Customer churn is a severe threat for firms operating online social networks. While prior research highlighted the role of peer influence for examining churn in social networks, little is known about the underlying network effects accounting for this relationship and how firms can proactively prevent churn resulting from peer influence. Combining research on self-determination theory and social networks, I examine to which degree network effects on an individual and group level affect churn and how different types of reward programs can be used to manage churn. Based on longitudinal field data from a large-scale social network, my results indicate that exposure toward already defected peers has a positive influence on churn, whereas interconnectedness with remaining peers has a negative influence on churn. Furthermore, I show that gamified rewards (i.e., "earning" a reward) as opposed to monetary rewards (i.e., merely receiving a reward) decrease customer churn and moderate the effects of peer influence. Specifically, gamified rewards attenuate the positive influence of exposure and facilitate the negative influence of interconnectedness on churn. These findings contribute to our current understanding of customer churn in social networks and provide practitioners with implications on how to increase social networks' odds of survival.

Keywords Churn · Social Networks · Exposure · Interconnectedness · Gamified Rewards · Monetary Rewards · Hazard Models · Managerial Simulation

Introduction

Customer churn, broadly defined as the loss of a customer (Ascarza et al. 2016) is a severe threat for firms' long-term profitability (Braun and Schweidel 2011; Datta et al. 2015; Rust et al. 2004). This is especially true for firms selling their products via online social networks that largely depend on an active and healthy community (Karnstedt et al. 2010). Specifically, recent studies found that more than 40% of customers use social networks because they want to connect with other peers (McGrath 2017) and that customers use social networks more frequently, when the presence of other peers increases (Mäntymäki and Riemer 2014). As a result, peers tend to have a significant impact on customer' decision to churn (Karnstedt et al. 2010), ultimately affecting social networks' odds of survival.

A growing body of research has examined to which degree peer influence may affect customer churn in social networks, with studies showing that customers' increasing exposure toward already defected peers facilitates churn (Backiel et al. 2016; Haenlein 2013; Nitzan and Libai 2011). Unlike peer influence arising from single and already defected peers, research lacks evidence as to whether customer churn is also affected by groups of multiple peers that still remain in a network. While first studies showed that customers' embeddedness into a social network decreases churn (Benedek et al. 2014; Richter et al. 2010), it remains unclear which specific network effects account for this type of peer influence on a group level. Furthermore, initial evidence is suggestive that loyal customers may be less susceptible to peer influence and, hence, have a lower hazard to churn (Nitzan and Libai 2011). To this end, many firms incentivize customer loyalty by using reward programs (Ascarza et al. 2016). While traditional programs primarily focused on monetary rewards (e.g., price discounts; Bolton et al. 2000), firms have recently begun to use gamified rewards to increase retention (Hamari and Lehdonvirta 2010; Huotari and Hamari 2011); that is, game elements (e.g., points, badges) incentivizing customers' mastery or achievement of a goal. Although prior research showed that games can strengthen customer-firm relationships (Berger et al. 2017), there is a dearth in literature whether gamified rewards also diminish customer churn, especially when it is induced by peer influence.

Drawing from research on self-determination theory (SDT; e.g., Deci 1975; Deci and Ryan 1985; Ryan 1982) and social networks (e.g., Coleman 1988; Freeman 1978), I propose that peer influence (i.e., relatedness), that is, customers' exposure toward already defected peers and interconnectedness with remaining peers affect churn. I also conjecture that gamified (i.e., competence-autonomy supportive) as opposed to monetary (i.e., competence-autonomy suppressive) rewards decrease customer churn and moderate the effects of peer influence. Specifically, gamified rewards should attenuate the positive effect of exposure and facilitate the negative effect of interconnectedness on churn, while the opposite may apply for monetary rewards. Based on longitudinal field data from a large-scale social network, I estimate a set of parametric proportional hazard models to test my theorizing. Moreover, I run managerial simulations to predict the financial impact of churn in consideration of different reward interventions.

This article makes three contributions to our understanding of customer churn in social networks: First, my findings show that network effects on an individual (i.e., exposure) and group (i.e., interconnectedness) level affect churn, thereby advancing prior studies that have either been limited to peer influence induced by single defectors (Backiel et al. 2016; Haenlein 2013; Nitzan and Libai 2011) or lacked evidence which network effects account for the positive influence of customers' social embeddedness on customer retention (Benedek et al. 2014; Richter et al. 2010). Second, contrary to public sentiment (e.g., Bolton et al. 2000; Lewis 2004; Verhoef 2003; Zhang and Breugelmans 2012) my findings suggest that reward programs are not always effective means for decreasing churn, but rather depend on whether they support or suppress customers' perception of competence and autonomy. Specifically, I find that gamified rewards (i.e., "earning" a reward) decrease, whereas monetary rewards (i.e., merely receiving a reward) increase customers' likelihood to defect from a social network. Finally, my results show that gamified as opposed to monetary rewards attenuate the positive effect of exposure and facilitate the negative effect of interconnectedness on customer churn. Extending prior research that found customer loyalty to diminish the negative effects of peer influence on retention (Nitzan and Libai 2011), my results show that firms can proactively prevent churn by using gamified reward interventions.

Next, I will review prior research on customer churn in social networks, before I detail my conceptual model and research hypotheses. Then, I will present the results of a field study to conclude with implications for marketing research and practice.

Churn in Social Networks

Customer churn is closely connected to a firm's bottom line (Reinartz and Kumar 2003; Rust and Chung 2006), with studies showing that churn decreases customer lifetime value (Braun and Schweidel 2011; Datta et al. 2015) and customer equity (Rust et al. 2004), ultimately threatening firms' long-term profitability (Ascarza et al. 2016). As a result, marketers are increasingly interested in both, revealing drivers of customer churn and assessing marketing instruments that can be used to prevent customers from defecting (Jamal and Bucklin 2006).

Much of prior research has examined the effects of firm- and customer-related factors on customer churn; for example, prior studies found that churn is not only triggered by firms' price increases (Dawes 2009), service failures, or their inadequate recovery (Jamal and Bucklin 2006), but also by customers' decreasing satisfaction (Bolton and Lemon 1999; Gustafsson et al. 2005), product usage, and purchase frequency (Chen and Hitt 2002; Verhoef 2003). Besides firm- and customer-related factors, Table 1 depicts that an increasing number of studies have examined how peer influence affects customer churn, that is, by customers' social interactions with other peers in a social network (Ma et al. 2014). Prior research found that customers are more likely to churn from social networks, when they have been exposed to an increasing number of already defected peers (Backiel et al. 2016; Haenlein 2013; Nitzan and Libai 2011). Unlike peer influence resulting from single and already defected peers, research lacks evidence as to whether customer churn may also be affected by groups of multiple peers that still remain in a network. While initial work is suggestive that customers are less likely to churn when they are strongly embedded into a social network (Benedek et al. 2014; Richter et al. 2010), it remains unclear which network effects on a group level reduce customer churn.

Furthermore, there is consensus that loyalty programs are effective means for firms to increase customer retention (e.g., Bolton et al. 2000; Lewis 2004; Verhoef 2003; Zhang and Breugelmans 2012). However, recent studies showed that loyalty programs may also lead to decreasing retention rates (Ascarza et al. 2016; Kim and Ahn 2017), raising the question which dimensions make loyalty programs more or less effective in preventing churn. Generally, loyalty programs incentivize the loyalty of customers with either price discounts or enhanced services (Bolton et al. 2000). While traditional loyalty programs are rather based on monetary rewards, marketers have recently become interested in using gamified rewards (Huotari and Hamari 2012), namely game elements (e.g., points, badges) that incentivize customers' mastery or achievement of a goal, to ensure customer retention (Hamari 2013). Prior studies suggest that gamified rewards may also reduce churn, with studies showing that games may increase customers' participation in online communities (Hamari 2013) and strengthen their relationships with a firm (Berger et al. 2017). However, as depicted in Table 1, it remains unclear whether firms can employ gamified rewards to diminish customer churn, which is particularly true for churn that is induced by peer influence.

Table 1 Relevant Literature on Churn in Social Networks

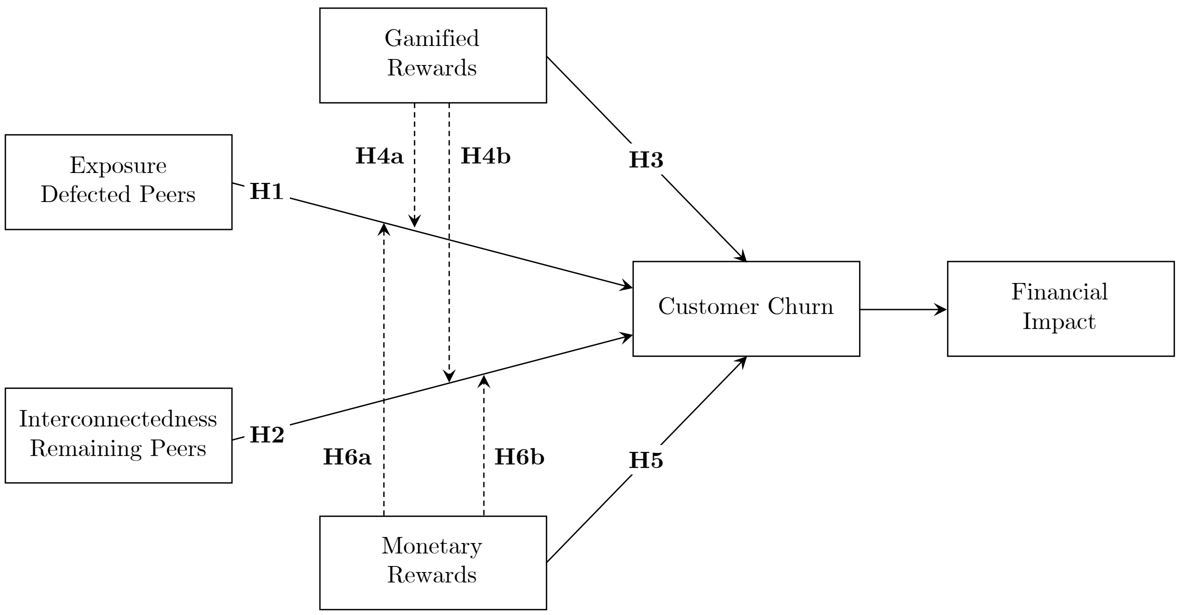
Reference	Individual Level Peer Influence	Group Level Peer Influence	Customer Churn	Financial Impact	Moderators	Estimation Approach	Key Findings
Defected Peers							
Backiel et al. (2016)	Exposure toward Defected Peers		Inactivity	✓		Cox Proportional Hazard Model	Exposure toward defected peers increases churn.
Haenlein (2013)	Exposure toward Defected Peers		Termination of Contract			Cox Proportional Hazard Model	Exposure toward defected peers increases churn.
Nitzan and Libai (2011)	Exposure toward Defected Peers		Announcement or Inactivity		Customer Loyalty	Cox Proportional Hazard Model	Exposure toward defected peers increases churn; customer loyalty attenuates the positive influence of exposure on churn.
Remaining Peers							
Benedek et al. (2014)		Embeddedness	Inactivity			Proportion z-tests	Embeddedness into a social network decreases churn.
Richter et al. (2010)		Social Subgroup	Termination of Contract			Decision Tree	Group size decreases churn.
Defected and Remaining Peers							
Current Research	Exposure toward Defected Peers	Interconnectedness with Peers	Termination of Account	✓	Reward Programs	Parametric Proportional Hazard Model	Exposure toward defected peers increases and interconnectedness with remaining peers decreases churn; gamified rewards attenuate the positive influence of exposure and facilitate the negative influence of interconnectedness on churn.

Addressing these gaps in research, I examine whether customer churn in social networks is influenced by individual level effects of already defected peers (i.e., exposure) and group level effects of remaining peers (i.e., interconnectedness). I also test to which degree firms can benefit from employing gamified as opposed to monetary rewards to reduce customer churn originating from peer influence. Next, I will outline my conceptual model and research hypotheses.

Conceptual Model

Combining research on SDT (e.g., Deci 1975; Deci and Ryan 1985; Ryan 1982) and social networks (e.g., Coleman 1988; Freeman 1978), I propose that customers' exposure toward already defected peers increases churn, whereas their interconnectedness with remaining peers decreases their hazard to churn from a social network. Additionally, I presume that gamified rewards attenuate the positive effect of exposure toward already defected peers and facilitate the negative effect of interconnectedness with remaining peers on customer churn, whereas the opposite should apply to monetary rewards. An overview of the conceptual model and research hypotheses is depicted in Fig. 1.

Fig. 1 Conceptual Model and Research Hypotheses



Motivation and Churn

SDT (Deci and Ryan 1985) examines the relationship between human motivation and behavioral regulation, thereby providing insights into the underlying mechanisms driving customer churn in social networks. In general, SDT draws the distinction between two basic forms of human motivation, namely intrinsic and extrinsic motivation (Ryan and Deci 2000). While intrinsically motivated people engage in an activity for its own sake, extrinsically motivated people engage in an activity as means to an end (Deci 1975; Deci and Ryan 1985). Vast evidence from social psychology has found that intrinsic motivation has a positive effect and extrinsic motivation a negative effect on the time that people pursue and maintain an activity, ranging from short-term assignments (Guay et al. 2000; Vansteenkiste et al. 2004) to long-term educational careers (Vallerand et al. 1997). In a similar vein, I propose that customers' intrinsic motivation to engage in a relationship with a firm extends their customer lifetime and, hence, lowers their likelihood to churn. Initial evidence for this assertion stems from Kim and Ahn (2017), demonstrating that intrinsically motivated customers tend to have a higher brand loyalty than extrinsically motivated customers. Thus, facilitating customers' intrinsic motivation to remain with a firm may be a key mechanism that decreases their likelihood to churn from a social network.

Specifically, SDT highlights three factors that either sustain or diminish peoples' intrinsic motivation, namely their perception of relatedness, competence, and autonomy (Ryan and Deci 2000). While prior work has found that relatedness, competence, and autonomy typically foster peoples' intentions to engage in an activity (Ryan et al. 2006), it remains unclear how these factors affect customer churn, which is particularly true in the context of social networks and under consideration of reward programs. Specifically, I presume that relatedness is a key factor explaining the effects of peer influence on customer churn, whereas competence and autonomy render the effects of (gamified versus monetary) rewards on customer churn.

Peer Influence

Relatedness refers to peoples' need to belong to a social sphere, accommodating their sense of security and closeness with others (Deci and Ryan 2000). People whose need for relatedness is satisfied are well-connected with others (La Guardia et al. 2000) and are, therefore less likely to feel isolated (Austin and Vancouver 1996). Similarly, marketing research found that the social value provided by other peers increases customers' participation in online communities (Karnstedt et al. 2010) and that customers use social networks more frequently, when the presence of other peers increases (Mäntymäki and Riemer 2014). Accordingly, I assume that customers' relatedness with other peers in a network reduces their hazard to churn. Specifically, I focus on two factors determining customers' perception of relatedness, namely their exposure toward already defected peers and interconnectedness with remaining peers in a social network.

Exposure. Customers' exposure toward peers that already defected from a social network captures peer influence on an individual level and refers to the number of churned peers that customers have previously been connected with (Freeman 1978). Consistent with SDT (Ryan and Deci 2000), I conjecture that customers that have been exposed to an increasing number of already defected peers will have decreasing sensations of relatedness in a social network, in turn increasing their hazard to churn. The underlying rationale is that when peoples' social connections with peers in a social network dissolute, their feelings of companionship and emotional support decrease, also lowering their intentions to remain members of a social network (Rosenbaum 2006). This finding is also supported by marketing studies, indicating that customers are more likely to defect from social networks, when they have been exposed to an increasing number of already defected peers (Backiel et al. 2016), which is particularly true when those peers churned recently (Haenlein 2013; Nitzan and Libai 2011). Thus, I propose that customers' increasing exposure toward already defected peers has a positive effect on customer churn in a social network.

H1: Customers' exposure toward already defected peers has a positive influence on their likelihood to churn from a social network.

Interconnectedness. Unlike exposure, interconnectedness describes peer influence occurring on a group level and refers to the formation of local network clusters that are characterized by dense and overlapping connections between a customer and his/her remaining peers in a social network (Katona et al. 2011). As suggested by SDT (Ryan and Deci 2000), I assert that customers characterized by a high interconnectedness with their remaining peers will sense higher levels of relatedness in a social network, ultimately lowering their propensity to churn. Initial evidence for this prediction showed that peoples' decision to maintain an activity, such as smoking is less affected by individual peers, but rather by groups of multiple peers that are strongly interconnected with one another (Christakis and Fowler 2008). The notion of cluster-specific influence is additionally supported by research on network closure (Coleman 1988), that is, if two people are connected to the same person and are, additionally, connected to each other, they have a greater influence on that person's decisions than if they were not connected. Thus, when a customer is connected with two other remaining customers and these customers are in turn also connected with each other, densely connected clusters evolve that may increase customer's perception of relatedness and retention in a social network. In the marketing domain, initial evidence found that customers' social embeddedness (Benedek et al. 2014), for example into social subgroups (Richter et al. 2010) decreases churn in social networks. Thus, I propose that customers' increasing interconnectedness with remaining peers in a social network has a negative effect on their likelihood to churn.

H2: Customers' interconnectedness with remaining peers has a negative influence on their likelihood to churn from a social network.

Rewards

According to SDT (Deci and Ryan 2000), churn may not only be affected by customers' perception of relatedness in a social network, but also by firms' reward programs (e.g., Bolton et al. 2000; Lewis 2004; Verhoef 2003; Zhang and Breugelmans 2012). Specifically, SDT suggests that the effectiveness of reward programs is largely dependent on whether customers perceive rewards as either intrinsically motivating, supporting their competence and autonomy, or extrinsically motivating, suppressing their competence and autonomy (Ryan 1982). Competence refers to peoples' need for challenge, mastery, and goal achievement during an activity, whereas autonomy is peoples' desire to self-organize and regulate their own behavior during an activity (Deci and Ryan 2000). Accordingly, prior research found that people obtaining rewards for the achievement of a skilled performance have a higher intrinsic motivation to maintain an activity than people obtaining rewards for merely doing a task (Enzle and Ross 1978). Similarly, I propose that gamified rewards support customers' perception of competence and autonomy (i.e., "earning" a reward), thereby reducing their likelihood to churn, whereas monetary rewards suppress customers' sensation of competence and autonomy (i.e., merely receiving a reward), ultimately increasing customer churn.

Gamified Rewards. Gamified rewards use game elements, such as progress bars, points, badges, or trophies to incentivize customers' mastery or achievement of a goal (Hamari et al. 2014), thereby engaging them in challenging activities (Berger et al. 2017). For example, many firms, such as Samsung or Verizon incentivize customers' level of participation or expertise in their online communities with gamified rewards (Stanley 2014). As a result, the attainment of gamified rewards is contingent upon the work and effort customers put into an activity, implying that they must "earn" gamified rewards, which is positively associated with their perception of competence and autonomy (Hamari 2013; Keller and Blomann 2008). In line with SDT (Ryan 1982), I conjecture that gamified rewards are competence-autonomy supportive, resulting in customers' lower hazard to churn from a social network (Hamari and Koivisto 2013;

Ryan 1982). Consistently, marketing research showed that games are engaging activities that increase customers' participation in online communities (Denny 2013; Hamari 2013) and strengthen their relationships with firms (Berger et al. 2017). Thus, I propose that gamified rewards reduce customer churn in social networks.

H3: Gamified rewards have a negative influence on customers' likelihood to churn from a social network.

Moderating Role of Gamified Rewards. Furthermore, I propose that gamified rewards moderate the effects of peer influence, namely customers' exposure toward already defected peers and interconnectedness with remaining peers on their likelihood to churn. Initial evidence for this assertion stems from educational psychology, with research showing that students' perception of relatedness increases their likelihood to pursue an educational career at college (i.e., no dropout) which is facilitated by their sensations of competence and autonomy (Larose et al. 2005). In a similar vein, I propose that (a) gamified rewards attenuate the positive effect of exposure toward already defected peers on customer churn, whereas (b) gamified rewards facilitate the negative effect of interconnectedness with remaining peers on customer churn.

H4a: Gamified rewards attenuate the positive influence of exposure toward already defected peers on customers' likelihood to churn from a social network, such that churn decreases (increases) when gamified rewards increase (decrease).

H4b: Gamified rewards facilitate the negative influence of interconnectedness with remaining peers on customers' likelihood to churn from a social network, such that churn decreases (increases) when gamified rewards increase (decrease).

Monetary Rewards. Monetary rewards, such as price discounts may be less effective in reducing churn than gamified rewards as customers typically receive them for merely buying more products or attending special deals (Deci 1971; Enzle and Ross 1978). As a result, customers establish an instrumental link between their buying behavior and the monetary reward (Graham 1994), reducing their sensation that obtaining an incentive is challenging as well as contingent upon the work and effort they invested in this activity (Keller and Blomann 2008). As monetary rewards therefore diminish customers' perception that they "earned" an incentive (Ryan 1982), I presume that monetary rewards are competence-autonomy suppressive, eventually increasing customers' hazard to churn from a social network. Consistently, prior marketing research showed that rewards undermining customers' perception of autonomy resulted in lower levels of customer loyalty than autonomy-supportive reward programs (Kim and Ahn 2017). Furthermore, studies revealed that monetary rewards can increase customers' likelihood to churn (Ascarza et al. 2016) and are less effective in reducing churn than gamified rewards (Zhang and Breugelmans 2012). Thus, I propose that monetary rewards increase customers' likelihood to churn from a social network.

H5: Monetary rewards have a positive influence on customers' likelihood to churn from a social network.

Moderating Role of Monetary Rewards. Finally, I presume that monetary rewards moderate the effects of peer influence, that is, customers' exposure toward already defected peers and interconnectedness with remaining peers on their propensity to churn from a social network. The underlying rationale is that when customers receive monetary rewards, their intrinsic motivation to remain in a social network should decrease, not only (a) facilitating the positive effect of exposure toward already defected peers on customer churn, but also (b) attenuating the negative influence of interconnectedness with remaining peers on customers' likelihood to defect from a social network. Finally, I hypothesize:

H6a: Monetary rewards facilitate the positive influence of exposure toward already defected peers on customers' likelihood to churn from a social network, such that churn increases (decreases) when monetary rewards increase (decrease).

H6b: Monetary rewards attenuate the negative influence of interconnectedness with remaining peers on customers' likelihood to churn from a social network, such that churn increases (decreases) when monetary rewards increase (decrease).

To sum up, prior research on SDT (e.g., Deci 1975; Deci and Ryan 1985; Ryan 1982) and social networks (e.g., Coleman 1988; Freeman 1978) suggests that peer influence (i.e., relatedness) affects customer churn, namely that customers' exposure toward already defected peers has a positive (H1) and that their interconnectedness with remaining peers has a negative (H2) influence on churn. Furthermore, I presume that gamified rewards (i.e., competence-autonomy supportive) have a negative effect on customer churn (H3) and, more importantly attenuate the positive influence of exposure (H4a) and facilitate the negative influence of interconnectedness (H4b) on customer churn, whereas the opposite should apply to monetary rewards (i.e., competence-autonomy suppressive; H5, H6a, H6b). In what follows, I present the results from a longitudinal field study that uses data from a large-scale social network to test my theorizing. Although not hypothesized, I also examine to which degree customer churn originating from peer influence affects a social network's future revenue streams under consideration of different rewards interventions.

Data

To examine the effects of peer influence and rewards on customer churn in social networks, I collaborated with a provider of a massive multiplayer online game (MMOG) that was founded in 2006 and has currently over 94 mi. customers.

Empirical Setting

For customers to participate in the MMOG they had to create an online account. While customers could purchase digital products in the MMOG (e.g., weapons, equipment, resources), an underlying gaming community also enabled them to exchange product opinions and information with other peers. An important feature of the gaming community is that customers could build up friendship connections with other peers by sending out friendship requests, resulting in a bidirectional social network structure underlying the MMOG. Furthermore, the MMOG incentivized the loyalty of its customers by either providing gamified rewards in the form of badges, when they achieved certain levels of expertise in the community, or monetary rewards in the form of price discounts, when they bought large amounts of digital items.

Sample and Measures

I obtained daily time series data for a random sample of 17,902 customers that had an online account at the beginning of the study period and, hence, were active members of the MMOG. Data was collected over a period of approximately five months (i.e., 159 days), starting on February 23, 2015 until July 31, 2015, and captured customers' account status, spending in the MMOG, friendship connections, participation in (gamified and monetary) reward programs, as well as further gameplay characteristics.

Churn and Spending. The primary dependent variable is customer churn ($Churn_{it}$). Churn was observed by tracking customers' daily account status in the MMOG, that is, whether a customer i's gaming account was still active or cancelled on a given day t during the study period. Thus, customer churn is measured as a binary variable, coded with 0 if customers did not cancel their accounts and with 1 if customers cancelled their accounts (Haenlein 2013; Nitzan and Libai 2011). Importantly, I consider that churned customers are lost for good; this assumption is reasonable given the fact that I measure churn by tracking customers' cancelled rather than inactive gaming accounts. As a secondary dependent variable I also tracked customer i's daily spending ($Spending_{it}$) on digital products (in EUR), allowing me to assess the financial consequences of customer churn by running managerial simulations.

Peer Influence. The first set of independent variables refers to peer influence originating from a customer i's immediate social network on day t, denoted as $SN_{it} = \{j_{1t}, ..., j_{nt}\}$ and, therefore measures the influence arising from a direct friendship connection between customer i and his/her peer j on day t. Consistent with prior work (Nitzan and Libai 2011), I measured customer i's exposure ($Exposure_{it}$) to already defected peers on day t as the following sum

$$Exposure_{it} = \sum_{j \in SN_{it}} \delta_{jt}, \tag{1}$$

where δ_{jt} is a binary variable that takes a value of 1 if peer j defected on day t and 0 if otherwise. By contrast, I assessed customers' interconnectedness with remaining peers as the density of friendship connections between a customer i and his/her peers in the immediate social network SN_{it}. Following Watts and Strogatz (1998) and Barabási and Oltvai (2004), interconnectedness ($Interconnect_{it}$) was measured as a customer i's daily clustering coefficient, defined as

$$Interconnect_{it} = \frac{2n_{it}}{\sum_{j \in SN_{it}} \gamma_{jt} \left(\sum_{j \in SN_{it}} \gamma_{jt} - 1 \right)}, \tag{2}$$

where γ_{jt} is a binary variable that takes a value of 1 if peer j remains in the social network on day t and 0 if otherwise, whereas n_{it} is the number of friendship connections linking $\sum_{j \in SN_{it}} \gamma_{jt}$ peers of customer i on day t with one another. Thus, the clustering coefficient measures the share of existing triangles that could possibly exist between customer i and his/her peers, therefore ranging from 0 (no connections) to 1 (all peers are connected with one another).

Rewards. The second set of independent variables refers to rewards. Specifically, I measured gamified rewards ($Gamified_{it}$) as the badge that customer i had received until day t. This variable is ordinal and has 20 different levels, ranging from beginner (i.e., level 1) to expert (i.e., level 20) level. Furthermore, I measured monetary rewards ($Monetary_{it}$) as the total amount of price discounts that customer i had obtained until day t of the study period.

Control Variables. Additionally, I measured the following control variables to test for the robustness of my findings. As suggested by Nitzan and Libai (2011), I included information on customer tenure to avoid problems from left-censoring in time series data. Customer tenure ($Tenure_{it}$) was measured as the total number of days elapsed since a customer had created his/her account. Furthermore, prior work is suggestive that customers' frequency of visiting a social network may be negatively correlated with churn (Chen and Hitt 2002). Therefore, I also controlled for customers' usage frequency ($Usage_{it}$), defined as the total number of days that customers had played the MMOG since signing up. Finally, prior research found that homophily, namely customer's similarity with his/her peers SN_{it}, may facilitate peer influence (Rogers 1983) and, therefore lead to biased model estimations (Nitzan and Libai 2011). Consistent with Brown and Reingen (1987), I controlled for homophily ($Homophily_{it}$) by measuring the share of peers that belonged to the same social subgroups in the MMOG as a customer (0 = no peer belonged to a customer's social subgroup, 1 = all peers belonged to a customer's social subgroup). Table 2 provides an overview of the variables' descriptive statistics and correlations.

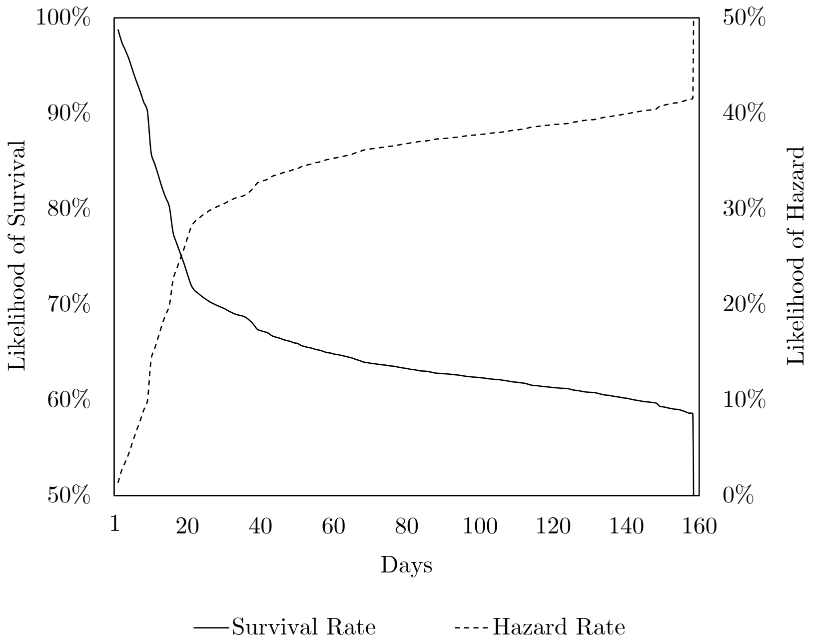
Table 2 Descriptive Statistics and Correlations

		Descriptive Statistics				Correlations								
		M	*SD*	*Min*	*Max*	1	2	3	4	5	6	7	8	9
1	Churn	.78	.41	.00	1.00	1.00								
2	Spending	.63	5.97	.00	381.76	−.16	1.00							
3	Exposure	.76	2.48	.00	132.00	.07	−.02	1.00						
4	Interconnectedness	.06	.17	.00	1.00	−.04	.15	.07	1.00					
5	Gamified Rewards	4.92	4.50	1.00	20.00	−.09	.35	.31	.29	1.00				
6	Monetary Rewards	22.56	17.62	.00	106.40	.02	.29	.11	.09	.33	1.00			
7	Tenure	341.84	264.19	7.29	738.63	−.12	.48	.24	.17	.52	.36	1.00		
8	Usage	43.92	30.67	.00	224.41	−.02	.44	.13	.14	.53	.11	.18	1.00	
9	Homophily	.42	.49	.00	1.00	−.07	.09	.21	.24	.51	.15	.27	.32	1.00

Model Estimation

To examine the effects of peer influence and rewards on customer churn I specified a set of parametric proportional hazard models with maximum likelihood estimation (Kleinbaum and Klein 2005); an approach that is frequently used in marketing research to model the duration of customer-firm relationships as a time-discrete process (De Paula 2009) and the probability of customers ending it (Bowman 2004). While hazard models take into account right censoring of the data, implying that an event of interest can occur after the study period has ended (Wowak et al. 2011; as decpited in Fig. 2, the overall churn rate was only 41.5%), the parametric specification allowed me to include time-varying independent variables, such as peer influence as well as gamified and monetary rewards. Notably, models addressing both, data truncation and variance over time were found to be most effective in correctly identifying peer influence in time-series data (Van den Bulte and Iyengar 2011).

Fig. 2 Baseline Survival and Hazard Rate in the Social Network



In a parametric proportional hazard model, a customer i's hazard rate $h_i(t \mid x_{it})$ to churn from a social network on day t is estimated by

$$h_i(t \mid x_{it}) = h_0(t) exp\left(\beta' x_{it}\right), \tag{3}$$

where $h_0(t)$ is the baseline hazard function, capturing the longitudinal effect, vector x_{it} denotes the independent variables of customer i at day t, and β' represents the effects of the independent variables composing x_{it} on the hazard rate. As depicted in Fig. 2, explorative analysis of the hazard rate revealed that customers' likelihood to churn was monotonously increasing over time, with a strongly increasing slope for the first three weeks which flattened until the end of the study period. To model monotonously increasing baseline hazards, prior research suggested the Weibull distribution as a suitable parametric specification (Stremersch and Tellis 2004). In the Weibull specification, the hazard $h(t)$ and survivor $S(t)$ function are defined by

$$h(t) = p\lambda t^{p-1}, \tag{4.1}$$

$$S(t) = exp\left(-\lambda t^{p}\right), \tag{4.2}$$

where p is the shape parameter that is estimated from the data and $\lambda = exp\left(\beta' x_{it}\right)$. Specifically, I estimated three hazard models to test my research hypotheses. Per Model 1, I examined the main effects of peer influence, that is, customers' exposure toward already defected peers ($Exposure_{it}$) and interconnectedness with remaining peers ($Interconnect_{it}$) on their hazard to churn ($Churn_{it}$), resulting in Eq. (5):

$$Churn_i(t) = h_0(t) exp \begin{pmatrix} & \beta_1 Exposure_{it} \\ + & \beta_2 Interconnect_{it} \end{pmatrix}. \tag{5}$$

Furthermore, Model 2 not only included the main effects of gamified ($Gamified_{it}$) and monetary ($Monetary_{it}$) rewards, but also their interactions with exposure and interconnectedness to examine the main and moderating effects of rewards on customer churn, leading to Eq. (6):

$$Churn_i(t) = h_0(t) exp \begin{pmatrix} & \beta_3 Exposure_{it} + \beta_4 Interconnect_{it} \\ + & \beta_5 Gamified_{it} + \beta_6 Monetary_{it} \\ + & \beta_7 Exposure_{it} \times Gamified_{it} \\ + & \beta_8 Interconnect_{it} \times Gamified_{it} \\ + & \beta_9 Exposure_{it} \times Monetary_{it} \\ + & \beta_{10} Interconnect_{it} \times Monetary_{it} \end{pmatrix}. \tag{6}$$

Finally, Model 3 controlled for customers' tenure ($Tenure_{it}$), usage frequency ($Usage_{it}$), and homophily ($Homophily_{it}$) as additional covariates to test for the robustness of my findings, finally denoted by Eq. (7):

$$Churn_i(t) = h_0(t) exp \begin{pmatrix} & \beta_{11} Exposure_{it} + \beta_{12} Interconnect_{it} \\ + & \beta_{13} Gamified_{it} + \beta_{14} Monetary_{it} \\ + & \beta_{15} Exposure_{it} \times Gamified_{it} \\ + & \beta_{16} Interconnect_{it} \times Gamified_{it} \\ + & \beta_{17} Exposure_{it} \times Monetary_{it} \\ + & \beta_{18} Interconnect_{it} \times Monetary_{it} \\ + & \beta_{19} Tenure_{it} + \beta_{20} Usage_{it} + \beta_{21} Homophily_{it} \end{pmatrix}. \tag{7}$$

All model estimations were carried out in Stata 14, using the "streg" command with a Weibull specification, standardized parameter estimates, and robust standard errors. Table 3 reveals that for all models the LRχ^2 statistics (likelihood ratio) were highly significant, indicating that my model specifications fit the data well.

Table 3 Estimation Results of Model 1 to Model 3

		Likelihood to Churn ($Churn_{it}$)																				
		Model 1							Model 2							Model 3						
			β	*HR*	*z*	*p*	CI_{95}			β	*HR*	*z*	*p*	CI_{95}			β	*HR*	*z*	*p*	CI_{95}	
Peer Influence																						
$Exposure_{it}$	H1	β_1	.199***	1.220	16.53	.001	.175	.223	β_3	.269***	1.309	13.94	.001	.231	.307	β_{11}	.255***	1.290	13.25	.001	.217	.292
$Interconnect_{it}$	H2	β_2	−.158***	.854	−16.00	.001	−.177	−.139	β_4	−.092***	.912	−8.30	.001	−.114	−.070	β_{12}	−.081***	.922	−7.33	.001	−.103	−.059
Rewards																						
$Gamified_{it}$	H3								β_5	−.409***	.665	−38.94	.001	−.429	−.388	β_{13}	−.395***	.674	−29.81	.001	−.421	−.369
$Monetary_{it}$	H5								β_6	.052***	1.054	5.75	.001	.034	.070	β_{14}	.039***	1.040	4.14	.001	.021	.058
Interaction Effects																						
$Exposure_{it} \times Gamified_{it}$	H4a								β_7	−.195***	.823	−16.57	.001	−.218	−.172	β_{15}	−.183***	.833	−15.47	.001	−.206	−.160
$Interconnect_{it} \times Gamified_{it}$	H4b								β_8	−.116***	.890	−11.41	.001	−.136	−.096	β_{16}	−.106***	.899	−10.37	.001	−.126	−.086
$Exposure_{it} \times Monetary_{it}$	H6a								β_9	.017**	1.017	2.94	.003	.006	.028	β_{17}	.016**	1.016	2.73	.006	.005	.028
$Interconnect_{it} \times Monetary_{it}$	H6b								β_{10}	.007	1.007	.82	.411	−.010	.025	β_{18}	.007	1.007	.78	.434	−.011	.025
Controls																						
$Tenure_{it}$																β_{19}	.065***	1.067	7.24	.001	.047	.082
$Usage_{it}$																β_{20}	−.006	.994	−.56	.573	−.025	.014
$Homophily_{it}$																β_{21}	−.181***	.834	−9.02	.001	−.221	−.142
Model Fit Indexes																						
$LR\chi^2$		729.54 ($p < .001$)							2,901.73 ($p < .001$)							3,032.46 ($p < .001$)						
Log Likelihood		−26,493.22							−25,407.12							−25,341.76						
AIC		52,994.44							50,834.24							50,709.51						
BIC		53,025.61							50,912.17							50,810.82						
Model Improvement																						
Log Likelihood Ratio Test									Model 1 → Model 2 ($p < .001$)							Model 2 → Model 3 ($p < .001$)						

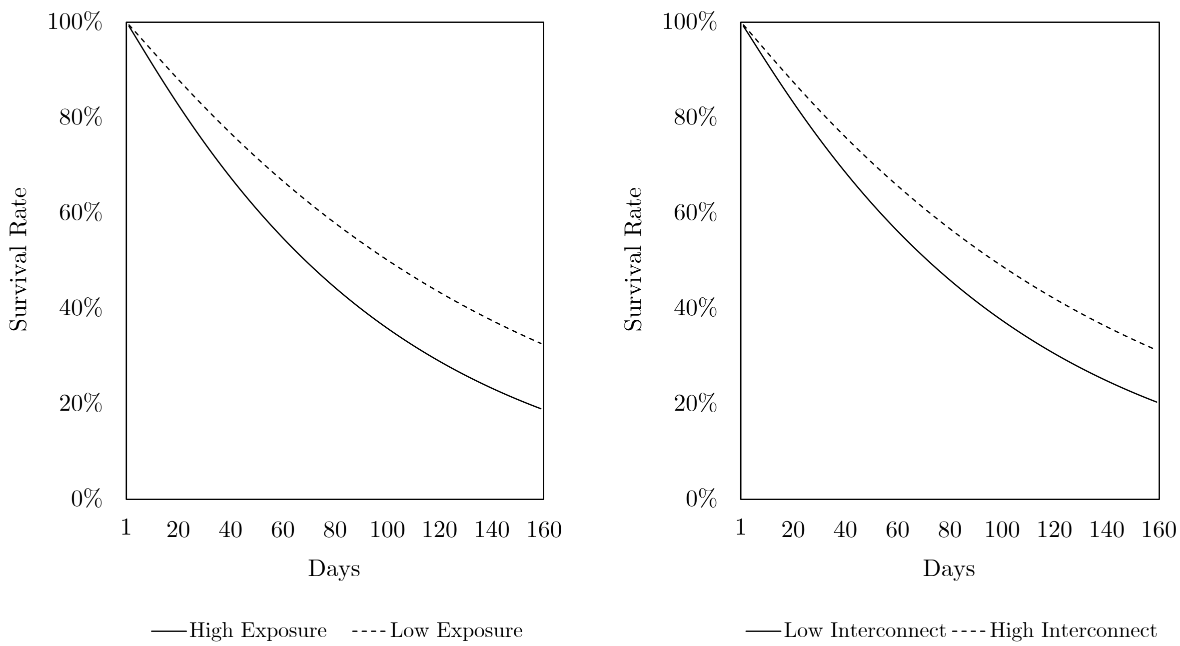
Note. *$p < .050$; **$p < .010$; ***$p < .001$; HR = Hazard Ratio; Standardized and Robust Parameter Estimates; $N = 17{,}902$

Results

Peer Influence

Per Model 1 (LR$\chi^2(2) = 729.54$, $p < .001$), I tested whether peer influence, that is, customers' exposure toward already defected peers (H1) and interconnectedness with remaining peers (H2) affects their hazard to churn from a social network. In line with my predictions, results showed that exposure had a positive influence on customer churn ($\beta_1 = .199$, $z = 16.53$, $p < .001$), indicating that a 1% increase in already defected peers was associated with an increase of 22.0% in a customer's hazard to churn from the social network. This finding supports H1. Besides exposure, I found that interconnectedness had a negative effect on customer churn ($\beta_2 = -.158$, $z = -16.00$, $p < .001$), revealing that when a customers' interconnectedness with remaining peers increased by 1%, their hazard to churn declined by 14.6%. This finding confirms H2. To predict how variations in exposure and interconnectedness affect customers' hazard to churn, I estimated the survival functions for the independent variables at one standard deviation below and above their mean (exposure: high, low; interconnectedness: low, high), resulting in two survival functions for each measure of peer influence (see Fig. 3).

Fig. 3 Effects of Exposure and Interconnectedness on Likelihood of Survival



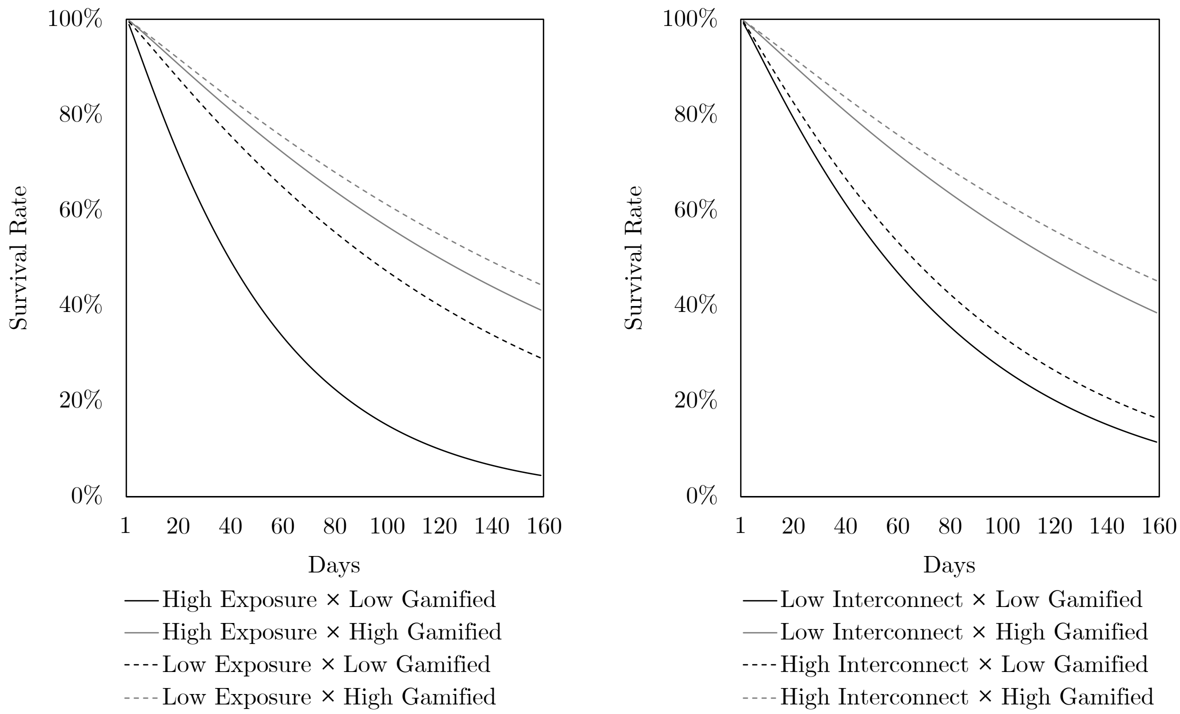
In the high exposure condition, only 18.9% of customers remained active members of the social network, while in the low exposure condition 32.7% of customers were still active. By contrast, in the low interconnectedness condition 20.2% of customers remained in the social network, whereas in the high interconnectedness condition 31.2% of customers survived. These results provide full support for my baseline predictions, namely that individual level effects of already churned peers increase customer churn (H1) and group level effects of remaining peers decrease customer churn (H2).

Rewards

Furthermore, I computed Model 2 (LR$\chi^2(8)$ = 2,901.73, $p < .001$) to test whether gamified (H3) and monetary (H5) rewards have an effect on customer churn and whether these types of reward programs moderate the effect of peer influence (gamified: H4a, H4b; monetary: H6a, H6b) on customer churn. Consistent with Model 1, results showed that the baseline effect of exposure had a positive ($\beta_3 = .269$, $z = 13.94$, $p < .001$) and interconnectedness a negative ($\beta_4 = -.092$, $z = -8.30$, $p < .001$) effect on customer churn.

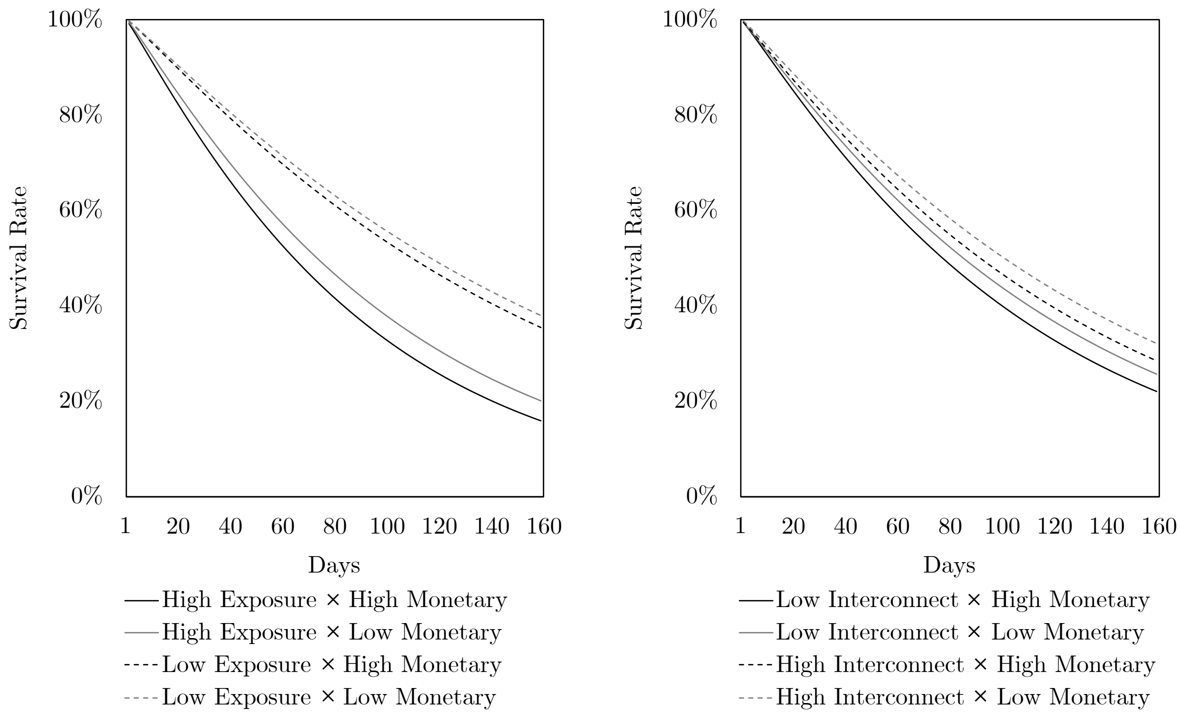
Gamified Rewards. As hypothesized, I found that gamified rewards had a negative effect on customers' hazard to churn ($\beta_5 = -.409$, $z = -38.94$, $p < .001$), revealing that a 1% increase in gamified rewards was associated with a 33.5% decrease in churn. This finding confirms H3. Furthermore, results showed negative two-way interactions between gamified rewards and both, customers' exposure toward already defected peers and interconnectedness with remaining peers. While gamified rewards attenuated the positive effect of exposure on customer churn ($\beta_7 = -.195$, $z = -16.57$, $p < .001$), they facilitated the negative effect of interconnectedness on customer churn ($\beta_8 = -.116$, $z = -11.41$, $p < .001$). In other words, when customers received a 1% increase in gamified rewards, the positive effect of exposure on churn was diminished by 17.7%, whereas the negative effect of interconnectedness on churn was facilitated by 11.0%. These results support H4a and H4b. To clarify the nature of these interactions effects, I estimated four survival functions for each measure of peer influence (see Fig. 4), that is, at one standard deviation below and above the mean of exposure and gamified rewards (exposure: high, low; gamified: low, high) as well as interconnectedness and gamified rewards (interconnectedness: low, high; gamified: low, high). Beginning with the interaction between exposure and gamified rewards, results indicated that gamified rewards particularly decreased customers' hazard to churn, when they had been exposed to many defecting peers ($S_{HighExposure\ \times\ LowGamified} = 4.3\%$, $S_{HighExposure\ \times\ HighGamified} = 39.0\%$), while this effect was smaller, when customers had been exposed to less defecting peers ($S_{LowExposure\ \times\ LowGamified} = 28.8\%$, $S_{LowExposure\ \times\ HighGamified} = 44.4\%$). I found a slightly different pattern for the interaction between interconnectedness and gamified rewards; that is, gamified rewards had similar effects for customers that were interconnected to either few remaining peers ($S_{LowInter\ \times\ LowGamified} = 11.4\%$, $S_{LowInter\ \times\ HighGamified} = 38.4\%$) or many remaining peers ($S_{HighInter\ \times\ LowGamified} = 16.4\%$, $S_{HighInter\ \times\ HighGamified} = 45.1\%$). These results indicate that gamified rewards are more effective in attenuating the positive effects of exposure than facilitating the negative effects of interconnectedness on customer churn.

Fig. 4 Gamified Rewards moderate the Effect of Exposure and Interconnectedness on Likelihood of Survival



Monetary Rewards. By contrast, I found that monetary rewards facilitated customer churn ($\beta_6 = .052$, $z = 5.75$, $p < .001$), implying that a 1% increase in monetary rewards was associated with a 5.4% increase in customers' hazard to defect. This finding confirms H5. Furthermore, results showed a positive two-way interaction between monetary rewards and customers' exposure toward already defected peers on customer churn ($\beta_9 = .017$, $z = 2.94$, $p < .003$); that is, when customers received a 1% increase in monetary rewards, the positive effect of exposure toward already defected peers on churn was increased by 1.7%. This result supports H6a. Contrary to my predictions, I found no significant two-way interaction between monetary rewards and customers' interconnectedness with remaining peers on churn ($\beta_{10} = .007$, $z = .82$, $p > .41$), rejecting H6b. To clarify the interaction between exposure and monetary rewards, I again estimated customers' survival likelihoods at one standard deviation below and above the means of the independent variables (exposure: high, low; monetary: high, low; see Fig. 5), resulting in four survival functions. My findings indicated that monetary rewards increased customers' hazard to churn, when they were exposed to many peers that had already defected from the social network ($S_{HighExposure \times HighMonetary} = 15.8\%$, $S_{HighExposure \times LowMonetary} = 20.1\%$), while this effect was slightly smaller for customers that were exposed to fewer defected peers ($S_{LowExposure \times HighMonetary} = 35.3\%$, $S_{LowExposure \times LowMonetary} = 37.9\%$). These results show that providing monetary rewards to customers that have been exposed to many defecting peers is particularly increasing their likelihood to churn from a social network.

Fig. 5 Monetary Rewards moderate the Effect of Exposure, but not the Effect of Interconnectedness on Likelihood of Survival



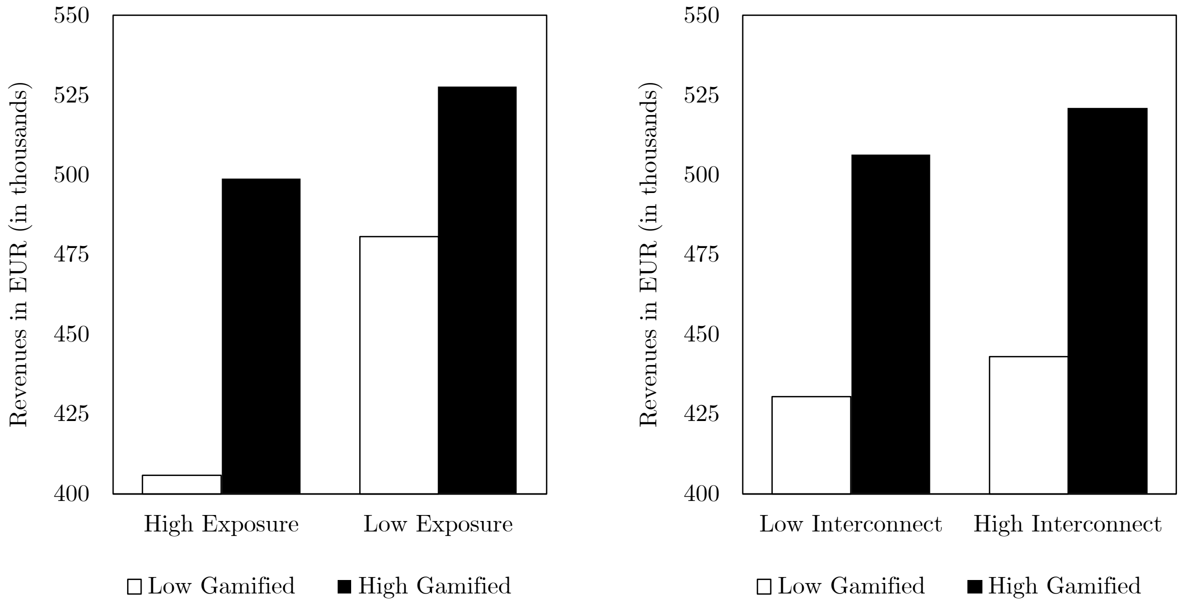
Robustness Checks

To test for the robustness of my findings, Model 3 consisted of customers' tenure, usage frequency, and homophily as additional controls (LR$\chi^2(11) = 3{,}032.46$, $p < .001$). Importantly, results indicated that all parameter estimates remained stable in both, significance and direction, underscoring the robustness of Model 1 and 2. Furthermore, I reran Models 1 to 3 using different time spans (i.e., 50 and 100 days) as well as parametric specifications for monotonously increasing hazard rates (e.g., exponential). However, the results remained the same, providing additional support for my findings.

Managerial Simulation

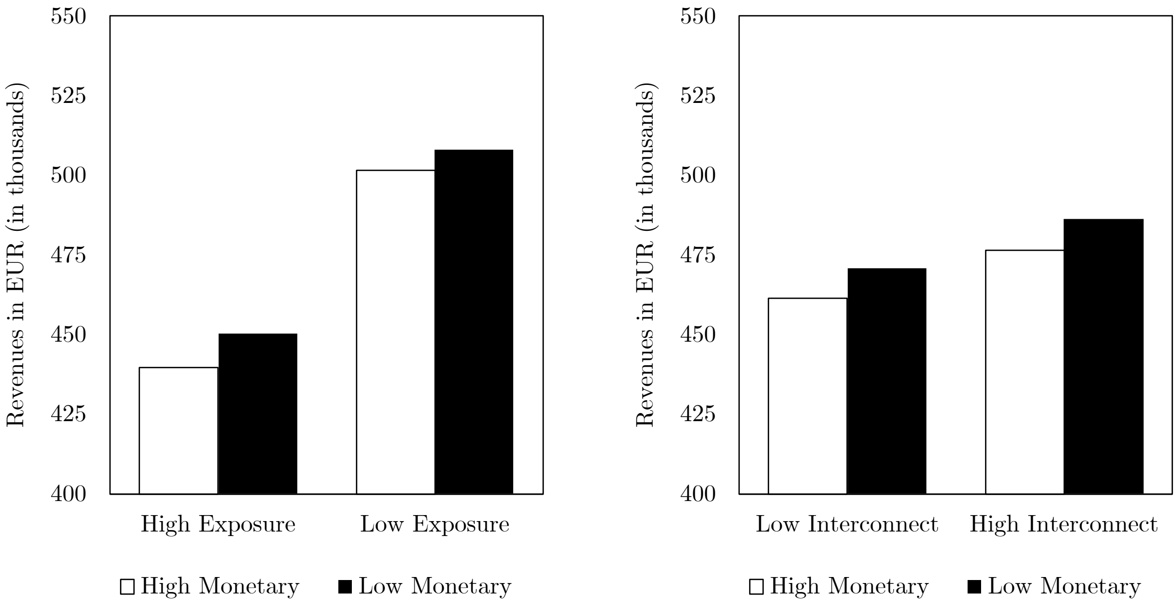
Finally, I sought to answer a managerially critical question: to which extent does churn induced by peer influence impact future revenues and to which degree can reward interventions be used to increase financial performance. Based on the parameter estimates of Model 2, I used customers' predicted hazard rates and spending behavior ($Spending_{it}$) to compute the expected revenue until the last day of the study period (t = 159). Specifically, I estimated the revenues based on the average daily spending in the network and at one standard deviation below and above the mean for each of the four two-way interactions, resulting in 16 conditions. Fig. 6 and 7 depict the results of the managerial simulation. I would like to outline the following key findings:

Fig. 6 Predicted Revenues for the Two-way Interactions between Gamified Rewards and Exposure *(left panel)* as well as Interconnectedness *(right panel)*



First, gamified rewards had a tremendous impact on the social network's financial performance, especially when customers had been exposed toward many already defected peers. Specifically, gamified rewards increased revenue by EUR 93,149 for customers with a high exposure toward already defected peers (+23.0%) and by EUR 47,398 (+9.9%) for customers with a low exposure toward already defected peers. Second, gamified rewards had the same financial impact for customers with a low and high level of interconnectedness. Specifically, for low levels of interconnectedness gamified rewards increased revenue by EUR 75,900 and for high levels of interconnectedness by EUR 78,001, which for both levels of interconnectedness was an increase of +17.6%.

Fig. 7 Predicted Revenues for the Two-way Interactions between Monetary Rewards and Exposure *(left panel)* as well as Interconnectedness *(right panel)*



Third, customers that received low levels of monetary rewards generated more revenue than customers that obtained high levels of monetary rewards, which is particularly true for customers that were exposed to many peers that had already defected. Providing low monetary rewards increased revenue by up to EUR 10,888 for customers with a high exposure and by up to EUR 6,862 for customers with a low exposure, accounting for revenue increases of +2.5% and +1.4%, retrospectively. Finally, in line with the non-significant interaction between interconnectedness and monetary rewards, the simulation indicated that low monetary rewards equally increased revenues for customers with both, a low (EUR 9,497; +2.1%) and high (EUR 9,737; +2.0%) level of interconnectedness. Taken together, the managerial simulation highlights the positive financial consequences that firms can generate from using gamified as opposed to monetary rewards, which is especially true when customers have been exposed toward many already defected peers in a social network.

General Discussion

In the current article, I combine research from SDT (e.g., Deci 1975; Deci and Ryan 1985; Ryan 1982) and social networks (e.g., Coleman 1988; Freeman 1978) to examine whether peer influence on an individual and group level affects customer churn in social networks and to which degree this relationship is attenuated or facilitated by using different types of reward programs. Based on longitudinal field data from a large-scale social network, my results indicate that customers' increasing exposure toward already defected peers (i.e., individual level) has a positive influence on their hazard to churn, whereas their increasing interconnectedness with remaining peers (i.e., group level) has a negative influence on their likelihood to churn. While these findings shed light on the specific network effects underlying customer churn in social networks, I also find that gamified as opposed to monetary rewards attenuate the positive influence of exposure and facilitate the negative influence of interconnectedness on customer churn. Advancing the current understanding of customer churn in social networks, this article has several implications for marketing research and practice.

Theoretical Implications

First, this article contributes to literature that has examined the effects of peer influence and customer churn. My findings show that customers' relatedness with other peers in a social network lowers their hazard to churn, that is, when their exposure toward already defected peers decreases (1% decrease reduces churn by −22.0%) or when their interconnectedness with remaining peers increases (1% increase reduces churn by −14.6%). Examining network effects on both, an individual and group level, this article advances prior studies that have been limited to peer influence induced by single defectors (Backiel et al. 2016; Haenlein 2013; Nitzan and Libai 2011) or lacked evidence for the specific network effects that may explain why customers' social embeddedness in a social network prevents them from churning (Benedek et al. 2014; Richter et al. 2010). Consequently, my results provide a more comprehensive perspective on how peer influence, namely the number as well as density of existing social connections in a social network affect customer churn. In so doing, this article also contributes to marketing studies that have begun to simultaneously examine individual and group level effects on other forms of consumer decision-making; for example, with research showing that exposure and interconnectedness also affect customers' product adoption in social networks (Katona et al. 2011).

Second, this article advances prior research that has studied the effects of reward programs on customer churn. While there is general consensus among marketing scholars that reward programs are effective means for building up customer retention (e.g., Bolton et al. 2000; Lewis 2004; Verhoef 2003; Zhang and Breugelmans 2012), this article provides a more detailed understanding for why some reward programs may be more successful in lowering customer churn than others. Specifically, my results indicate that gamified rewards supporting customers' competence and autonomy (i.e., "earning" a reward) decrease their hazard to churn (1% increase reduces churn by −33.5%), whereas monetary reward suppressing customers' competence and autonomy (i.e., merely receiving a reward) increase churn (1% increase raises churn by +5.4%). While these findings contribute to prior studies showing that gamified rewards improve customers' participation in online communities (Denny 2013; Hamari 2013) and their relationships with firms (Berger et al. 2017), the results also align with prior research indicating that monetary rewards may weaken customer loyalty (Ascarza et al. 2016; Kim and Ahn 2017).

Finally, my findings provide insights into the interplay between peer influence and reward programs. Specifically, my results show that gamified as opposed to monetary rewards attenuate the positive influence of customers' exposure toward already defected peers and facilitate the negative influence of interconnectedness with remaining peers on customer churn. By showing that firms can use gamified rewards to proactively prevent customer churn from peer influence, this article advances initial evidence that customer loyalty moderates the effect of peer influence on churn (Nitzan and Libai 2011). Furthermore, these findings also contribute to prior studies on SDT that have lacked a closer examination regarding the interplay between relatedness, competence, and autonomy (Deci and Ryan 2000; Ryan and Deci 2000). Specifically, I demonstrate that there is a multiplicative effect between relatedness (i.e., exposure and interconnectedness) and competence/autonomy-supportive (i.e., gamified) versus -suppressive (i.e., monetary) rewards. In so doing, my results provide preliminary insights into the interdependencies between SDT's key factors and extend the theory's applicability to the context of social networks.

Managerial Implications

The current article also provides implications for marketing practitioners that are interested in both, identifying factors that drive customer churn in social networks and employing marketing instruments that can proactively be managed to prevent customers from defecting (Jamal and Bucklin 2006). My findings highlight that peer influence and reward programs are two key factors that firms should consider to increase a social network's odds of survival and maintain its long-term profitability.

Peer Influence. My results suggest that network effects on both, an individual and group level play an important role for predicting customer churn in social networks. Specifically, the findings indicate that a 1% decrease in exposure toward already defected peers and a 1% increase in interconnectedness with remaining peers can reduce customers' hazard to churn by up to 36.6%. Consequently, firms operating social networks should thoroughly track customers' social connections in a social network and employ tactics to enhance their perception of relatedness. In the case of defecting peers, firms should try to compensate customers' deficit of relatedness by encouraging them to build up new social connections with peers. Firms like Facebook combine massive amounts of customer data and machine learning algorithms for link prediction, namely suggestions of new peers that, for example went to the same school, or share similar hobbies and professions. In the case of interconnectedness, firms should encourage the formation of densely connected clusters among customers and their peers. Based on social network metrics, such as the clustering coefficient firms are able to identify sparse parts within the social network and should run targeted interventions to enhance their interconnectedness. Again, firms can benefit from using link prediction by suggesting customers new friendship connections that they have in common with their peers (i.e., "a friend of a friend is a friend"), or employ group discussion boards and chats to facilitate the cohesion among members of social clusters.

Rewards. Furthermore, my results suggest that firms should favor the usage of gamified over monetary reward programs. Specifically, managerial simulation indicated that customers who received high levels of gamified rewards generated up to 23.5% more revenue within six months. In my study context, the MMOG used gamified rewards in the form of badges that customers obtained for an increasing expertise in the underlying gaming community, facilitating their perception of competence and autonomy. Although badges belong to the most common type of gamified rewards (Hamari 2013), it is likely that firms can also use other game elements, such as points, ranking systems, trophies, or awards to increase customer retention. Notably, Berger et al. (2017) found in a recent study across multiple industries and game designs that gamified interactions are effective means for firms to improve relationships with their customers as long as they facilitate their competence (e.g., challenging games) and ensure their perception of autonomy (e.g., no compulsion to participate in gamified reward programs). Evidently, gamified rewards also provide firms with an economical advantage, that is, each monetary reward (i.e., price discount) is associated with a revenue downside for the firm. Thus, using gamified instead of monetary rewards is not only more effective in decreasing customer churn, but also in skimming consumer surplus and maximizing firms' long-term profitability.

Limitations and Future Research

The article also has some limitations that may guide future research. First, in the current research customer churn was the primary dependent variable of interest, indicating whether a customer churned or remained in a social network. However, future studies could also regard customer churn as a "competing" event to customer acquisition and use competitive risk models to examine how peer influence affects customers' decision to either churn or become, for example, a paying member of a social network (Srinivasan et al. 2008). Second, I examined network effects on an individual and group level that are induced by a customer's immediate social network. However, prior research found that customers' decision-making may also be affected by peer influence that originates beyond their immediate (local) network (e.g., Katona et al. 2011) and, therefore depends on their embeddedness into the global network (Krackhardt 1998). Thus, future studies could test to which extent global network measures, such as customers' closeness and betweenness centrality (Freeman 1978) affect their hazard to churn. Finally, for the managerial simulation I predicted the revenue streams of the MMOG based on the daily average spending in the network and customers' individual hazard rates. To enhance this approach, future research may use customers' past spending behavior and take into account the cost of reward programs to improve the accuracy of predicting the financial impact of customer churn under consideration of different types of loyalty programs.

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