

Online Gambling Behavior: The Impacts of Cumulative Outcomes, Recent Outcomes, and Prior Use

This paper is forthcoming in the *Information Systems Research*

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Final version: December 2013

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Abstract

The objective of this work is to examine various psychological forces underlying the behavior of people's online gambling, an increasingly popular form of entertainment in the gaming industry. Drawing on extant theories, we first developed a model of how cumulative outcomes, recent outcomes, and prior use affect online gambling behavior differently. We empirically tested the model using longitudinal panel data collected over eight months from 22,304 actual users of a gambling website. The results of a multilevel panel data analysis strongly supported our hypotheses. First, consistent with gambling theory, individuals' online gambling was found to increase with any increase in a cumulative net gain or cumulative net loss. Second, as the availability heuristic prescribes, a recent loss reduced online gambling, whereas a recent gain increased it. Third, consistent with the literature on repeated behavior, regular use and extended use moderated the relationship between current and subsequent gambling. Taken together, the present study clarifies how people react differently to immediate and cumulative outcomes and also how regular use and extended use facilitate routine behavior in the context of online gambling. In general, our findings suggest that the three perspectives, i.e., gambling theory, the availability heuristic, and repeated behavior, should be taken into account to understand online gambling, which is in essence a series of risk-taking attempts with the potential of eventually becoming routine behavior. This study is expected to offer valuable insights into other types of online games that could engage people in risking real or cyber money and, at the same time, could be easily enmeshed with everyday life (e.g., fantasy sports, online virtual worlds).

Key Words: online user behavior, online gambling, repeated behavior, decision-making under uncertainty, panel data, multilevel analysis, hierarchical analysis

Acknowledgement: The authors greatly appreciate the invaluable guidance from Senior Editor Viswanath Venkatesh throughout the review process. They also thank the three anonymous reviewers for constructive and insightful comments. All errors are the authors' own. This paper utilized data from the Transparency Project (www.thetransparencyproject.org), Division on Addiction, the Cambridge Health Alliance, a teaching affiliate of Harvard Medical School. This research was partially supported by the Singapore Ministry of Education Academic Research Fund, NUS (R-253-000-089-112).

1. Introduction

Online gambling is a type of online entertainment that represents a growing share of the worldwide gaming industry (Business Insights 2010). According to the American Gaming Association (2009), more than 2,000 Internet gambling websites operate worldwide, with a total annual revenue of \$21 billion. In the U.S., online gambling is largely prohibited, but online gambling on horse races remains legal (Takahasi 2009, Wyatt 2011). Similarly, fantasy sports—games in which participants select real players for hypothetical teams and compete against each other based on the statistics generated by the real players (e.g., *ESPN* and *Yahoo! Sports*)—are exempt under certain conditions from the U.S. prohibition on online gambling (Sullum 2008). Currently, some U.S. lawmakers propose to legalize the online gambling industry, a measure that would provide the government with additional annual revenue of \$5 billion (Eggen 2010). Although recreational when appropriately used, online gambling could develop into pathological, obsessive and compulsive behavior (Gupta and Derevensky 1998, Johansson et al. 2009, Lam and Mizerski 2009). As such, the issue of online gambling has a wide variety of ramifications for individuals, practitioners, and researchers. Yet, our understanding of how people use online gambling in everyday life is severely limited, which poses as an obstacle for the constructive discussion of this increasingly important subject.

Information Systems (IS) researchers have recently begun to pay attention to how the Internet is used for recreation. Research in this area mainly focuses on online games that provide unique and unprecedented foundations for entertainment (e.g., *World of Warcraft*, *Second Life*) (Holsapple and Wu 2008, Mennecke et al. 2008). Although it sheds some light on online gambling as a pastime, this stream of research largely fails to analyze the wagering of money, which is the key characteristic of gambling. In contrast, several studies of traditional casino gambling attempt to analyze individuals' betting patterns (Croson and Sundali 2005, Narayanan and Manchanda 2012).¹ This literature focused on how people react to the outcomes of their bets, i.e., gains and losses (Lam and Mizerski 2009, Rachlin 1990). However, the offline gambling

¹ Traditional research on gambling focused on problem gambling such as adolescent gambling (Gupta and Derevensky 1998) and pathological gambling (Toneatto et al. 1997). However, research has shown that only a very small portion (i.e., 2%) of adult gamblers can be categorized as pathological gamblers (Shaffer et al. 1999). As a result, recent research has been generally treating gambling activity as a common pastime (Lam 2007, Mizerski et al. 2004, Nisbet 2009, Oh and Hsu 2001, Sprott et al. 2001).

literature is relatively silent about the changing dynamics of wagering behavior over time. Whereas visiting casinos for gambling often requires additional costs such as travel expenses and devoted time for the trip, online gambling significantly reduces such costs, as the online casino games are readily accessible and virtually costless to play. Therefore, unlike casino gambling that tends to be discrete and transient because of the limitation in space and time, online gambling is more likely to be continual and long-term (Cotte and LaTour 2009). Thus, it is essential for researchers to examine whether certain amounts of gains or losses will elicit different reactions at different points in time. Furthermore, most gambling websites offer a variety of online games (e.g., poker, casino games, video games, sports gambling) that are essentially available anytime, anywhere, and thus can be easily integrated into everyday life (Cotte and LaTour 2009). However, our knowledge is limited regarding how online gambling changes with respect to one's prior interactions with the website such as the regularity of website visits and the variety of games played. Overall, the literature lacks a systematic approach to the study of online gambling that takes into account its unique features that distinguish it from either online entertainment or casino gambling.

The objective of this work is to propose a conceptual model of online gambling and use longitudinal data to empirically test it. Considering that the size of the stake is one of the most important metrics in online gambling, our focus is particularly on explaining how betting behavior changes according to prior outcomes and prior interactions with a website. First, drawing on the theory of gambling developed by Thaler and Johnson (1990), we attempt to explain individuals' betting decisions based on their calculation of cumulative outcomes. This theory of gambling provides a realistic account of gambling behavior under the existence of prior outcomes. Next, we introduce the perspective of the availability heuristic, which is used to provide a theoretical account of individuals' immediate reactions to recent outcomes (Bazerman and Moore 2008, Gilovich et al. 1985, Koehler and Conley 2003). The availability heuristic perspective offers cogent explanations of why people react to the more recent events differently than expected (Tversky and Kahneman 1973, 1974). In particular, this study notes a superficial logical discrepancy between gambling theory and the availability heuristic perspective, but it points out that this discrepancy can be resolved by carefully distinguishing recent outcomes from cumulative outcomes. Finally, we borrow theories of repeated

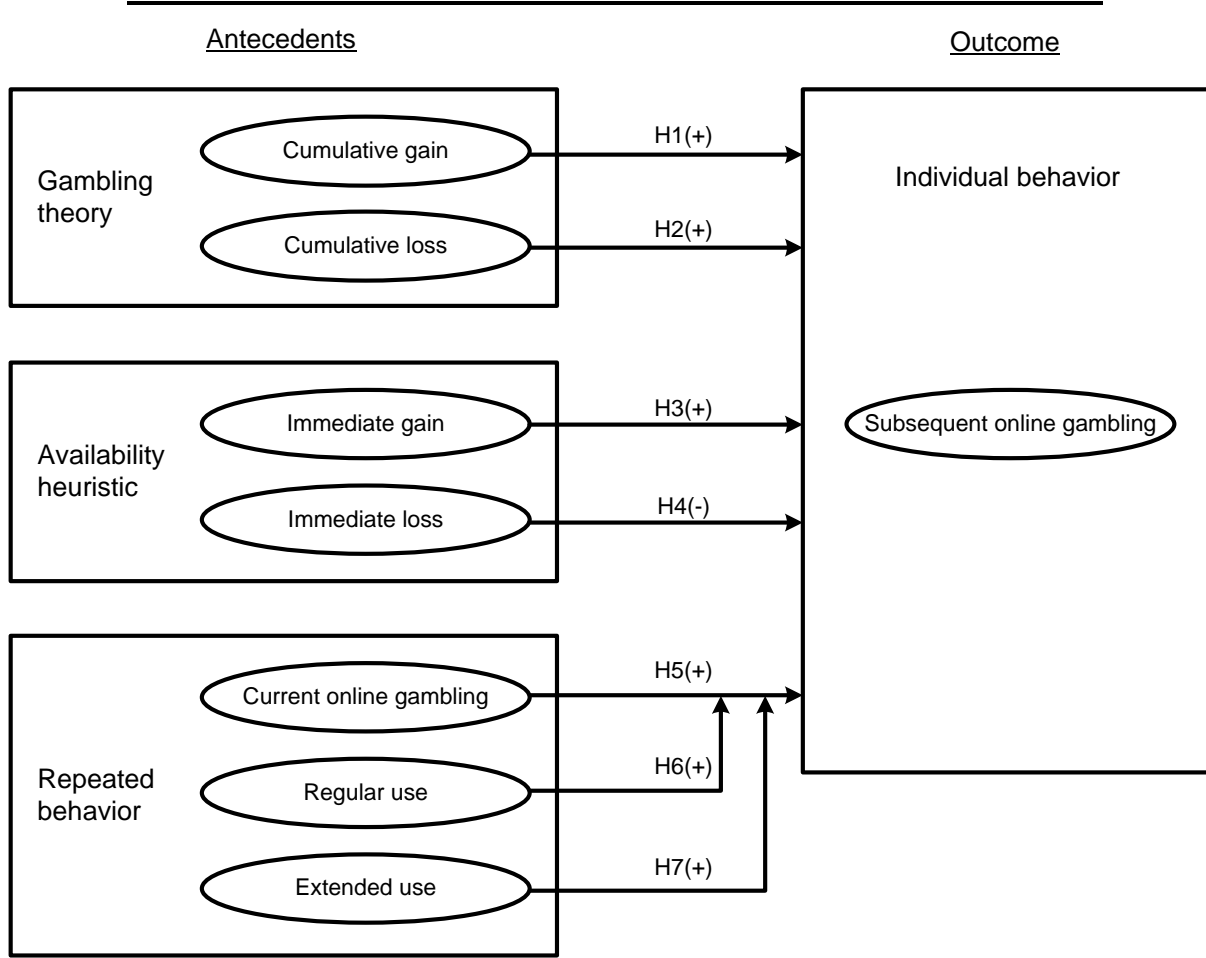
behavior to describe routine behavior (Kim 2009, Kim and Malhotra 2005, Ouellette and Wood 1998, Venkatesh et al. 2000) that could drive, at least partly, online gambling. Specifically, to explain how prior interactions with IT artifacts change the nature of routine behavior, we build on the propositions by de Guinea and Markus (2009) that highlight the pivotal roles of regular use and extended use of an IT application in characterizing the nature of routine behavior. Overall, our model, which is rooted strongly in existing theories, specifies (1) cumulative outcomes, (2) immediate outcomes, and (3) prior use (e.g., regular use and extended use) as important factors affecting online gambling.

In order to empirically test our model, we used longitudinal panel data collected from 22,304 actual online gamblers. The data were collected by tracking detailed histories of individuals' wagers and their corresponding wins and losses for eight months. This dataset allows us to carefully assess the effects of cumulative outcomes, immediate outcomes, and prior use on online behavior. We demonstrate that the three perspectives—gambling theory, the availability heuristic, and repeated behavior—are together vital to an explanation of online gambling; if researchers ignore one of these perspectives, they will derive a biased view of how people participate in gambling on the Internet. This study clarifies various psychological forces behind online gambling; such a clarification is a necessary step toward informed debate on public policies and managerial practices surrounding the issue (Wyatt 2011). Besides, our findings offer valuable insights into other types of online games that have the potential to engage people in risking real or cyber money and, at the same time, become easily enmeshed with their everyday life (e.g., fantasy sports, online virtual worlds).

2. Conceptual Model and Research Hypotheses

This section develops our conceptual model of online gambling. We begin with a discussion of gambling theory that provides a theoretical account of how people react to cumulative gains and losses in the context of online gambling (Thaler and Johnson 1990). Then, we introduce the notion of the availability heuristic to explain how recent outcomes are perceived differently from cumulative outcomes (Gilovich et al. 1985). Finally, we discuss the routine nature of online gambling by drawing on theories of repeated behavior (Aarts and Dijksterhuis 2000, Kim et al. 2005, Ouellette and Wood 1998, Venkatesh et al. 2000). Figure 1 depicts a conceptual model representing the antecedents of online gambling and the corresponding hypotheses.

Figure 1. Conceptual Model



In Online Appendix 1, we provide a table that summarizes past studies related to gambling behavior in terms of several criteria including theories, methodologies, and findings. Each of these prior studies sheds light on a certain aspect of our examination into online gambling, but none of them cover the same spectrum of the present study.²

2.1. Gambling Theory: Cumulative Gains and Losses

² The present study is expected to offer valuable insights into the amount bet by online gamblers in reactions to the short- and long-term outcomes of their prior bets. Nevertheless, it is important to highlight that our model does not control for such micro-level factors as the order of gains and losses, which is considered an important element in experimental studies (Thaler and Johnson 1990). In addition, the model proposed in this study is mainly designed to explain betting amount, and it is not necessarily applicable to other types of gambling behaviors such as the number of casino visits, the number of bets placed, or frequency of purchase. Finally, our model is specific to online gambling, and thus the findings of this study cannot be used to dispute any of the theories established in the offline context. Altogether, despite that the present study is novel and unique in its focus, the boundaries of our model should also be properly understood for its accurate interpretation and application.

A core characteristic of gambling is the wagering of money with the possibility of winning more money. Although online gambling tends to become routine with experience, it essentially involves betting something of value. Therefore, it is easy to anticipate that individuals base their gambling decisions on conscious assessments of the consequences of prior bets (Narayanan and Manchanda 2012). Prospect theory is one of the most well-known theories used to describe how individuals make decisions under conditions of risk (Kahneman and Tversky 1979). In essence, prospect theory postulates that individuals tend to avoid risks in the face of potential gains but take risks in the face of potential losses. This descriptive decision-making theory has been applied in a variety of contexts, including personal investments, organizational investments, and gambling (Cook and Clotfelter 1993, Croson and Sundali 2005, Keasey and Moon 1996, Narayanan and Manchanda 2012, Odean 1998).

Thaler and Johnson (1990) point out that the original prospect theory formulated by Kahneman and Tversky (1979) works well for a one-shot experiment with no implication of prior gains or losses, but they note that the theory is not specifically designed to explain individuals' decisions made in association with the outcomes of prior decisions. Accordingly, Thaler and Johnson (1990) proposed an extended version of prospect theory that is intended to account for decisions when there is a history of gains or losses. Specifically, their extended version predicts a "house-money effect" in the domain of prior gains and a "break-even effect" in the domain of prior losses, what we hereafter call gambling theory (Thaler and Johnson 1990). The house-money effect suggests that individuals are willing to take a risk after gains. The rationale for the house-money effect is that prior gains act as a cushion against a future loss, and thus people become liberal in spending from this bonus account. Meanwhile, the break-even effect indicates that people attempt to break even if losses are recoupable. Ample empirical evidence in various contexts, including investments and gambling, supports the house-money effect when a decision is made against a background of prior gains (Keasey and Moon 1996, Massa and Simonov 2005). In addition, much research empirically supports the break-even effect in the domain of prior losses (Rachlin 1990, Odean 1998). It consistently indicates that people try to avoid realizing losses and thus become risk takers in the domain of losses. We expect that with a net cumulative gain, online gamblers will take risks because of the house-money effect. In

addition, we propose that with a net cumulative loss, online gamblers will also take risks because of the break-even effect. Thus, we hypothesize:

H1: *A net cumulative gain will be positively associated with subsequent online gambling.*

H2: *A net cumulative loss will be positively associated with subsequent online gambling.*

2.2. Availability Heuristic: Immediate Gains and Losses

Research suggests that the most recent outcome affects gambling behavior differently than a long-ago outcome (Bazerman and Moore 2008, Gilovich et al. 1985, Koehler and Conley 2003). Such a phenomenon stems from the availability heuristic. A main principle of the availability heuristic is that individuals reach a decision based on what they can easily remember and that memory is biased in favor of stimulating events over complete information (Bazerman and Moore 2008, Tversky and Kahneman 1973, 1974). This principle suggests that people often are persuaded by a vivid memory and, as a result, deviate from a deliberative process. For example, research has established that people with direct experience of a natural disaster are more likely to purchase insurance than people without such an experience (Kunreuther et al. 1978). The probability of experiencing a natural disaster is the same as before and after the unfortunate event, but people tend to be persuaded by the vividness of the fresh memory.³

The availability heuristic implies that recent experiences powerfully influence decision-making in various domains, which includes gambling behavior (Clotfelter and Cook 1989, Croson and Sundali 2005, Guryan and Kearney 2008). For example, Clotfelter and Cook (1989) point out that people prefer to exchange a winning lottery ticket for more tickets instead of cashing it in. In addition, Croson and Sundali (2005) showed that 80% of subjects quit roulette gambling after losing on a spin, but only 20% did so after a winning spin. Even more interesting, Croson and Sundali (2005) found from the same study that winning a bet significantly increases subsequent betting activities. The findings of these gambling studies consistently indicate that gamblers respond as the availability heuristic predicts. Like offline gamblers, online gamblers are

³ Another example of the availability heuristic is the so-called “hot hand” in sports, which has been shown to be more illusion than fact (Gilovich et al. 1985). Empirical research has shown that the future performance of an athlete aligns more with his or her long-term success rate than with recent short-term outcomes (Koehler and Conley 2003). However, sports fans often think that an athlete who scored previously is more likely to make a goal on his or her next attempt than one who previously failed to score.

likely to be sensitive to recent gains and losses. If so, their short-term gambling behavior will follow the pattern that the availability heuristic predicts. In particular, we expect that online gamblers will gamble more after winning because their fresh memory of success leads them to overestimate the probability of winning in the next round. In contrast, online gamblers are presumed to play less after they lose because they take their failure as a painful reminder that they have little chance of winning.⁴ Thus, we hypothesize:

H3: *An immediate gain will be positively associated with subsequent online gambling.*

H4: *An immediate loss will be negatively associated with subsequent online gambling.*

It is important to note that the availability heuristic and gambling theory do not mesh perfectly. They coincide in their prediction of risk-taking behavior in the domain of gains, but they diverge in the domain of losses. The availability heuristic predicts that a person faced with losses will be wary of risk, but gambling theory predicts this person will tend to take risks. Our point about this divergence is to note that the availability heuristic explains individuals' responses to short-term losses, but gambling theory describes individuals' reactions to long-term losses. Therefore, we have proposed both H2 (gambling theory) and H4 (the availability heuristic), and believe both will work, although under different situations, as explained earlier. Few attempts have been made to reconcile the two seemingly paradoxical perspectives so as to explain complex, dynamic decision-making behavior under uncertainty. Thus, our findings will be important not only to further reveal the nature of online gambling in particular, but also to cultivate a better understanding of individuals' decision-making processes in general.

2.3. Repeated Behavior: Current Behavior, Regular Use, and Extended Use

In the field of psychology, past behavior is considered a good indicator of future behavior. For example, Fredricks and Dossett (1983) found that prior class attendance was a significant predictor of subsequent class attendance. In a variety of other activities, such as cheating, shoplifting, lying, seat belt use, and coffee

⁴ The availability heuristic suggests that subsequent gambling is affected by the signs and magnitudes of immediate outcomes. Nevertheless, Thaler and Johnson (1990) argue that to better predict subsequent gambling, recent patterns of gains and losses should be controlled for beyond the signs and magnitudes of their results. This is because the effect of gains and losses on subsequent gambling differs with respect to whether prior wins and losses were consecutive or mixed (Thaler and Johnson 1990). Our study does not control for these micro-level factors, but if our hypotheses receive empirical support despite the lack of such factors, it would be taken as general evidence indicating the validity of the availability heuristic in the context of online gambling. We thank an anonymous reviewer for pointing out this important aspect of online gambling.

drinking, the past behavior-future behavior relationship has consistently been shown to be significant (Beck and Ajzen 1991, Ouellette and Wood 1998). In the IS discipline, a large number of studies demonstrate the powerful impact of past behavior on future behavior at the postadoption stage (Kraut et al. 1999, Kim 2009, Venkatesh et al. 2003, 2012). As with many activities, gambling is often found to follow a general pattern in which future behavior is predictable, based on past behavior (Lam and Mizerski 2009, Mizerski et al. 2004, Oh and Hsu 2001). People initially engage in gambling to satisfy personal motives including excitement, fun, profit, and social recognition (Cotte and LaTour 2009). However, as they gamble frequently over time, the same activity becomes routine (Lam and Mizerski 2009, Mizerski et al. 2004). Online gambling is expected to be even more conducive to becoming routine behavior than its offline counterpart because it occurs in the same environment in which people live their daily lives and thus is easily integrated into one's day-to-day routine (Cotte and LaTour 2009). In summary, online gambling tends to follow highly predictable patterns that can be inferred from past behavior. Thus, we predict that current online gambling will have a positive relationship with subsequent online gambling.⁵ Thus, we hypothesize:

H5: Current online gambling will be positively associated with subsequent online gambling.

Some people gamble only in the short term during a vacation or holidays, but others visit casinos regularly. Compared with traditional casinos, online gambling is more readily accessible, more affordable, and less intrusive. Thus, regular use—which is defined as how consistently a specific IT application is employed over time (de Guinea and Markus 2009)—is expected to be even more salient in the online world than in a traditional setting (Cotte and LaTour 2009). According to the literature on repeated behavior, regularity strengthens the extent of repeated patterns, and therefore, the relationship between current behavior and subsequent behavior (Aarts and Dijksterhuis 2000, Ouellette and Wood 1998). Research suggests that in a stable environment, one's behavior tends to be repetitive; yet, in an unfamiliar situation, it is rarely so

⁵ This hypothesis, however, conflicts with a study of offline gambling by Narayanan and Manchanda (2012) who found that prior behavior did not have a positive impact on subsequent behavior. Their study is among the first studies of gambling to use a rigorous econometric technique to analyze a rich set of longitudinal data. Yet, a potential reason for the lack of a positive relationship between current gambling and subsequent gambling lies in the way their data were analyzed. Specifically, in their offline gambling study, all variables such as recent and cumulative outcomes were reset at the beginning of each trip; as a result, current gambling is modeled to be affected only by several plays within a trip that lasts typically a day. In such a within-trip analysis, it is relatively difficult to observe repeated patterns. In contrast, once inter-trip phenomena are examined over a long period of time, it is more likely to observe repeated behavioral patterns.

(Ouellette and Wood 1998). Within the context of online gambling, this psychological mechanism implies that if one's visits to a website are random and sporadic, the effect of current gambling on subsequent gambling is weak. In contrast, regular and frequent online gambling tightly integrates the mental link with everyday life and eventually forges a stronger relationship between current gambling and subsequent gambling. Overall, the earlier discussion suggests that regular use is a moderating factor in the relationship between current and subsequent gambling. More specifically, we predict that the more regular online gambling is, the stronger the relationship between current gambling and subsequent gambling will be. Thus, we hypothesize:

H6: Regular use of a gambling website will strengthen the relationship between current and subsequent online gambling.

According to the IS literature, IT users go through different developmental phases after initial adoption of an IT application (Ahuja and Thatcher 2005, Saga and Zmud 1994). The first stage of postadoption is known as routinization in which the use of an IT application is viewed as a part of everyday activities (Saga and Zmud 1994). A new IT application is perceived initially as something out of the ordinary, but with the accumulation of experience, people see it as a mundane tool (Ahuja and Thatcher 2005). The next phase, extended use, is a more advanced stage of postadoption than routinization. In this stage, the IT tool is employed in a more comprehensive manner to fulfill a person's higher-level goals (Saga and Zmud 1994). A transition from routinization to extended use is a strong indication that the online service under investigation has begun to be embedded within a person's day-to-day activities (Ahuja and Thatcher 2005, Hsieh and Wang 2007, Saga and Zmud 1994).

Online casinos try to stimulate the occurrence of this type of extended use by offering numerous gambling options such as poker, blackjack, roulette, bingo, slots, and sports betting. Online gamblers may initially sign up with an online casino to play their favorite game (e.g., poker). After getting comfortable with the online casino environment, they may want to try other games such as roulette or blackjack. Thus, at some point after the routinization stage, these people could increase their repertoire in terms of game types as they use the website more fully. In our study, this form of gambling behavior is termed extended use.⁶ Although

⁶ Limayem et al. (2007) similarly examined, in the context of Web usage, comprehensiveness of usage, which refers to the extent to which a person uses the different features of a single application. We believe that comprehensiveness of

researchers have been aware of the concept of extended use, few studies have examined how extended use affects postadoption phenomena. A notable exception is Limayem et al.'s (2007) habit study, which maintains that those who use only one feature of an application are found to develop a weaker habit than those who use many features of the same application. Similarly, Kim and Son (2009) suggest that extended use in the form of the number of features a person employs on a certain website is positively related to Web usage and to other behavioral outcomes. These studies consistently imply that with the increase in the number of features used, a person's usage is more tightly linked with everyday life. As with the case of regular use, we predict that extended use of a gambling website will strengthen the effect of current gambling on subsequent gambling. Thus, we hypothesize:

H7: Extended use of a gambling website will strengthen the relationship between current and subsequent online gambling.

3. Method

3.1. Sample and Data Collection

We obtained the data used for this study from the Transparency Project (Division on Addiction 2009), an initiative of the Cambridge Health Alliance (CHA). One of the main objectives of the Transparency Project is to make datasets related to public health freely available for research. The dataset chosen for this study was collected through joint collaboration between CHA and bwin Interactive Entertainment, AG (bwin). Headquartered in Vienna, Austria, bwin is one of the major providers of worldwide Internet gambling services. bwin offers various types of online gambling such as poker, casino games (e.g., roulette), video games (e.g., pinball games), and sports gambling. From February 1, 2005, to February 27, 2005, bwin assigned a unique ID number to each person who opened an account with bwin. Consequently, a large cohort of 42,647 participants was established. For the eight full months immediately after February 1, 2005, bwin recorded each of these participants' Internet gambling activities.

3.2. Measures

usage in Limayem et al. (2007) corresponds well to extended use in the IS infusion literature (Ahuja and Thatcher 2005, Hsieh and Wang 2007, Saga and Zmud 1994, de Guinea and Markus 2009).

The original dataset contained records of actual daily online gambling that summarize the measures of betting behavior. Identified by date and type of gambling service, these records document the aggregate number of bets made, monies wagered, and winnings credited to participants' accounts. Other measures in the data include: (1) participants' (anonymous) unique IDs; (2) demographics such as the country of residence, gender, and age upon opening the account; and (3) registration entries such as the date the account was opened and the date of deposit of a registrant's money. The total number of daily aggregate records included in the original dataset was 1,740,196.

The 42,647 participants in the original dataset live in 81 countries. Of these participants, about 80% reside in five European countries; Germany represents the majority (56.68%), followed by Turkey (5.81%), Poland (5.67%), Spain (5.64%), and Greece (5.61%). We chose the sample from the top-five countries on the list in terms of the number of participants so as to reduce uncontrolled disturbances resulting from cross-national differences among 81 countries. Despite the reduction in the number of countries, the sample chosen in this study sufficiently represents the entire population of interest (i.e., 79.41%).⁷ In addition to this reduction, we excluded from our selected sample those participants who had been dormant over the period of this study. As a result, the final sample used for the model calibration has 22,304 participants, which is about 65.86% of the original sample from the five countries.

We aggregated the daily gambling data into weekly data. We chose a week, instead of a day, as the time unit of data analysis mainly for two reasons. First, the literature suggests that a behavior becomes routine if it is performed regularly on a weekly basis in a stable context (Ouellette and Wood 1998). Accordingly, unless the chosen unit of analysis spans at least a week, some forms of routine behavior may go undetected. Second, online gambling, as with other types of entertainment, such as watching a movie or participating in sports, is likely to exhibit a weekly cycle. This occurs because leisure activities often are performed on weekends when people have time off from work. Therefore, a behavioral pattern that is believed to occur weekly might have been overlooked if the original daily aggregate dataset was used for data

⁷ The five countries represent a majority of the participants available. Including all of the countries would have resulted in inserting numerous dummy variables for each country, which would have increased the overall multicollinearity in the model.

analysis. After aggregating daily measures into weekly measures, we obtained a final dataset of 170,877 weekly aggregate records.⁸

3.3. Model Specification

Similar to their use in Khare and Inman’s (2006) study, our data are characterized as a three-level hierarchical structure in which the time-series observations (Level 1) are nested within subjects (Level 2) which, in turn, are nested within countries (Level 3). A Hierarchical Linear Model (HLM) is preferred because of the statistical inefficiency of using an Ordinary Least Squares (OLS) regression model to analyze such multilevel data (Raudenbush and Bryk 2002). In addition, an HLM allows us to model the heterogeneity among subjects and countries with unequal numbers of observations within subjects and unequal numbers of people within countries (Khare and Inman, 2006).

Our model is specified as shown in Table 1.⁹ Weekly gambling activity is one of its key variables. We measured this variable by the aggregate amount of monies (“stakes” hereinafter) wagered by a subject during each week ($STAKES_{j,i,t}$ and $STAKES_{j,i,t-1}$).¹⁰ Several major independent variables measure prior outcomes, including both cumulative and immediate outcomes. Cumulative outcomes—such as net cumulative gain ($CUMUGAIN_{j,i,t-1}$) and net cumulative loss ($CUMULOSS_{j,i,t-1}$)—represent the long-term balance of a subject’s account from the first play until the end of the preceding week.¹¹ In contrast, immediate outcomes such as net immediate gain ($GAIN_{j,i,t-1}$) and net immediate loss ($LOSS_{j,i,t-1}$) measure the

⁸ Although we believe that weekly aggregation of online gambling is the most desirable way of aggregation in our context, in Online Appendix 4 we consider and discuss, as a robustness check, alternative time windows for aggregation.

⁹ The multilevel models reduce to the integrated model by substituting the Level 2 and Level 3 equations into the Level 1 equation.

¹⁰ Both $STAKES_{j,i,t}$ and $STAKES_{j,i,t-1}$ are transformed into their natural log, becoming $\ln(STAKES_{j,i,t})$ and $\ln(STAKES_{j,i,t-1})$. Because raw data are nonnegative (e.g., stakes wagered by definition cannot be less than zero), and large standard deviations compared with means are observed in the raw data of these measures, natural log transformation helps mitigate the nonlinearity and nonnormality in both variables that otherwise would harm our HLM model (Gelman and Hill 2006). Specifically, transformation is done by first adding 0.5 units to each observation and then taking the natural log of the derived data. No substantial differences were observed between the results of our final model and those obtained when adding a number different from 0.5 units, i.e., 0.33 and 1.

¹¹ Cumulative gains and losses are easily tracked in the bwin system. They represent a user’s long-term account balance, which equals the amount of difference between the current balance and total deposits made into the account. Not only is the current balance highlighted in yellow on top of the site during the entire time users remain logged in, but also the complete history of deposits is clearly reported when users click on the current balance and go into their account management page named “My bwin.” Besides tracking the history of their deposits, users can also track their detailed betting and gaming activities for each game type, as well as any withdrawal, in “My bwin.”

short-term balance during the prior week. Other variables include regular use ($RU_{j,i,t-1}$) and extended use ($EU_{j,i,t-1}$), along with several control variables.

Table 1. Model Specification

Level 1: Time-series equation

$$\begin{aligned} \ln(STAKES_{j,i,t}) = & \beta_{j,i,0} + \beta_1 CUMUGAIN_{j,i,t-1} + \beta_2 CUMULOSS_{j,i,t-1} + \beta_3 GAIN_{j,i,t-1} + \beta_4 LOSS_{j,i,t-1} \\ & + \beta_{j,i,5} \ln(STAKES_{j,i,t-1}) + \beta_6 RU_{j,i,t-1} + \beta_7 EU_{j,i,t-1} \\ & + \beta_8 RU_{j,i,t-1} \ln(STAKES_{j,i,t-1}) + \beta_9 EU_{j,i,t-1} \ln(STAKES_{j,i,t-1}) + \varepsilon_{j,i,t} \end{aligned} \quad (1)$$

Here, we model $\varepsilon_{j,i,t} = \varphi_{j,i,t} + \rho\varepsilon_{j,i,t-1}$

Level 2: Subject equations

$$\beta_{j,i,0} = \pi_{j,0,0} + \pi_{1,0} FreqUse_{j,i} + \pi_{2,0} OccaUse_{j,i} + \pi_{3,0} \ln(AGE_{j,i}) + \pi_{4,0} GENDER_{j,i} + v_{j,i,0} \quad (2)$$

$$\beta_{j,i,5} = \pi_{j,0,5} + v_{j,i,1} \quad (3)$$

Level 3: Country equations

$$\pi_{j,0,0} = \delta_{0,0,0} + \delta_{1,0,0} GREECE_j + \delta_{2,0,0} POLAND_j + \delta_{3,0,0} SPAIN_j + \delta_{4,0,0} TURKEY_j + \omega_{j,0,0} \quad (4)$$

$$\pi_{j,0,5} = \delta_{0,0,5} + \omega_{j,0,1} \quad (5)$$

Integrated model

$$\begin{aligned} \ln(STAKES_{j,i,t}) = & \delta_{0,0,0} + \delta_{1,0,0} GREECE_j + \delta_{2,0,0} POLAND_j + \delta_{3,0,0} SPAIN_j + \delta_{4,0,0} TURKEY_j \\ & + \omega_{j,0,0} + \pi_{1,0} FreqUse_{j,i} + \pi_{2,0} OccaUse_{j,i} + \pi_{3,0} \ln(AGE_{j,i}) + \pi_{4,0} GENDER_{j,i} \\ & + v_{j,i,0} + (\delta_{0,0,5} + \beta_8 RU_{j,i,t-1} + \beta_9 EU_{j,i,t-1} + \omega_{j,0,1} + v_{j,i,1}) \ln(STAKES_{j,i,t-1}) \\ & + \beta_1 CUMUGAIN_{j,i,t-1} + \beta_2 CUMULOSS_{j,i,t-1} + \beta_3 GAIN_{j,i,t-1} + \beta_4 LOSS_{j,i,t-1} \\ & + \beta_6 RU_{j,i,t-1} + \beta_7 EU_{j,i,t-1} + \varphi_{j,i,t} + \rho\varepsilon_{j,i,t-1} \end{aligned} \quad (6)$$

Note: Definitions and additional explanations of the variables and symbols in this table can be found in Online Appendix 2.

In the time-series Equation (1), weekly gambling ($\ln(STAKES_{j,i,t})$) is the dependent variable. The effects included in this equation are as follows: (1) an intercept ($\beta_{j,i,0}$); (2) two cumulative prior outcomes (β_1 and β_2); (3) two immediate prior outcomes (β_3 and β_4);¹² (4) current use of online gambling ($\beta_{j,i,5}$), the main effect of $RU_{j,i,t-1}$ (β_6) and its interaction with $\ln(STAKES_{j,i,t-1})$ (β_8) as well as the main effect of $EU_{j,i,t-1}$ (β_7)

¹² Although some studies include the quadratic effects of prior outcomes (e.g., Narayanan and Manchanda 2012), we do not include them; instead we focus on the main effects of prior outcomes with a stronger theoretical foundation. However, we have used the quadratic effects of prior outcomes as an alternative specification and confirmed that our results are robust.

and its interaction with $\ln(\text{STAKES}_{j,i,t-1})$ (β_9); and finally, (5) a random effect ($\epsilon_{j,i,t}$) that is allowed to correlate with its lagged term ($\epsilon_{j,i,t-1}$).¹³

In the subject Equations (2) and (3), the Level 1 intercept ($\beta_{j,i,0}$) and the effect of current online gambling ($\beta_{j,i,5}$) are both modeled as a function of an intercept ($\pi_{j,0,0}$ and $\pi_{j,0,5}$) and a random effect ($u_{j,i,0}$ and $u_{j,i,1}$). In addition, Equation (2) for $\beta_{j,i,0}$ also includes control variables such as age ($\pi_{3,0}$), gender ($\pi_{4,0}$), and group effects ($\pi_{1,0}$ for frequent users; $\pi_{2,0}$ for occasional users).¹⁴ Pursuant to prior IS research (Kim et al. 2005, Limayem et al. 2007), we posit that people have different levels of routinization exhibited through their initial gambling. To control for this individual heterogeneity, the entire dataset is divided into two parts: (1) an initial period that captures users' first eight weeks of activities; and (2) a postadoption period that incorporates the rest of the users' activities. We sorted the aggregate number of bets during the initial period to categorize the cohort into three segments: frequent (top 7%, when $\text{FreqUse}_{j,i} = 1$), moderate (middle 53%), and occasional (bottom 40%, when $\text{OccaUse}_{j,i} = 1$) users (Jackson et al. 2008).¹⁵

Finally, in the country Equation (4), the Level 2 intercept ($\pi_{j,0,0}$) from Equation (2) is modeled as a function of an intercept ($\delta_{0,0,0}$), four country fixed effects (e.g., $\delta_{1,0,0}$) as control variables, and a random effect ($\omega_{j,0,0}$). Similarly, the country Equation (5) models the Level 2 coefficient $\pi_{j,0,5}$ from Equation (3) as a function of an intercept ($\delta_{0,0,5}$) and a random effect ($\omega_{j,0,1}$).

These five equations at all of the three levels can be rewritten as an integrated model, wherein the Level 1 submodel includes variables that are relevant to each subject's dynamic behavior pertaining to the three theoretical perspectives—gambling theory, the availability heuristic, and repeated behavior. The Level 2 submodel treats each individual subject as an observation and tests the time-invariant effects specific to each

¹³ Independent errors within a subject alone may not be sufficient to capture the dynamic feature of time-series error structure; it is reasonable to assume first-order autoregressive error correlation between adjacent time periods, with the correlation coefficient ρ as estimated in the model. If ρ is truly different from 0, a correlated within-subject error structure is preferred.

¹⁴ Recent healthcare research points out that age and gender are important factors influencing gambling behavior (i.e., Jackson et al. 2008).

¹⁵ We tested whether different categorizing methods affected our findings. The results are very similar. We provide additional details in Online Appendix 4.

subject. The Level 3 submodel groups the sample into five country groups and controls for any country differences. Therefore, the three levels are unique to each other, as are the variables included at each level.

Estimating the aforementioned effects would help us assess the validity of several of our model specifications. Specifically, the random effects for $\{\nu, \omega\}$, respectively, control for the unobservable subject- and country-level heterogeneity. By using their estimated variances $\{\hat{\tau}\}$, we are able to calculate the Intra-Class Correlation (ICC) as a criterion of whether an HLM framework is legitimate for our study (Raudenbush and Bryk 1986, 2002).

The descriptive statistics are reported in Table 2. Note that the prior outcome variables are rescaled to units of 1,000 Euros. Because we use HLM, variable centering is of special importance to parameter estimation and thus to hypotheses testing. Essentially, because our hypothesized effects are all at Level 1, we used the Centering Within Cluster method (as so termed in Enders and Tofighi 2007) for all Level 1 variables. Meanwhile, we left all the Level 2 and Level 3 variables uncentered. According to prior literature, this approach estimates Level 1 effects most reliably, and the results are the most straightforward to interpret (Enders and Tofighi 2007, Hofmann and Gavin 1998).

4. Results

First, we will illustrate an interesting pattern of individuals' online gambling behavior that occurs in our final sample. Figure 2 plots the time-series Pearson correlation statistics between the stakes wagered in week t and week $t - 1$ by group categories as described earlier. As expected, in comparison with the moderate- and occasional-user groups, the frequent-users demonstrate a higher level of correlation in current-subsequent online gambling. The highest correlation for the frequent-users group happens in the 19th week ($\rho = 0.94$); there are five weeks in which this correlation for this group exceeds 0.8; for as many as 17 out of 27 weeks, the correlation is larger than that of either of the other groups. Interestingly, although moderate users and occasional users are at similar levels of correlation overall, the behavior of occasional users is more unstable than that of the moderate users in terms of this correlation, except over the last several weeks. The up-and-down fluctuation from week to week for the occasional users is more dramatic, in the sense of both the degree of the fluctuation across weeks and the absolute change between adjacent weeks.

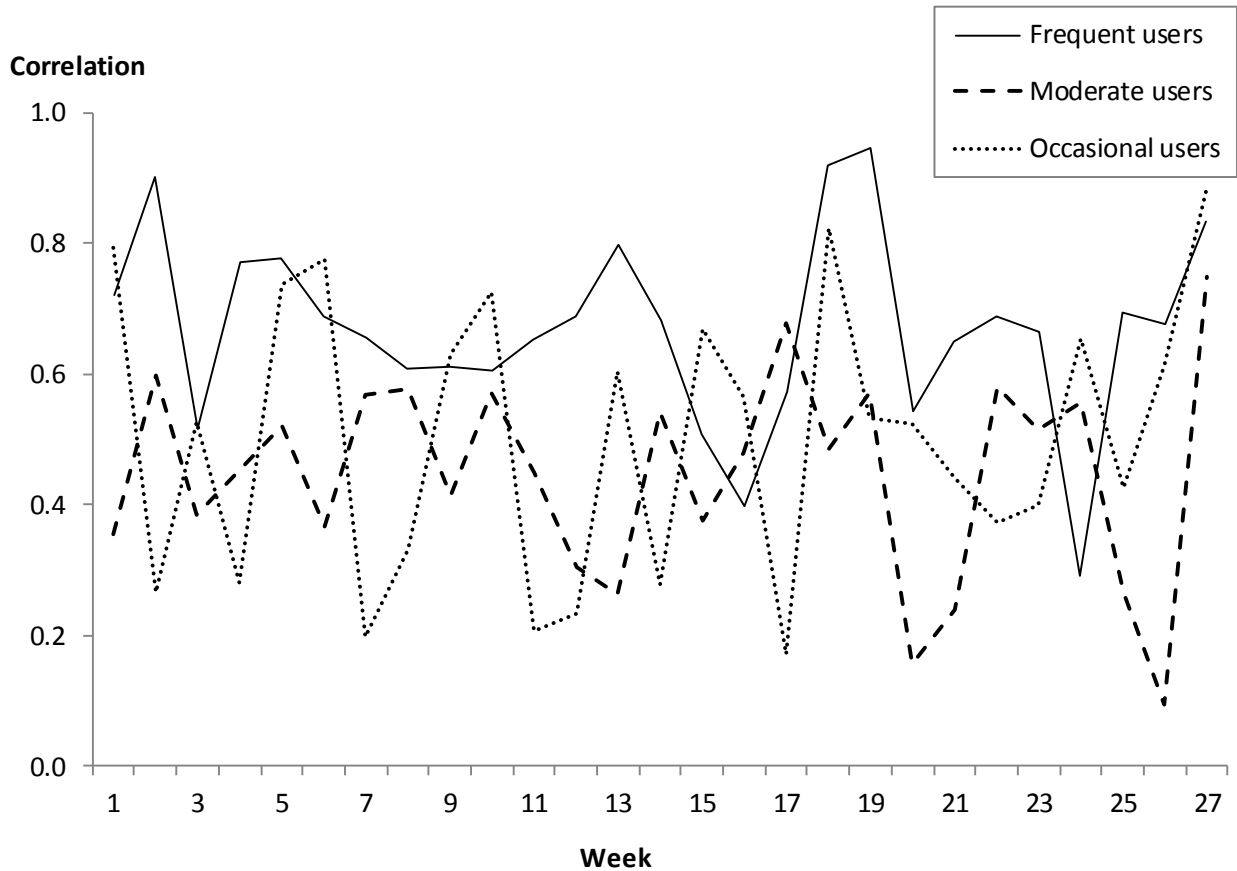
Table 2. Descriptive Statistics and Correlations

		Mean	(s.d.)	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	
1	ln(STAKES _{j,i,t})	3.32	(1.82)	-0.69	12.50	----																
2	ln(STAKES _{j,i,t-1})	2.49	(2.45)	-0.69	12.50	0.58	----															
3	CUMUGAIN _{j,i,t-1}	0.04	(0.35)	0	36.25	0.13	0.10	----														
4	CUMULOSS _{j,i,t-1}	0.27	(0.92)	0	28.43	0.37	0.29	-0.04	----													
5	GAIN _{j,i,t-1}	0.01	(0.13)	0	15.81	0.17	0.17	0.40	0.05	----												
6	LOSS _{j,i,t-1}	0.03	(0.13)	0	8.44	0.30	0.36	0.08	0.47	-0.02	----											
7	RU _{j,i,t-1}	3.83	(2.02)	0	6	0.20	0.51	0.05	0.12	0.05	0.13	----										
8	EU _{j,i,t-1}	0.95	(0.79)	0	7	0.28	0.48	0.03	0.15	0.05	0.16	0.58	----									
9	FreqUse _{j,i}	0.10	(0.31)	0	1	0.29	0.24	0.04	0.29	0.04	0.15	0.16	0.19	----								
10	OccaUse _{j,i}	0.30	(0.46)	0	1	-0.17	-0.19	-0.01	-0.13	-0.02	-0.07	-0.28	-0.17	-0.22	----							
11	ln(AGE _{j,i})	3.44	(0.30)	2.89	4.65	0.16	0.13	0.01	0.11	0.02	0.07	0.12	0.05	0.09	-0.04	----						
12	GENDER _{j,i}	0.94	(0.24)	0	1	0.03	0.01	-0.01	0.01	0.00 [‡]	0.01	0.00 [‡]	-0.01 [‡]	0.00 [‡]	-0.01	-0.05	----					
13	GREECE _j	0.07	(0.26)	0	1	0.16	0.11	0.05	0.09	0.05	0.08	0.05	0.05	0.12	-0.08	0.02	0.00 [‡]	----				
14	POLAND _j	0.05	(0.23)	0	1	-0.06	-0.02	-0.01	-0.03	-0.01	-0.02	0.01	0.04	0.00 [‡]	-0.01	-0.05	0.00 [‡]	-0.07	----			
15	SPAIN _j	0.06	(0.25)	0	1	0.07	0.04	0.01	0.06	0.01	0.04	0.00 [‡]	0.04	0.05	-0.03	-0.04	0.03	-0.07	-0.06	----		
16	TURKEY _j	0.04	(0.20)	0	1	0.01	0.01	0.02	0.01	0.01	0.01	-0.02	0.04	0.03	-0.02	-0.09	0.00 [‡]	-0.06	-0.05	-0.05	----	

Note:

- All correlation coefficients are significant at $p < 0.01$ level except noted by ‡ $p > 0.05$.

Figure 2. Time-series Correlation between $STAKES_{j,i,t}$ and $STAKES_{j,i,t-1}$ by Group Category



For example, except for the last week, the largest change in correlation for moderate users happens in the 20th week ($\Delta\rho = 0.42$), but for the occasional users, there are five weeks in which this change in correlation is even larger than 0.42 (weeks 2, 5, 7, 11, and 18). Across weeks, on average, the correlation in current-subsequent online gambling is 0.61 for frequent users, 0.29 for moderate users, and 0.40 for occasional users.

We adopted the Full Maximum Likelihood estimation technique, which provides us with several key statistics useful for direct model comparisons: (1) estimations of the sum of squared error terms that are used to calculate adjusted R-squared;¹⁶ (2) the deviance statistic, computed as negative two times the log likelihood, on which Chi-squared difference tests are conducted to determine the better goodness of fit between one model and its partial models (Raudenbush and Bryk 2002); and finally, (3) Akaike Information Criterion (AIC)

¹⁶ We followed the same method of calculating the R-squared value as other researchers who use HLMs (e.g., Ang et al. 2002, DeHoratius and Raman 2008).

and Bayesian Information Criterion (BIC), whose smaller magnitudes indicate the superiority of a model compared with its partial models (Cameron and Trivedi 2005).

4.1. The Null Model

Before analyzing the specific effects of our research variables, we needed to examine whether the use of an HLM is appropriate for our data. To do this, we analyzed a fully null model by following prior research (Deadrick et al. 1997, Hofmann et al. 2000). Table 3 presents the result of this fully null model. The results indicated the following. First, the between-individual random effect is significant (Variance component = 1.731, $SE = 0.021, p < .0001$), which means that our data contains a significant amount of between-individual differences regarding the stakes even after controlling for within-individual differences. Second, ICC is 57.5%, a much higher level than the commonly accepted threshold of 10%.¹⁷ In addition, we calculated the sample-mean reliability estimate (Raudenbush and Bryk 2002), also referred to as ICC2 by Bliese (2000), which reflects the reliability of the Level 2 group means. Such a reliability estimate is 0.91, which is also high according to Bliese (2000).¹⁸ Therefore, based on these results, our use of an HLM framework to carry on the analyses is appropriate.

Table 3. Null Model Results

Fixed effects	Coefficient	Standard error	t	p
INTERCEPT	3.084	0.010	306.2	<.0001
Random effects	Variance component	Standard error	z	p
Between-individual	1.731	0.021	84.1	<.0001
Within-individual error	1.281	0.006	208.5	<.0001

Note: n = 170,877

4.2. Model Comparison and Selection

To empirically testify to the advantage of integrating the three theoretical perspectives—gambling theory (GT), the availability heuristic (AH), and repeated behavior—into one coherent analytical framework, we

¹⁷ We used the equation $\frac{\tau_{\text{Between}}}{\tau_{\text{Between}} + \tau_{\text{Within}}}$ to calculate ICC. We analyzed an additional fully unconditional model according to Raudenbush and Bryk (2002). As shown in Table 3, the error and random terms are $\tau_{\text{Within}} = 1.281$ and $\tau_{\text{Between}} = 1.731$.

¹⁸ The sample-mean reliability estimate was calculated by using the equation $\frac{N_t \cdot ICC}{1 + (N_t - 1) \cdot ICC}$ wherein N_t equaling 7.9 represented the average number of weeks that a subject gambled online.

followed the same approaches as used in much of the previous research (e.g., Mehra et al. 1998) and analyzed eight different models. Specifically, Model 1 was an unconditional model (Raudenbush and Bryk 2002) that incorporated only control variables. In addition to control variables, Model 2 included GT, Model 3 included AH, and Model 4 included repeated behavior. In addition to their inclusion of control variables, Model 5 included AH and repeated behavior, Model 6 included GT and repeated behavior, and Model 7 included GT and AH. Finally, Model 8 was the integrated model in the sense that it included variables pertaining to all of the three theoretical perspectives as well as control variables. Table 4 reports the estimation results from these eight HLMs.

Estimating these eight models enabled us to understand the validity of each of the three theoretical perspectives at several different horizons. Most important, by comparing Model 8 with Models 5, 6, and 7, we demonstrated the statistical power of a single theoretical perspective even after controlling for the other two (Mehra et al. 1998). Particularly, GT in Model 8 boosted the adjusted R-squared in Model 5 by 4.0% ($47.0\% - 43.0\% = 4.0\%$). Similarly, AH in Model 8 increased the adjusted R-squared in Model 6 by 3.6% ($47.0\% - 43.4\% = 3.6\%$). Even more pronounced, repeated behavior in Model 8 boosted the adjusted R-squared in Model 7 by 21.5% ($47.0\% - 25.5\% = 21.5\%$). Further, we verified whether the additional proportion of variance explained by each perspective was statistically significant even after controlling for the other two perspectives. Chi-squared tests of the “delta” deviance indicated that GT significantly enhances a model that already includes AH and repeated behavior ($\chi^2 = \Delta\text{Dev} = |532,891 - 535,421| = 2,530$, $df = 2$, $p < .001$). Significant results were also obtained regarding the contribution of adding AH ($\chi^2 = \Delta\text{Dev} = |532,891 - 535,517| = 2,626$, $df = 2$, $p < .001$) and repeated behavior ($\chi^2 = \Delta\text{Dev} = |532,891 - 538,592| = 5,701$, $df = 5$, $p < .001$), respectively, into a model that already controls for the other two perspectives. Therefore, in assessing the explanatory power of the alternative models, Model 8 outperformed Models 5, 6, 7, and all of the other models.

In addition, AIC and BIC for Model 8 were considerably lower than their values in Models 5, 6, and 7, indicating that the significant results of decreased deviance statistics when one perspective is added atop the other two remain valid even after considering both the number of increased parameters and, in our case,

Table 4. HLM Results

Variables		Models								
		Control	Singular				Partial		Integrated	
		1	2	3	4	5	6	7	8	
CUMUGAIN _{j, i, t-1}	β_1		0.3602*** (0.0172)					0.3062*** (0.0158)	0.2536*** (0.0183)	0.2251*** (0.0166)
CUMULOSS _{j, i, t-1}	β_2		0.0610*** (0.0081)					0.0492*** (0.0071)	0.0731*** (0.0083)	0.0685*** (0.0072)
GAIN _{j, i, t-1}	β_3			0.4684*** (0.0211)		0.3766*** (0.0217)			0.3753*** (0.0224)	0.2879*** (0.0229)
LOSS _{j, i, t-1}	β_4			0.0382 (0.0235)		-0.2109*** (0.0249)			-0.0013 (0.0240)	-0.2585*** (0.0253)
ln(STAKES _{j, i, t-1})	$\delta_{0,0,5}$				0.1117*** (0.0019)	0.1039*** (0.0015)	0.1024*** (0.0015)			0.1046*** (0.0015)
RU _{j, i, t-1}	β_6				-0.0191*** (0.0024)	-0.0099*** (0.0023)	-0.0116*** (0.0024)			-0.0118*** (0.0023)
EU _{j, i, t-1}	β_7				0.0223*** (0.0045)	0.0425*** (0.0045)	0.0426*** (0.0045)			0.0441*** (0.0045)
RU _{j, i, t-1} ln(STAKES _{j, i, t-1})	β_8				0.0129*** (0.0008)	0.0153*** (0.0007)	0.0145*** (0.0007)			0.0149*** (0.0007)
EU _{j, i, t-1} ln(STAKES _{j, i, t-1})	β_9				0.0159*** (0.0018)	0.0229*** (0.0017)	0.0225*** (0.0017)			0.0232*** (0.0017)
FreqUse _{j, i}	$\pi_{1,0}$		1.3959*** (0.0364)	1.4430*** (0.0365)	1.1491*** (0.0331)	1.2482*** (0.0335)	1.2018*** (0.0333)	1.3863*** (0.0363)		1.1016*** (0.0329)
OccaUse _{j, i}	$\pi_{2,0}$		-0.3770*** (0.0194)	-0.3840*** (0.0196)	-0.3040*** (0.0178)	-0.3271*** (0.0181)	-0.3219*** (0.0178)	-0.3753*** (0.0193)		-0.2963*** (0.0176)
ln (Age _{j, i})	$\pi_{3,0}$	0.8263*** (0.0335)	0.7215*** (0.0316)	0.7329*** (0.0320)	0.6392*** (0.0288)	0.6640*** (0.0293)	0.6524*** (0.0289)	0.7180*** (0.0315)		0.6359*** (0.0286)
GENDER _{j, i}	$\pi_{4,0}$	0.1813*** (0.0391)	0.1853*** (0.0371)	0.1836*** (0.0376)	0.1574*** (0.0337)	0.1731*** (0.0344)	0.1744*** (0.0339)	0.1841*** (0.0370)		0.1627*** (0.0333)

(Continued on next page)

(Table 4, continued)

Variables		Models							
		Control	Singular			Partial			Integrated
		1	2	3	4	5	6	7	8
INTERCEPT	$\delta_{0,0,0}$	-0.0043 (0.1227)	0.4747*** (0.1159)	0.4536*** (0.1172)	0.7803*** (0.1061)	0.6872*** (0.1074)	0.7148*** (0.1059)	0.4855*** (0.1154)	0.7229*** (0.1053)
GREECE _j	$\delta_{1,0,0}$	1.1205*** (0.0392)	0.8800*** (0.0372)	0.8985*** (0.0377)	0.7879*** (0.0340)	0.8162*** (0.0344)	0.7960*** (0.0339)	0.8770*** (0.0371)	0.7609*** (0.0337)
POLAND _j	$\delta_{2,0,0}$	-0.2140*** (0.0424)	-0.2483*** (0.0399)	-0.2538*** (0.0404)	-0.2649*** (0.0364)	-0.2575*** (0.0369)	-0.2519*** (0.0364)	-0.2477*** (0.0398)	-0.2683*** (0.0361)
SPAIN _j	$\delta_{3,0,0}$	0.4595*** (0.0389)	0.3552*** (0.0367)	0.3626*** (0.0371)	0.3084*** (0.0335)	0.3294*** (0.0339)	0.3214*** (0.0334)	0.3535*** (0.0366)	0.3062*** (0.0332)
TURKEY _j	$\delta_{4,0,0}$	0.1667*** (0.0440)	0.0604 (0.0416)	0.0649 (0.0421)	0.0283 (0.0380)	0.0420 (0.0384)	0.0367 (0.0379)	0.0605 (0.0414)	0.0139 (0.0376)
Model comparison statistics									
Adjusted R-squared		0.0%	22.6%	22.1%	40.0%	43.0%	43.4%	25.5%	47.0%
Deviance (-2 log likelihood)		541,053	538,821	538,756	535,766	535,421	535,517	538,592	532,891
Akaike information criterion (AIC)		541,071	538,847	538,782	535,802	535,461	535,557	538,622	532,935
Bayesian information criterion (BIC)		541,161	538,978	538,913	535,983	535,662	535,758	538,773	533,156

Notes:

- Standard errors in parentheses
- † $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

the large sample size. In conclusion, these results clearly demonstrate, on the basis of our large sample, how well Model 8 fits our data. Most important, any one of the three theoretical perspectives adds significantly more insight than a partial model that covers only part of the story; statistically, a partial model may lead to a bias in estimates because of omitted variables. Therefore, Model 8 is superior to any of the partial models (i.e., Models 1 through 7). Consequently, we will next focus on further assessing the performance and estimation results of Model 8.¹⁹

4.3. Tests of Hypotheses Results

All seven hypotheses were supported based on asymptotic t statistics. H1 hypothesizes that a net cumulative gain will be positively associated with subsequent online gambling ($\beta_1 > 0$); this hypothesis is supported ($\beta_1 = 0.2251$, $SE = 0.0166$, $p < .001$). Because the net cumulative gain is rescaled as the number of 1,000 Euros (so are the other prior outcome variables), it means that every 1,000 extra Euros of net cumulative gain until the end of week $t - 1$ equates to a 22.51% increase in subsequent online gambling. Similarly, H2 proposes that a net cumulative loss will be associated positively with subsequent online gambling ($\beta_2 > 0$). H2 also is supported ($\beta_2 = 0.0685$, $SE = 0.0072$, $p < .001$). For every 1,000 extra Euros of net cumulative loss until the end of current week, subsequent online gambling increases 6.85%, more than two thirds less magnitude than the effect of the net cumulative gain.

H3 states an immediate gain will be positively associated with subsequent online gambling ($\beta_3 > 0$). The results support this hypothesis ($\beta_3 = 0.2879$, $SE = 0.0229$, $p < .001$). For every 1,000 extra Euros of immediate gain, subsequent online gambling increases 28.79%. H4 posits that an immediate loss will be *negatively* associated with subsequent online gambling ($\beta_4 < 0$). This also is supported ($\beta_4 = -0.2585$, $SE = 0.0253$, $p < .001$). For every 1,000 extra Euros of immediate loss, subsequent online gambling plummets 25.85%.

¹⁹ There are some interesting results to be noted, such as how the baseline of online gambling behavior differs by country, demographic groups, and individuals. We provide additional explanations of these parameter estimates in Online Appendix 3 for interested readers.

H5 posits a positive relationship between current and subsequent online gambling ($\delta_{0,0,5} > 0$).

According to the estimations in Table 4, H5 is supported ($\delta_{0,0,5} = 0.1046$, $SE = 0.0015$, $p < .001$). Because both the dependent variable (i.e., $\ln(\text{STAKES}_{j,i,t})$) and the focal independent variable (i.e., $\ln(\text{STAKES}_{j,i,t-1})$) are in the natural log form, the coefficient being hypothesized here perfectly represents a partial elasticity;²⁰ that is, elasticity after holding everything else constant (Wooldridge 2002). Therefore, it indicates here that for each 1% increase in current online gambling, subsequent online gambling will rise 0.1046% after controlling for other variables in the model. In the context of offline gambling, Narayanan and Manchanda (2012) argue that the elasticity of the similar carry-over effect of a magnitude of -0.25% for a mean consumer is fairly large.²¹ Also noted is that such an elasticity in their model is not constant, i.e., the magnitude of this elasticity for a consumer with a median level of prior betting activity quickly drops to -0.08%, but in our model, the “pooled” baseline elasticity of prior online gambling on subsequent online gambling is constant. Given the prior literature and the fact that the p value is very small, we deem an effect size of 0.1046% not only nontrivial but also close to a realistic scale (Aguinis et al. 2010).

H6 states that regular use of a gambling website will strengthen the relationship hypothesized in H5 ($\beta_8 > 0$). This interaction effect is supported ($\beta_8 = 0.0149$, $SE = 0.0007$, $p < .001$). If regular use increases by one week, the relationship between current and subsequent online gambling increases by 1.49 percentage point. Although this moderation effect appears relatively small, it is noteworthy that this corresponds to a 14.2 percent ($0.0149\%/0.1046\% = 14.2\%$) boost in the relationship between current and subsequent online gambling. Specifically, if a person gambled one more week during the last six weeks, the partial elasticity becomes 0.1195% ($0.1046\% + 1 \times 0.0149\% = 0.1195\%$), meaning for each 1% of increase in current online gambling, subsequent online gambling will increase about 0.1195%.

Finally, H7 proposes that extended use of a gambling website will strengthen the relationship between current and subsequent online gambling ($\beta_9 > 0$). This hypothesis is also supported ($\beta_9 = 0.0232$,

²⁰ In technical terms, the partial elasticity of y with respect to x , with everything else constant, is the approximate percentage increase (decrease) in y when x increases (decreases) by 1% (Wooldridge 2002).

²¹ In their study, the largest magnitude of elasticity is -0.31%, which reveals the effect size of cumulative losses on subsequent amounts bet; moreover, elasticity for the significant primary marketing effect is 0.11% on subsequent amounts bet (Narayanan and Manchanda 2012).

$SE = 0.0017, p < .001$). In particular, if a person gambled in one more different type of gambling, for each 1% hike in current online gambling, subsequent online gambling would increase about 0.1278% ($0.1046\% + 1 \times 0.0232\% = 0.1278\%$). Note that such a moderation effect for one more extended use amplifies the current-subsequent relationship in online gambling by as much as 22.2% ($0.0232\% / 0.1046\% = 22.2\%$).

We did many additional analyses to examine whether our findings are robust to alternative specifications, including the time window choices in measuring key research variables. The details are provided in Online Appendix 4.

5. Discussion and Conclusion

The objective of this work was to develop and test a model of online gambling that simultaneously takes into account cumulative outcomes, recent outcomes, and prior use. Drawing on disparate theories, we hypothesized that the effects on online gambling of cumulative outcomes, immediate outcomes, and prior use would not be identical because their underlying mechanisms are fundamentally different. Our hypotheses were tested based on field data collected over eight months from 22,304 actual users of a gambling website. The results of a multilevel panel data analysis strongly support our hypotheses. First, as predicted by gambling theory, individuals' online gambling increased with an increase in a cumulative net gain or cumulative net loss. Second, as the availability heuristic prescribed, a recent loss was shown to reduce online gambling, but a recent gain increased it. Third, consistent with the repeated behavior literature, regular use and extended use of a website were found to moderate the effect of current gambling on subsequent gambling. Taken together, this study clarifies how people react differently to immediate and cumulative outcomes and also how regular use and extended use facilitate routine behavior in the context of online gambling. In general, our findings suggest that the three perspectives, i.e., gambling theory, the availability heuristic, and repeated behavior, should be taken into account to understand online gambling, which is in essence a series of risk-taking attempts with the potential of eventually becoming routine behavior.

5.1. Theoretical Implications

5.1.1. A Longitudinal Model of Online Gambling with Multiple Perspectives

A rigorous study of online gambling requires a long-term investigation of individuals' behavior because the loss of \$100 today may not be perceived the same as the loss of \$100 a year ago. Further, online gambling has the potential, over time, to become part of a daily routine. Despite the importance of understanding the dynamics of online gambling, little was known about behavioral changes in online gambling that unfold over a long period of time. One of the major contributions of this study to the literature is our longitudinal model of online gambling that describes both short-term and long-term mechanisms underlying postadoption phenomena. Our findings clearly indicate that researchers should take into account both recent outcomes and cumulative outcomes. In addition, this study shows that routine behavior explains a certain aspect of online gambling that cannot be explained by individuals' reactions to betting outcomes. We have integrated gambling theory, the availability heuristic, and theories of repeated behavior into a powerful and coherent framework to explain online gambling over time. To show the efficacy of our integrative perspective, we formally compared alternative models in terms of model fit and predictive power. Our findings indicate that the proposed model is significantly better than the partial models that ignore one or more of the core mechanisms underlying online gambling. Thus, the present study is expected to serve as a sound basis for future research on online gambling. As with online gambling, numerous online games involve (cyber or real) money staked on future events and can easily be routine (e.g., fantasy sports, online virtual worlds). Thus, we hope that our findings will shed light on the dynamics of online behavior related to these new types of games.

5.1.2. Cumulative and Immediate Outcomes

Gambling is basically a game of betting on an uncertain outcome. Naturally, a betting outcome in the form of gains or losses is assumed to affect subsequent betting behavior. Gambling theory is a well-tested explanation of how people make decisions based on prior outcomes. Although the theory has been applied to a variety of decision-making problems, the present study, to the best of our knowledge, is the first to test it in the context of online gambling. As expected, gambling theory turns out to be a highly effective explanation of individuals' online gambling behavior. In particular, this study provides empirical support for a "house-money effect," which suggests that online gamblers bet more when cumulative gains offset cumulative losses. In addition, we observed a "break-even effect" in which individuals place more bets when

they are losing overall. Although house-money and break-even effects have been repeatedly shown in various contexts, our findings are unique in that those effects are revealed even after controlling for other powerful impacts such as immediate outcomes and repeated behavior.

Meanwhile, our findings indicate that online gamblers are less likely to increase their stakes when they lose their recent bets. Although consistent with the availability heuristic that suggests risk-aversion in the domain of losses, these findings seemingly contradict what gambling theory predicts about risk-taking behavior in the domain of losses. However, the present study shows that the two theories are not mutually exclusive and instead represent complementary mechanisms underlying individual behavior. The findings of this study imply that whereas one generally attempts to break even in the domain of losses, vivid memories of recent failures tend to keep one from undertaking additional risk. Thus, our study reveals how people react differently to cumulative losses and recent losses. It is important to note that Narayanan and Manchanda (2012) similarly examined individuals' reactions to recent outcomes and cumulative outcomes in the context of casino gambling. However, contrary to our study, their study indicated that cumulative gains and losses are entirely irrelevant, whereas recent gains and losses are still significant in subsequent online gambling. We suspect that these conflicting findings result mainly from the short-term nature of the casino gambling study. In particular, Narayanan and Manchanda (2012) conducted a within-trip analysis of casino visits that is based on the assumption that the outcomes of previous trips do not affect subsequent gambling. Such an assumption might be reasonable for casino gambling, but it seems unrealistic for online gambling. In contrast, our study carefully considers inter-trip phenomena and shows that cumulative and immediate losses are both significant, but their effects on online gambling are not the same. Overall, the present study contributes to IS research by showing, from both theoretical and empirical perspectives, the complex effects of cumulative and recent outcomes on online gambling behavior.

5.1.3. Repeated Behavior, Regular Use, and Extended Use

Narayanan and Manchanda (2012) tested an econometric model of traditional gambling using data collected over a two-year period. Although they showed the significant impact of prior outcomes on subsequent behavior, prior behavior did not positively affect subsequent behavior. In contrast, our study clearly

demonstrates the routine nature of gambling behavior in the context of online gambling. Although not reported because of brevity, our analysis indicates that repeated behavioral patterns exist among 45% of online gamblers. This result is in contrast to Narayanan and Manchanda (2012) that indicates that only 8% of the casino gamblers exhibit repeated behavioral patterns. The discrepancy in the findings stems possibly from the contextual difference. Compared with the offline setting, the online setting offers convenient access to gambling. The presence of an Internet-enabled computer at home is believed to facilitate frequent visits to a gambling website, which leads eventually to routine behavior. Our study conceptually and empirically shows the routine pattern of online gambling that was not prevalent in the context of offline gambling.

Our study presents initial evidence that regular use, or the consistency of IT use, actually strengthens repeated behavior. Specifically, we found that regular use increases the impact of current behavior on subsequent behavior; this finding indicates that regular use is conducive to further solidifying a routine behavioral pattern. We believe that the notion of behavioral regularity is becoming more important in the Internet Age in which geographical and time factors are no longer as crucial as they once were in the performance of personal activities. Thus, another contribution of this study lies in its demonstration of the important, yet overlooked, role that regular use plays in regulating repeated behavior.

Our findings indicate that extended use strengthens the current behavior-subsequent behavior relationship. This finding suggests that as individuals learn to play additional games on a gambling website, their gambling activity becomes more tightly integrated into everyday life and thereby strengthens the tendency for such a behavior to become routine. Some may consider extended use not to be conducive to habit formation because extra tasks present unfamiliar situations to individual users. However, according to our findings, the use of novel games seems to occur progressively as individuals expand their comfort zones; accordingly, extended use facilitates, rather than hinders, repeated behavior. Although routine behavior is known as a precursor to extended use in IS research (Cooper and Zmud 1990), our study demonstrates that extended use also strengthens repeated behavior. A major contribution of this study to IS research, therefore, is its discovery of the feedback effect that extended use has on routine behavior at the postadoption stage. This effect has rarely been mentioned in the literature.

5.2. Practical Implications

This study demonstrates that extended use facilitates routine behavior. This finding should encourage online providers to promote extra services to customers as a way to increase revenue. For example, practitioners can easily identify customers who continue to use only a limited number of services. To encourage such customers to explore different services, the practitioners may unobtrusively remind them of other services through automatic, instant customization. As customers' use of other services expands and diversifies, the website becomes tightly enmeshed into their daily life. However, in the case of online gambling, extended use may also be taken as an early indicator of heavy gambling. Thus, a monitoring program is needed that discerns any problematic behavioral patterns, especially among gamblers whose usage continually expands to other types of games. In cases in which an additional sign of heavy gambling is identified in addition to extended use (e.g., huge losses, high frequency bets), the program may remind the user of information on how to get professional help when needed, and at the same time, warn the management team so that it can possibly take corrective measures.

Our findings reveal that online gamblers become risk-averse when their recent bets are unsuccessful. However, the memory of failure does not last long, and as long as their losses are within a recoupable range, they soon begin taking risks to get even. These findings suggest that for a healthier entertainment environment, online gamblers need to be regularly reminded of their prior losses as well as the odds against outplaying the house. Unlike in an offline setting, this type of objective information—which will help users recognize the reality of online gambling and thus avoid reckless risk-taking—can be provided easily to online gamblers. Although online gambling is conducive to routine use because of its accessibility, it also presents new opportunities to help prevent problematic gambling. Our findings are believed to be valuable for practitioners who strive to offer a safe and fair online entertainment service and for policymakers who are responsible for developing a sound regulatory environment.

5.3. Limitations and Further Research

A few limitations of our paper need to be noted. First, the generalizability of our findings may be limited because we collected our data from a single Internet gambling service. Second, gambling theory has rich

implications, but we did not incorporate all facets of its rich framework into our model. For example, gambling theory suggests that because an individual's mental accounting rules differ across various situations, losing \$10 may not always have the same implication. Thus, until the rich nuances of gambling theory are fully understood in the context of online gambling, our findings should be interpreted cautiously. Third, an implicit assumption of this study was that a reference point at which people evaluate their gain and loss is zero. However, this assumption may not hold as people could have different reference points. For example, assume a person who recently found unexpected \$100 cash that he placed in his drawer long time ago. If he plans to use this cash for online gambling and does not mind losing it entirely, his reference point is -\$100 instead of \$0. In such a case, his gambling behavior is unlikely to be identical to that of others whose reference point is zero. Thus, caution should be exercised in interpreting our findings because of the assumption made in this particular study.

Fourth, although we distinguish conceptually between immediate and cumulative outcomes of online gambling, the distinction between them is not always clear-cut. For example, a large gain or loss two weeks ago may affect subsequent online gambling through the availability heuristic. Similarly, although the role of fresh memory in decision-making is highlighted within the framework of the availability heuristic, this perspective does not necessarily preclude the involvement of deliberate processing in one's reactions to recent events. For these reasons, our taxonomy of immediate and cumulative outcomes should be understood as a relative term rather than as a definitive dichotomous classification.

Fifth, because only limited datasets were available for research, our model may involve a missing variable, especially at the level of an individual user. For instance, the income or starting wealth of users may be an influential variable that should be included in analysis, as evidenced by Thaler and Johnson (1990). Individual responses to loss and gain may differ depending on the wealth of users. In addition, research suggests that the frequency with which people evaluate the outcomes of their decisions could affect their appetite for risk (Benartzi and Thaler 1995). However, the nature of our data does not permit us to examine the role of feedback frequency in online gambling. Besides, because of a lack of data, our online gambling model does not incorporate possible effects (if any) of prior *offline* gambling experiences. Although not

perfect, our random effect terms are expected to account for aforementioned time-invariant individual specific effects. Also, some individual specific variables may vary over time (e.g., availability of time for leisure) but are not captured by our model; however, the relatively short period covered by our dataset likely reduces the seriousness of this potential problem.

Sixth, our results may be subject to operationalization of variables, which is somewhat inherent in any analysis employing secondary data.²² For example, although we aggregated gambling activities across different game types, a game-level analysis may reveal idiosyncrasies in different types of games, a topic we leave for our future research. Furthermore, gambling activities were aggregated to weekly totals whereby the daily-level information may be lost. Nevertheless, weekly-level measurement is well established in prior IS research (e.g., Kraut et al. 1999, Venkatesh et al. 2008). We also went through several steps to ensure that our results are robust to alternative aggregation methods.

Finally, in our hypotheses, the proposed relationships are assumed to be strictly linear. However, such an assumption is rarely true because actual relationships in social sciences tend to show some curvilinear patterns. For example, our first two hypotheses state that cumulative wins and losses will increase subsequent gambling. These hypotheses seem to imply that the average gambler will never stop gambling. However, in reality, people do not continue online gambling indefinitely even if their cumulative outcomes increase. In particular, although not reported for the sake of brevity, our ad hoc analysis with the quadratic terms of cumulative outcomes shows that some threshold points exist beyond which more cumulative gains or losses do not necessarily lead to more gambling. Thus, it should be noted that our hypotheses suggest only general linear tendencies, and in reality, actual relationships are not necessarily exactly linear.

Extensions of our work can go in several directions. First, we could analyze the per-visit or daily activities rather than the activities aggregated into a certain time period. With such an approach, we would be able to focus on more immediate responses to users' previous experiences. This approach also would offer an opportunity to study users' choices of particular games based on their prior use and outcomes (i.e., gains and losses). Second, a study on the effect of macroenvironments would be of special interest to policymakers

²² We thank an anonymous reviewer for bringing this issue to our attention.

and managers. For example, how will a regulatory intervention affect users' gambling behavior? How will managerial interventions (e.g., promotions, advertising, and loyalty programs) influence users' gambling?

Third, we could examine whether our model is applicable to other online entertainment contexts such as online computer games involving virtual currencies. For example, in a virtual world (e.g., *Second Life*), cyber money is used to buy, sell, or even rent online properties (e.g., land, resorts, condominiums) in the pursuit of profit (Wilson 2007). Such cyber money transactions are quite similar to online gambling because, in some cases, the results of prior stakes (i.e., prior outcomes) and personal histories of Web interactions (i.e., prior use) are likely to play important roles in regulating subsequent behavior. Thus, our model will provide a useful framework for understanding individual behaviors in online entertainment services such as online games.

Fourth, it would be interesting to examine underlying factors that lead to cross-national differences such as those observed in the present study. For example, our findings indicate that despite a relatively high gross domestic product (GDP) per capita, Germans bet less money in a given week than Greeks or Spaniards. Interestingly, among the countries examined in our study, Germany turns out to be the highest in individualism, which is a cultural dimension believed to relate to a tendency to avoid risk (Hsee and Weber 1999). Probably, Germans gamble less online because of their individualistic culture; however, future research is required to provide refined tests that will better clarify the roles of cultural factors in online behavior.

6. Conclusions

An investigation into online gambling use has profound implications to various research domains which include, but are not limited to, IT use, habitual behavior, decision-making under uncertainty, economic behavior, and online consumer behavior. Despite the advantageous position the IS discipline occupies in dealing with such a multifaceted issue, it is unfortunate that little attention has been paid to the subject in IS research. The present study takes a close look at online gambling behavior, by integrating three perspectives, i.e., gambling theory, the availability heuristic, and repeated behavior, into a unified framework. We believe that the proposed model and associated findings provide valuable insights not only into online gambling, but

also into other types of online gaming that involve the staking of real or cyber money on a regular and routine basis. Given the economic potential of the online gaming industry and the rise in the recent debate on legalizing online gambling in the U.S., we hope that this study will help inform researchers, practitioners, and public policymakers as they move forward with decisions in this important area.

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