Applying the Cox Model to Study Online Gambling Behavior

Completed Research Paper

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Abstract

Although a key objective of Internet gambling service providers is player retention, there is a concomitant need to reduce the social costs of gambling. Our study shows how habit and prospect theories help build an integrative framework for decision support in regulated Internet gambling environments. To illustrate the practical implication of this framework, we applied the Cox model with time-dependent covariates on real gambling data collected from 4,222 users of a gambling website. The results help establish the positive association of key indicators such as the prior outcomes on the activity lifespan of an Internet gambler and the moderating effect of gambling frequency on the positive association between prior outcomes and gambling lifespan. This research is expected to contribute to the literatures on IT adoption and diffusion in general, and IT-based addictive behavior in particular.

Introduction

What factors can predict the addictive use of online casino gambling, for instance, the "lifespan"—the timespan of significant length that involves gambling activities online—of an online gambler? Although limited literatures have examined this question, the recent development of relevant technologies has made it more important (Turel et al. 2011). Over the past 15 years, the pervasive and ubiquitous nature of the Internet has led to its universal adoption and its use in an ever increasing number of ways. Online

gambling – defined by its traditional terms as the wagering of something of value on a contingency – is one such example of an online service that has a growing community of users (Basham and Luik 2011, Griffiths 1999, Hume and Mort 2011). Lawmakers assert that the convenience and accessibility of the Internet makes online gambling more likely to be addictive than offline gambling (Griffiths and Barnes 2008). This problem of addiction is considered one of the key factors deterring the legalization of online gambling (Watson et al. 2004). New Jersey nearly became the first state to legalize in-state Internet gambling, but the state governor vetoed the bill in March, 2011. The impetus to legalize online gambling can be further seen in the report by Eggen (2010) that legalization would add almost $5 billion to annual government revenues. This leads us to conclude that, as Bell (1999) predicted, online gambling is likely to be gradually legalized in the same way casino gambling was.

Information Systems (IS) researchers have only recently explored the behavioral aspects of online gambling (Ha et al. 2007). For example, Ma et al. (2014) explored the influence of factors such as prior use and prior outcomes on subsequent use in the context of online gambling. From a modeling perspective, their work closely resembles that of Li et al. (2011), who studied the factors influencing online customers' purchasing decisions. Instead of subsequent use, our study employs as dependent variable another important behavioral marker of addictive gambling behavior (Braverman et al. 2013), that is, an online gambler's lifespan of using the service (hereinafter referred to as gambling lifespan). Gambling can be a healthy entertainment insofar as it is kept under control; thus arguably, the longer the gambling lifespan of an online gambler, the more the risk of addictive use and negative consequences. The research by Ng and Wiemer-Hastings (2005), which determined that gambling lifespan is positively associated with compulsive habits, provides further motivation for our study.

Oh and Hsu (2001) have shown that gambling facilitates the formation of compulsive habit. Thus, drawing from habit theory and literatures in IS (e.g., Limayem et al. 2007), we first explore the relationship between frequency of use, which is considered an indicator of habit, and gambling lifespan. Although gambling often takes the form of a habitual behavior, the core characteristic of online gambling is outcome, measured in terms of the money wagered. Venkatesh et al. (2008) pointed out that both internal motivation and external factors, such as prior cumulative balances, affect the duration of system use. Taking inspiration from Thaler and Johnson's refined prospect theory (1990), which describes a gambler's behavior in terms of perceived risk, our study explores the relationship between prior cumulative outcomes and gambling lifespan. By combining theories from IS, economics, and psychology, we posit the following: (1) The impact of prior outcomes is positively associated with gambling lifespan, especially for the biggest winners and worst losers; (2) gambling frequency, considered an indicator of habit, is positively associated with gambling lifespan (particularly, it ought to serve as a moderator, strengthening the previously mentioned relationship between outcome and lifespan); and (3) the internal motivation of online gamblers positively affects gambling lifespan. Given the specific characteristics of the gambling lifespan data, we used survival analysis methods based on the Cox model (Cox 1972), instead of traditional regression analysis methods, to test our hypotheses.

This study contributes significantly to the IS literatures related to online gambling and addictive gambling behavior. Most important, our extensive literature search confirms that previous studies have not used the Cox proportional hazard model to identify the significant factors that affect gambling lifespan in online casino gambling services. Second, we emphasize that a widely ignored premise underlying the formation of habit is that the frequency of gambling should necessarily link to a gambler's individual motives. Finally, we investigate how Thaler and Johnson's refined prospect theory (Thaler and Johnson 1990), which addressed casino gamblers, can be extended to apply to compulsive gamblers' behavior in online gambling.

Gambling companies are aware of the advantages that the transformation from offline gambling to online gambling brings, especially lowered operational costs, less staff, and less need of land-based resources. Moreover, it is imperative that the ease of access and the convenience of gambling online do not result in any adverse impact on public health. We expect the results of this study to help us understand whether the problem of addiction is serious enough to justify the ban on most forms of online gambling in the U.S. The insights gained will facilitate effective decision making by policymakers with respect to regulating the online gambling industry. Also, our application of survival analysis (Cox 1972) based on the Cox model sheds light on the design of decision support systems to monitor and regulate the behavior of online gamblers.

Theory and Hypotheses

Literature Review: Information Technology (IT)-based Compulsive Behavior

This research is related to the literature on information technology (IT) adoption and diffusion in general and IT-based compulsive behavior in particular. In the recent decade, researchers have begun to realize and examine the potential behavioral risks associated with IT-based dependency, formally referred to as addictive or compulsive behavior, e.g., Internet addiction (Chen et al. 2014, Turel et al. 2011). Internet addiction has been recognized as the most salient IT-based addictive behavior thanks to the fast development of the Internet technology (Yang and Tung 2007). Though not related to specific substance usage, Internet addiction is recognized by a converging literature stream as a type of addiction, namely, behavioral addiction or disorder (Holden 2001). Partially related to compulsive habits, Internet addiction is defined as a psychological overdependence on the use of the Internet (Turel et al. 2011, Ng and Wiemer-Hastings 2005). According to Block (2008), Internet addiction mainly consists of four symptomatic criteria: (1) withdrawal, i.e., the feelings of distress and anxiety at the separation with the IT artifact, (2) tolerance, i.e., a tendency to undergo a prolonged period of usage, (3) excessive use, i.e., a high level of usage intensity, (4) adverse social and safety consequences, i.e., neglecting appropriate etiquettes in a social situation or neglecting critical safety precautions in potentially hazardous activities.

Although various examples of Internet addiction have been discussed in the recent IS literature, their antecedents and consequences are not uniformly theorized (Turel and Serenko 2010). It is recognized that Internet addiction is not a generalized concept but rather it is highly contingent on the types and characteristics of the IT services that the addicted user engages with (Turel et al. 2011). Whereas an addictive use of online competitive services such as online gambling and online gaming primarily hinges on the personal entertainment interests (Ma et al. 2014, Ng and Wiemer-Hastings 2005, Turel and Serenko 2010), an addictive use of smartphone technologies such as texting and emailing, and that of social media services in general depend heavily on the context of social relationships (e.g., friends, coworkers, love partners). Therefore, online competitive service addiction pertains more to the symptom of excessive use because gaming in the forms of gambling, auction, or video games entail a high level of competition and intensity that lead to a strong sense of immersion (Turel et al. 2011). Consequences thus often include severe personal financial crisis following uncontrollable investment of money. On the other hand, online social service addiction pertains to a greater degree to the symptom of adverse social and safety consequences (Turel and Serenko 2010). For instance, texting-while-driving and inappropriate use of personal phones during face-to-fact meetings have been documented (Bayer and Campbell 2012).

This research is closely related to the addictive behavior of online competitive services. As with conventional gambling, online casino gambling involves a chain of wins, losses, and the susceptibility to excessive and intensive use (Ma et al. 2014). The extant IS literatures on addictive behavior of online competitive services have been limited. They have mainly analyzed the characteristics of addictive behavior in the online version as compared with the more conventional offline version (Ng and Wiemer-Hastings 2005). The exceptions are Turel et al. (2011) and Ma et al. (2014). Turel et al. (2011) surveyed a sample of eBay auction users and developed a structural model of the links between online auction addiction and distorted attitudes and usage intention of online auction services. In their study, addictive use of online auction is framed as an antecedent of future use. However, they did not focus on the factors that may lead to the addictive behavior. Using objective data of a large sample of online gamblers, Ma et al. (2014) examined the factors that can predict the actual spending of online gambling, an established behavioral marker of potential addiction to online gambling (Braverman et al. 2013). However, limited research has investigated factors that can predict other important behavioral markers, e.g., the "lifespan" of an online gambling user, which should have a better generalizability than spending in IT-based addictive behavior research. More research is needed on such relevant metrics of addictive behavior in order to gain a more complete picture of the online gambling addiction in specific, and addictive behavior of online competitive services in general. The focal research contributes to this limited literature. Besides adopting an underexplored dependent variable, we identified and investigated the predictive strength of several factors that specifically pertain to the addictive use of online competitive services, including the financial outcomes and balances of the gaming activities.

Building on the theories and literatures in IS, economics, and psychology, below we develop six hypotheses about the factors and underlying mechanisms that predict gambling lifespan.

The Impact of Frequent Use on Lifespan

In the IS discipline, Limayem et al. (2007) defined habit as the extent to which individuals tend to perform IS use automatically. In addition, they mentioned that continued usage of IS would lead to formation of a habit. Venkatesh et al. (2008) determined that an online user's habitual behavior is positively associated with the duration of system use. In the context of online games, a large number of online gamers keep playing out of habit (Wu 2010). Similarly, online gambling, which is another kind of online gaming, is readily accessible and convenient, thus easily resulting in formation of a habit. It is reasonable to believe that habitual gamblers continue to gamble online for a long time.

Numerous empirical studies have shown that the frequency of use is a significant indicator of habit (Bagozzi and Warshaw 1990, Bergeron et al. 1995, Ouellette and Wood 1998, Saba and Di Natale 1998). For example, Bagozzi and Warshaw (1990) proposed that the frequency of past behavior is associated with habit. Past frequent performance would form a habit in the future (Ouellette and Wood 1998). Bergeron et al. (1995) measured habit in terms of the frequency of use in the context of executive information systems. Thus, we believe that frequency of use is a good representation of habit. Thus, it is plausible that frequent gamblers will continue to gamble longer. Based on this consideration, we formulate the following hypothesis.

H1: The frequency of gambling online is positively associated with gambling lifespan.

The Impact of Outcome on Lifespan

Online gambling is not just a habit-forming type of entertainment but is also filled with risk, because the motivation for most gamblers is money (Fisher 1993). Thus, online gamblers will consciously deliberate as they gamble. Thaler and Johnson (1990) proposed that refined prospect theory could predict a casino gambler's subsequent decision based on prior balances. The authors used a two-stage experiment involving first a "house money effect" and then a "break even effect" to describe an individual's behavior. The "house money effect" suggests that individuals tend to take risk after gains. The reason for this behavior is that individuals believe that prior gains can reduce the psychological distress associated with current or future losses. Thus, individuals will continue to gamble out of a big winning account. By contrast, the "break even effect" suggests that individuals will keep gambling as long as they feel that their losses are recoupable. Furthermore, if the losses seem too big to recoup, they will stop gambling to avoid further risk. Thus, according to the refined prospect theory, one of the key characteristics that affects whether gamblers keep betting is their perceived risk. Individuals with gains will keep gambling because the perceived risk becomes smaller, whereas those with increasing cumulative losses will quit gambling because of the perception of escalated risk.

In the second stage of Thaler and Johnson's (1990) experiment, they measured prior outcomes by the absolute value of the balance. In fact, because the implicit assumption in the second stage of the experiment was that all the subjects' prior stakes were equal, they used the absolute value of the balance instead of the relative value of balance referred to as the ratio of balance to prior stakes. Loewenstein and Thaler (1989) proposed that the relative value of balance (i.e., the ratio of balance to prior stakes) is much better than the absolute value of balance in reflecting the real effect of outcomes on a gambler's behavior. Our study, therefore, uses the ratio of balance to cumulative stakes to represent prior outcomes. As previously discussed, the higher the prior outcomes, the longer online gamblers continue to gamble. This leads to the following hypothesis.

H2: The ratio of balance to cumulative stakes is positively associated with gambling lifespan.

Because, based on refined prospect theory, perceived risk is negatively associated with gambling lifespan, gamblers will keep gambling as long as perceived risk decreases. As mentioned earlier, perceived risk is negatively associated with prior balance. Thus, significantly increased winnings will lead to a sharp decrease in gamblers' perceived risk, which further leads to their continued gambling. In our study, we categorized the top 5% of winners as big winners who are likely to continue gambling for a long time. Thus, Hypothesis 3 follows that:

H3: Higher winnings are positively associated with gambling lifespan.

Similarly, based on refined prospect theory, one would predict that gamblers with significantly increased losses would quit gambling immediately. However, refined prospect theory ignores a very important point: It implicitly assumes that individuals are rational. In other words, refined prospect theory cannot predict the behavior of gamblers who cannot control themselves. These gamblers with hindered self-control are categorized as impulsive gamblers—gamblers with compulsive gambling habits (Turel et al. 2011, Ng and Wiemer-Hastings 2005). Ainslie (1975) found that compulsive habit was negatively associated with self-control. Ladouceur and Walker (1996) argued that impulsive gamblers kept gambling out of distorted beliefs that at the outset made them overestimate their chances of winning. Accordingly, the key characteristic that affects impulsive gamblers is low self-control or distorted beliefs instead of perceived risk. Furthermore, Govoni et al. (1996) categorized 8.1% of adolescents in Ontario as problem gamblers. Shaffer et al. (1997) proposed that 3% to 5% of the adult population could be classified as compulsive gamblers. Rachlin (1990) found that because of their biased beliefs, compulsive gamblers kept gambling for a long time even under significant losses. Breen and Zuckerman (1999) found that compulsive gamblers were more likely to keep gambling even after successive losses. Therefore, we have tried to categorize the top 5% of losers as gamblers with compulsive habits who constitute a major category of problem gamblers (Blaszczynski and Nower 2002, Custer 1984, Rosenthal and Lorenz 1992). The following hypothesis helps represent the behavior of these compulsive gamblers whose behavior is of particular interest to us.

H4: Higher losses are positively associated with gambling lifespan.

As proposed earlier, relative balance is positively associated with gambling lifespan (H2). As also discussed previously, gamblers tend to consciously deliberate in order to win more money. In addition, the ability to perceive risk acts as a catalyst to accelerate conscious deliberation. Payne et al. (2009) noted that such ability was positively associated with the experience of repeatedly performing a specific task. Therefore, gambling frequency is believed to improve conscious deliberation, which in the present study may further strengthen the link between the ratio of balance to cumulative stakes and lifespan. Specifically, we propose the following hypothesis:

H5: The positive relationship between the ratio of balance to cumulative stakes and gambling lifespan will be stronger as gambling frequency increases.

The Impact of Internal Motivation on Lifespan

Several researchers have examined the relationship between internal motivation and the act of continuous use. For example, Venkatesh et al. (2008) proposed that internal motivation and external factors, such as prior cumulative balance could predict the duration of system use. Csikszentmihalyi and LeFevre (1989) proposed that internal motivation could predict the amount of time spent on an activity. Webster and Martocchio (1992) also found that internally motivated individuals are more likely to spend time on a system-related activity.

A gambling website typically incorporates various types of casino games. On a typical online gambling site's home page, it takes a user two steps to reach the page of a specific type of game. The site requires each user to first register for membership. Once granted access, a user logs into the home page and can then choose from among the site's numerous games. It is reasonable to argue that the time gap between membership registration and the first active bet in a specific type of online gambling game may to a great extent represent the degree of a gambler's internal motivation to play that specific type of game. In other words, the time gap decreases as internal motivation increases. Drawing on the argument made by Venkatesh, et al. (2008), we propose our last hypothesis as follows:

H6: The time gap between membership registration and the first active bet in any type of online gambling game is negatively associated with gambling lifespan.

Method

Sample

The original dataset used in this study was collected from a collaborative research project between the Division on Addictions (DOA), a Harvard Medical School affiliate, and bwin Interactive Entertainment

("bwin" hereinafter), headquartered in Vienna, Austria, which provides various kinds of online gambling games, such as casino (e.g., blackjack, slot machines), poker, and betting on sports games (e.g., horse races). The original dataset included 48,114 individuals who opened an account with bwin from February 1, 2005, through February 28, 2005. However, a large number of these gamblers only bet on sports. The dataset for the study was therefore reduced to 8,472 members who play online casino games, thus accounting for 18% of the total members. Even though the majority of bwin accounts did not play casino games during the research period, bwin remained the second largest operator of online casino websites in the European Union.[1] Among the 8,472 members, we excluded the data pertaining to 4,225 members because they played for fewer than four days. Of the rest, 10 members only played with free promotional stakes. Moreover, data was missing for 15 members. As a result, we obtained a longitudinal cohort dataset that included 4,222 members with daily betting activities for the period February 1, 2005, to January 31, 2007. The betting data pertaining to the casino gambling games only were used for analyses.

For our study, we randomly divided the dataset into two parts: a calibration dataset and a validation dataset. The calibration dataset included data pertaining to 603 gamblers. It accounted for about 14% of our final dataset. The rest of the data were used to validate our proposed model.

Measures

The information pertaining to each user included in the analysis was: (1) a user's unique ID number; (2) demographics, such as country of residence, primary language of residence, gender, and age; (3) registration entries, such as the date of registration in bwin (BwinDate), and the date of the first active bet on the gambling site (CasinoDate). Betting-related information was computed by summing the daily data in the original dataset. The corresponding measures consisted of the cumulative number of active days (Bets), the cumulative stakes per user (Stake), the cumulative winnings per user (Win), and the number of days from the first to the last bet on the gambling site (Lifespan). Numerous research has adopted a measure of lifespan (i.e., number of days in a continuous period) from the first day of being a customer until the last day of purchasing activity to measure "time until the event" variable. In survival models, the dependent variable—survival time—may be in any consistent time unit (e.g., second, minute, hour, day, month, year, etc.). For details, refer to these examples (Meyer-Waarden 2007, Jung et al. 2012).

Table 1. Definition of key variables used in the study	
Variable	Definition
Dependent variables	
Lifespan	Number of days from the first to last bet online during the study period
Status	1 if the user plays during the last two-week period; 0 otherwise.
Independent variables----Main effects	
Frequency	Defined as the ratio of cumulative active days to lifespan per user
BalanceRatio	Defined as the ratio of cumulative balances to cumulative stakes per user
Timegap	Defined as the timespan (days) from registration in bwin to first bet online
Top5PcnWinner	The value is 1 if the user is in the top 5% of winners, otherwise it is 0.
Top5PcnLoser	The value is 1 if the user is in the top 5% of losers, otherwise it is 0.
Independent variables----Control	
Age	Age at the time of registration in bwin
Gender	User's gender. Female: 1 Male: 0

Table 1. Definition of Key Variables

Other measures were derived as follows. Gambling frequency (Frequency) was measured as the ratio of Bets to Lifespan. The time gap (TimeGap) was calculated as the time difference between CasinoDate and

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[1] According to reports at Bwin.com.

BwinDate and the cumulative balance as the difference between Win and Stake (Balance). As mentioned earlier, the relative value of balance is much better than the absolute value of balance in reflecting the real effect of outcomes on different gamblers' behavioral patterns. Thus, relative balance (BalanceRatio) was computed as the ratio between Balance and Stake. Finally, dummy variables were used to indicate whether a gambler was among the Top 5% of losers (Top5PcnLoser) or the Top 5% of winners (Top5PcnWinner). Table 1 lists the definitions of each of these research variables.

Tables 2 and 3 contain summary statistics and correlation metrics.

Table 2. Calibration Dataset: Descriptive Statistics and Correlation Matrix											
Variable	N	St. Dev.	Min	Max	1	2	3	4	5	6	7
Age	603	9.25	17.00	65.00	1.00						
Gender	603	0.27	0.00	1.00	0.12	1.00					
Frequency	603	0.22	0.01	1.00	0.12	-0.02	1.00				
BalanceRatio	603	0.13	-1.00	1.28	0.05	0.02	-0.02	1.00			
Top5PcnLos	603	0.22	0.00	1.00	0.14	-0.04	0.05	0.05	1.00		
Top5PcnWin	603	0.22	0.00	1.00	0.01	-0.01	0.02	0.35	-0.05	1.00	
TimeGap	603	179.40	0.00	705.00	-0.08	-0.09	0.10	-0.05	-0.06	-0.02	1.00

Table 2. Calibration Dataset: Descriptive Statistics and Correlation Matrix

Table 3. Validation Dataset: Descriptive Statistics and Correlation Matrix											
Variable	N	St. Dev.	Min	Max	1	2	3	4	5	6	7
Age	3619	8.89	16.00	87.00	1.00						
Gender	3619	0.25	0.00	1.00	0.10	1.00					
Frequency	3619	0.21	0.01	1.00	0.06	0.02	1.00				
BalanceRatio	3619	0.11	-1.00	0.80	0.02	-0.01	0.07	1.00			
Top5PcnLos	3619	0.22	0.00	1.00	0.12	0.00	0.07	0.05	1.00		
Top5PcnWin	3619	0.22	0.00	1.00	0.01	0.00	-0.03	0.28	-0.05	1.00	
TimeGap	3619	185.85	0.00	718.00	-0.01	-0.08	0.10	0.01	-0.06	0.01	1.00

Table 3. Validation Dataset: Descriptive Statistics and Correlation Matrix

Model Development

The nature of the gambling lifespan data is such it is uncertain at the end of the study period whether any specific player is still active. This is referred to as right censoring. Helsen and Schmittlein (1993) pointed out that using classical regression models to estimate censored lifespan data has inherent analytical limitations and would lead to biased estimates of the covariate results. On the contrary, survival analysis techniques guarantee unbiased handling of right-censored data. Therefore, we used survival analysis based on the Cox model to estimate our data instead of relying on classical regression methods.

Cox (1972) proposed the proportional hazard model (referred to as the Cox model hereinafter) to estimate the relationship between survival and one or more covariates; as a covariate changes, its effect on the hazard rate will change proportionally. Moreover, the Cox model is a semiparametric method that assumes nothing about the specific nature or shape of the underlying survival distribution $h_o(t)$. Therefore, we believe that the Cox model is the most general and robust model that can be used to identify the factors affecting survival in the context of online gambling.

Kalbfleisch and Prentice (2002) have shown that the Cox model is widely used in management science and economics. For example, in the marketing discipline, Schweidel et al. (2008) used a survival analysis

model to assess the factors that underlie service retention in a contractual setting. In the IS discipline, Goo et al. (2007) applied survival analysis to investigate the factors influencing the lifespan of an IT outsourcing relationship. Li et al. (2010) applied survival analysis to examine why firms fail or survive in the volatile software industry. Although very few IS researchers have investigated the factors influencing online users' survival, we believe that it is appropriate to use the survival model to analyze the behavior of online gamblers.

Applying the Cox Model

Our survival analysis model is specified as follows. An online gambler's survival status, which is our primary outcome of interest, is operationalized as a binary variable. It is set to 1if a user bets on the casino game website during the last two weeks of our study period (from January 15, 2007, to January 31, 2007). In other words, from a survival modeling perspective it indicates that a user is surviving and is still actively participating in online gambling. Otherwise, it is set to 0, indicating that a user is unlikely to return to the casino game website, indicating that the user is dead or in other words has quit gambling online. T denotes a random variable indicating the time of death that we are interested in (lifespan time hereinafter). Under such a case of uncensored survival lifespan, we denote a user i's lifespan time Ti to be equal to the value of Lifespan. Meanwhile, for those who log onto the online casino game website during the last two weeks of our study period, right censoring occurs because we are not sure when, or even if, these gamblers die (i.e., they quit). The failure function F(t) refers to the likelihood of death before time t. The failure function is denoted as F(t)= Pr (T ≤ t). Thus, the survival function S(t)= 1 − F(t) refers to the likelihood of surviving up to time t. The hazard rate, h(t), refers to the failure rate of a subject at time t, conditioned on the fact that the subject is still alive by time t; that is, in our study, h(t) refers to the likelihood that an online gambler has not died by time t and will die during the infinitesimally small interval (t + Δt). Thus, the hazard rate is specified as follows:

$$(1) \quad h(t) = \frac{f(t)}{S(t)} = \frac{dF(t)/dt}{S(t)} = \frac{d(1-S(t))/dt}{S(t)} = \frac{-dS(t)/dt}{S(t)} = \lim_{dt \to 0} \frac{p(t < T < t + \Box t \mid T > t)}{dt}$$

Correspondingly, the Cox model is specified as follows:

$$(2) \quad h(t,x) = h_0(t)\exp(\beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_i x_i)$$

Wherein $\{x_j\}$ is a vector of the explanatory variable (risk factor hereinafter), and $\{\beta_j\}$ is a vector of the coefficients to be estimated. Therefore, we need to divide the Cox model into two parts as follows:

A nonparametric part defined as the baseline hazard $h_0(t)$, which makes no assumption on the underlying distribution, is a function that only involves time variable t but none of the variables in $\{x_j\}$. In other words, it indicates the natural risk without considering any specific risk factor. Also, $h_0(t)$ could potentially take any shape over time.

A parametric linear function of a set of risk factors (Griffiths and Barnes 2008). Because the function of risk factors is then introduced into the exponential function, the effects $\{\beta_j\}$ will adjust the baseline hazard up or down proportionally to reflect the relative importance of each of the risk factors.

Model Specification

We elaborate below on how the partial likelihood function is specified. Let:

   t = 1, 2 … T_{MAX} denotes the death time (measured in number of days) for the online gamblers, where t_{MAX} = 730 for our study;

   i = 1, 2 … D_{MAX} denotes an online gambler who dies at time t_i, where D_{MAX} denotes the number of online gamblers who are dead by time T_{MAX}

   k = 1, 2 … S_{MAX} denotes an online gambler who is still alive at time t_i,

S_{MAX} denotes the maximum number of online gamblers who are alive by time t_i;

x_{ij} = the jth covariate of online gambler i;

x_{kj} = the jth covariate of online gambler k;

As mentioned earlier, the hazard rate h(t) estimates the probability of death occurring at time t for an individual who survived to time t. In our case, this applies to an online gambler i who has survived until time t, denoting the probability that this gambler dies at time t. The partial likelihood is specified as below:

$$L(i \mid t, k_1, ..., k_m) = \frac{h_0(t)\exp(\beta_1 x_{i1}, ... \beta_n x_{ij})}{\sum\limits_{k=1}^{m} h_0(t)\exp(\beta_1 x_{k1}, ..., \beta_n x_{kj})}$$

$$(3) \qquad = \frac{\exp(\beta_1 x_{i1}, ... \beta_n x_{ij})}{\sum\limits_{k=1}^{m} \exp(\beta_1 x_{k1}, ..., \beta_n x_{kj})}$$

Using Eq. (3), we will use Maximal Likelihood Estimate (MLE) to estimate the partial likelihood L(i | t, k_1....k_m) in order to obtain the coefficient value β.

Results

In this section, we report the estimates for the Cox model based, respectively, on the calibration and the validation datasets. As the results in Table 4 demonstrate, the estimates for both datasets are highly consistent. The likelihood ratio estimates of our model in the two datasets are, respectively, 412.898 and 2,528.590, both of which are significant at the 0.0001 level. Therefore, we believe that the Cox model is robust enough to test our hypotheses.

Table 4. Determinants of online casino users lifespan: Estimates (hazard ratio)				
	calibrate dataset (N=603)		validate dataset (N=3619)	
	hazard ratio	Std. error	hazard ratio	Std. error
Age	0.990*	0.006	0.994***	0.002
Gender	1.009	0.167	1.136*	0.071
Frequency	4451.024***	0.953	1282.934***	0.349
BalanceRatio	0.155***	0.464	0.233***	0.154
Top5PcnWinner	0.552**	0.232	0.823**	0.090
Top5PcnLoser	0.038***	0.693	0.063***	0.390
TimeGap	1.002***	0.000	1.002***	0.000
Frequency * BalanceRatio	0.004**	2.330	0.007***	0.626
Age * Frequency	0.895***	0.026	0.924***	0.010
Age * Top5PcnLoser	1.064***	0.018	1.032***	0.010
Gender * Top5PcnWinner	28.497***	0.855	1.947**	0.301
Likelihood Ratio	412.898***		2528.590***	

* p < .01; ** p < .05; ***p < .001 .

Table 4. Determinants of Online Casino Users' Lifespan: Estimates (Hazard Ratio)

The hazard rate in our study refers to the instantaneous failure rate at time t, assuming a player was still making risky bets up until that time. The hazard ratio refers to the marginal impact of a one-unit change of the covariate xi on the hazard rate. We are reporting the hazard ratio because it is easy to interpret (the hazard ratio is simply exp(βj)). Also, Le (1997) proposed that in the logit model, the statistical effect of the

hazard ratio was similar to the marginal effect on failure. Moreover, the author distinguishes between the hazard rate and the hazard ratio. In our study, a hazard ratio of less than 1 indicates that an increase in the covariate decreased the hazard rate of "death" of a gambler, which implies an increase in the gambling lifespan (Helsen and Schmittlein 1993). On the other hand, a hazard ratio greater than 1 indicates that an increase in the covariate increased the hazard rate of the "death" of a gambler and thus decreased the gambling lifespan.

Hypotheses Testing

We test our hypotheses using the estimates reported in Table 4. Table 5 provides a summary of the hypotheses testing results. H1 hypothesizes that gambling frequency is positively associated with gambling lifespan (H1: hazard ratio < 1). However, the coefficient estimate for Frequency is positive and significant with a hazard ratio greater than 1 (calibration model: $\beta 1=8.40089$, p<0.0001, Hazard Ratio=4451.024; validation model: $\beta 1= 7.15691$, p<0.0001, Hazard Ratio=1282.934). As the gambling frequency of a gambler increases, gamblers are more likely to quit online gambling sooner. Thus, Hypothesis 1 is not supported.

Table 5. Summary of Hypotheses Testing Results	
Hypotheses	Supported?
H1: The frequency of gambling online is positively associated with gambling lifespan.	No
H2: The ratio of balance to cumulative stakes is positively associated with gambling lifespan.	Yes
H3: Higher winnings are positively associated with gambling lifespan.	Yes
H4: Higher losses are positively associated with gambling lifespan.	Yes
H5: The positive relationship between the ratio of balance to cumulative stakes and gambling lifespan will be stronger as gambling frequency increases.	Yes
H6: The time gap between membership registration and the first active bet in any type of online gambling game is negatively associated with gambling lifespan.	Yes

Table 5. Summary of Hypotheses Testing

H2 hypothesizes that the ratio of balance to cumulative stakes will be positively associated with gambling lifespan (H2: hazard ratio < 1). The coefficient estimate for BalanceRatio is negative and significant with a hazard ratio of less than 1 (calibration model: $\beta 4=-1.86125$, p=0.0001, Hazard Ratio=0.155; validation model: $\beta 4= -1.45734$, p<0.0001, Hazard Ratio=0.233). As BalanceRatio increases, gamblers will be less likely to quit gambling online, thus continuing to gamble longer. Hypothesis 2 is therefore supported.

H3 predicts that the top 5% of winners are positively associated with gambling lifespan (H3: hazard ratio < 1). The coefficient estimate for Top5PcnWinner is negative and significant with a hazard ratio of less than 1 (calibration model: $\beta 4=-0.59401$, p<0.0105, Hazard Ratio=0.552; validation model: $\beta 4=-0.19456$, p<0.0228, Hazard Ratio=0.823). The results indicate that the top 5% of winners will be less likely to quit online gambling sooner and more likely to continue gambling longer. Thus, Hypothesis 3 is supported.

Similarly, H4 predicts that the top 5% of losers are positively associated with gambling lifespan (H4: hazard ratio < 1). The coefficient estimate for Top5PcnLoser is negative and significant with a hazard ratio of less than 1 (calibration model: $\beta 4=-3.27344$, p<0.0001, Hazard Ratio=0.038; validation model: $\beta 4= -2.75833$, p<0.0001, Hazard Ratio=0.063). Thus, the top 5% of losers will be less likely to quit gambling online sooner and, therefore, more likely to continue gambling longer. Thus, Hypothesis 4 is supported.

H5 proposes that the effect of the ratio of balance to cumulative stakes on gambling lifespan will strengthen as gambling frequency increases (H5: hazard ratio < 1). The estimate for this interaction effect is negative and significant with a hazard ratio of less than 1 (calibration model: $\beta 2-5.61971$, p=0.0159, Hazard Ratio=0.004; validation model: $\beta 2= -4.97485$, p<0.0001, Hazard Ratio=0.007). As gambling frequency increases, the impact of BalanceRatio on a gambler's hazard rate of "death" will decrease significantly, meaning the positive relationship between BalanceRatio and gambling lifespan will become stronger. Thus, Hypothesis 5 is supported.

Finally, H6 (hazard ratio > 1) is also supported because the coefficient estimate of TimeGap is positive and significant with a hazard ratio of greater than 1 (calibration model: $\beta7=0.00190$, p<0.0001, Hazard Ratio=1.002; validation model: $\beta7= 0.00224$, p<0.0001, Hazard Ratio=1.002). The results indicate that as the time gap increases sharply, gamblers will be more likely to quit gambling online sooner; by contrast, the shorter the gap time, the longer the gambling lifespan. Thus, Hypothesis 6 is supported.

Discussion

A high frequency of betting would lead to the conclusion that gamblers' habit has been formed and they are likely to stay gambling online longer (Cotte and Latour 2009). Thus, we first attempted to explore whether merely using a high frequency of betting as an indicator of habit would lead to the conclusion that gamblers stay gambling online for a long time (H1). Surprisingly, the hypothesized relationship between frequency of gambling and gambling lifespan was not validated. This contradicts the well-known positive relationship between habit and lifespan in the case of system use (Venkatesh et al. 2008). In other words, our analysis suggests that in the context of online gambling, frequency cannot be considered an indicator of true habit. As an ad-hoc analysis, we examined the correlation between top 5% of losers and gambling frequency, and we found an insignificant correlation in both the calibration and validation datasets. This additional analysis again indicated that frequency alone is not sufficient to indicate problematic gambling behavior.

A positive relationship between true habit and gambling lifespan is based on the underlying premise of the formation of habit, i.e., frequently performed behavior should satisfy a gambler's personal motives in the first place (Limayem and Cheung 2011). On the other hand, we also explored in our study whether an external factor, such as a frequent positive outcome, the dream of gamblers, will easily lead to the formation of true habits. Building upon this, we attempted to investigate whether the frequency of gambling moderates the relationship between outcomes and gambling lifespan. Interestingly, the result is consistent with our expectation (H5). This implies that a frequent gambler with a high BalanceRatio will gamble for a longer lifespan, and a frequent gambler with a low BalanceRatio will survive for a lesser period. To the best of our knowledge, the relationship between frequency of betting and gambling lifespan has not been investigated in detail or elaborated upon clearly by other researchers in the context of online gambling. Further, our results demonstrate the need to test both H1 and H5 simultaneously to understand the relationship between habit and gambling lifespan.

Many researchers have attempted to explore how prior outcomes influence online gamblers' behavior (Clotfelter and Cook 1993, Croson and Sundali 2005). Recently Ma et al. (2014) proposed that cumulative outcomes would positively affect subsequent use of the gambling website. Despite the importance of this finding to understanding the relationship between prior cumulative outcomes and subsequent use in the context of online gambling, it has some weaknesses. As proposed earlier, the addiction problem, the central topic in the discussion of legalizing online gambling, is positively associated with gambling lifespan. Thus, instead of investigating the factors affecting subsequent use, it is equally important to determine those factors affecting gambling lifespan. In addition, in their study, Ma et al. (2014) merely used an individual's absolute balance to represent the prior cumulative outcome; by doing this, they ignored individuals' heterogeneity, i.e., the differences in their status because of their income levels. Aware of this weakness, this study overcomes this issue of lack of heterogeneity by using the ratio of balance to cumulative stakes to represent the prior outcome.

Finally, the result of H4 indicates that the top 5% of losers are positively associated with gambling lifespan. This finding doesn't conform to the refined prospect theory, the main postulation of which is that gamblers' decisions are the result of rational and unbiased decision-making. Thus, we contend that problem gamblers' gambling lifespan is more likely influenced by their compulsive gambling habits that could be formed following a chain of biased reactions to losses (Ainslie 1975, Ladouceur and Walker 1996, Rachlin 1990, Turel et al. 2011).

Managerial Implications

The results of this study, as summarized in Table 6, have several implications for the making of public policy related to the gambling industry in general and the online gambling sector in particular. The insights gained are of interest also because hardly any legislation at either the state or federal level has

been enacted to legalize online gambling (Williams and Wood 2007). The rapid diffusion and adoption of the Internet has also provoked major changes in how it is used, in the behavior of its users, and in how consumers make their decisions. At the same time, online entertainment activities have proliferated (Shim et al. 2002). However, the ability to monitor user behavior on the Internet implies the possibility to build decision support systems (DSS) to aid public policymakers, regulatory agencies, online gambling companies, and even online gamblers in progressing toward an overall objective of creating a healthy online gambling environment. In the following discussion we highlight several such policy implications linked directly to our research findings.

Table 6. Summary of findings and their implications to decision support		
Findings	Implications	
	Public policymakers	Online gambling company
A high frequency of gambling is not positively associated with gambling lifespan	Legalize online gambling	Retain the more frequent gamblers by providing them with incentives to stay
The ratio of balance to cumulative stakes is positively associated with gambling lifespan	Mandate that online gambling companies alert gamblers based on their BalanceRatio	Motivate gamblers through pop-up messages and random takeaway gifts
Higher losses are positively associated with gambling lifespan.	Mandate that online gambling companies periodically submit a list of the top 5% of losers to the regulatory authority for monitoring purposes	Provide some interesting online gambling games with nominal stakes or play money
Higher winnings are positively associated with gambling lifespan		Encourage players to bet more money and provide real time feedback through appropriate situation awareness aids
The positive relationship between the ratio of balance to cumulative stakes and gambling lifespan will be stronger as gambling frequency increases.	Carefully track the accounts of gamblers who not only have obtained significant prior outcomes but also have gambled online frequently	Provide promotional incentives to frequent gamblers who have a positive BalanceRatio
Internally motivated players are more likely to continue gambling online for a long period	Compute a score to estimate an online gamblers' degree of stickiness to a specific type of online gambling game based on the time gap and the frequency of betting in a specific game	Provide better incentives and targeted advertisements in order to stimulate interest in other games for gamblers with high stickiness scores

Table 6. Summary of Findings and Their Implications

Implications for Public Policymakers

First, our findings indicate that frequent gambling behavior cannot be used as the indicator of a habit that induces longer gambling lifespan (H1). Because frequent gamblers are unlikely to continue gambling for a long period, less concern exists about this issue's deterring public policymakers from legalizing online gambling. Instead, any concerned regulatory body needs to pay particular attention to those frequent gamblers with a high ratio of balance to cumulative stakes (H5). Gamblers in this category should be subject to policies that effectively regulate or restrict the time they can spend gambling online. For example, regulations may require freezing the access to online gambling websites of those gamblers who not only have obtained significant prior outcomes but also have exhibited a tendency to gamble

frequently. Furthermore, because betting frequency is one of the factors indicating the formation of an online gambler's habit, frequent gamblers may be unobtrusively monitored and warned as soon as their BalanceRatios relative to other regular online gamblers exceed a set limit.

Second, monitoring the BalanceRatio of online gamblers frequently is a challenging task in casino gambling unlike in online gambling. Online gambling service providers may be required by law to give access to such information on a periodic basis or even in real time to regulatory agencies. Moreover, as Hypothesis 2 stated, the BalanceRatio of online gamblers is positively associated with gambling lifespan. The memory of recent losses will not last long, thus, we suggest that policymakers require online gambling websites to show players their recent gains or losses, such as for instance the cumulative balance of the last 20 bets, through pop-up windows that appear during an online gambling session. Specifically, the background of the pop-up window could change with the value of BalanceRatio to alert the player of his status. For example, as the balance ratio turns more negative, the background of the pop-up window could change from bright red to dark red. Similarly, if the BalanceRatio is in an acceptable range, for example slightly positive, the background of the pop-up window could be set to dark green, subsequently turning brighter as the BalanceRatio increases. Thus, online gamblers would be constantly aware of their BalanceRatio and thereby be encouraged to regulate their behavior.

Hypothesis 3 indicates that problem gamblers will gamble online for a long time. However, problem gamblers, such as those with an impulsive control disorder (Black and Moyer 1998) should not be forbidden from accessing online gambling sites. We feel that policymakers need to be very patient in dealing with such gamblers. For example, they could require online gambling sites to provide gambling options with nominal stakes of play money to satisfy the cravings to play of such gamblers instead of forbidding their access outright. Moreover, regulators may require online gambling websites to submit the list of the top 5% of losers to a regulatory authority that can then administer or monitor the problem gamblers' continued use of the site.

Finally, to accomplish the objective of promoting a healthy online gambling environment, H6 suggests that online gambling sites be required to limit an individual's time spent on a specific type of online gambling game, which our study shows has implications for internally motivated online gamblers. Furthermore, online gambling websites could be required to calculate a score that could indicate an online gamblers' degree of stickiness to a specific type of online gambling. Such a score could be based on the time gap from membership registration and the frequency of gambling in a specific type of online gambling game. This would help provide a metric for limiting online gamblers' duration of time spent, which in effect indicates addiction to a game.

Implications for Online Gambling Companies

A central question for every gambling website is how to acquire more revenue while maintaining a healthy online gambling environment. Our research undertook to study the factors influencing gambling lifespan, which may also be interpreted as a determinant of customer retention (Bhattacherjee 2001).

First, because frequency of gambling online is not a positive indicator of long duration of time spent gambling online, we recommend that online gambling companies realize the importance of frequent betting, which is yet another determinant of customer retention (Bhattacherjee 2001). Furthermore, we suggest that online gambling companies provide incentives to frequent gamblers with not-so-high BalanceRatios who may be considered nonproblematic gamblers.

Second, as the results of Hypothesis 2 suggests, the BalanceRatio of an online gambler is positively associated with the duration of time spent gambling online. Acquiring a new customer costs as much as five times the cost of recruiting a new one (Bhattacherjee 2001). It would be advisable, therefore, to retain those customers who have a positive BalanceRatio. In particular, we recommend that online gambling companies provide incentives to stay to online gamblers who are not in the category of problem gamblers and whose values of BalanceRatio are in a reasonably high range. Moreover, online gambling companies could motivate their members to stay longer through the use of pop-up messages and through random takeaway gifts. As Hypothesis 3 mentioned, the top 5% of winners will gamble online for a long time. The larger their wins, the less risk they perceive. Thus, we suggest that online gambling companies specifically encourage such players to risk more money but at the same time monitor their continued behavior.

Conclusion, Contributions, and Limitations

This study builds upon Venkatesh's (2008) theory related to system use to systematically explore the external factors and internal motivation that affect gambling lifespan. We have proposed several hypotheses and tested them by applying the Cox model to a longitudinal dataset that included the online gambling behavior of 4,222 actual gamblers for 24 months. The most important results related to external factors confirm the following: (1) Outcome has a positive effect on gambling lifespan; (2) extreme outcomes as measured by the highest 5% of winners and highest 5% of losers have a positive association with gambling lifespan. The findings related to internal factors and gambling lifespan validate the following: (1) Habit as measured by gambling frequency is not positively associated with gambling lifespan; (2) gambling frequency strengthens the relationship between outcome and gambling lifespan; and (3) internal motivation as measured by the time gap is positively associated with gambling lifespan.

As previously mentioned, the Internet allows for easy monitoring of online users, thereby facilitating the regulation of problem gamblers (Boncella 2001, Dellarocas 2003). However, public policymakers and researchers, who always focus on problem gamblers constitute a serious challenge to the viability of online gambling because of the likelihood they will transfer their views on the regulation of casino gambling to the regulation of online gambling. Although the Unlawful Internet Gambling Enforcement Act (UIGEA) restricts most forms of online gambling in the U.S., there seems to be a trend toward allowing a few categories of exemptions, thereby indicating a tendency towards gradual legalization of the online gambling industry (Williams and Wood 2007).

There does not seem to be any reported research in the IS literature that has systematically investigated gambling lifespan as a dependent variable in the study of the behavior of online gamblers. Unlike prior studies of offline and online gambling, our study used survival analysis methods to systematically explore the factors affecting gambling lifespan. Although all of the earlier studies used data collected through survey questionnaires (Guryan and Kearney 2008, Odean 1998, Oh and Hsu 2001, Rachlin 1990, Sprott et al 2001), we analyzed our model using a real dataset of actual gambling behavior from over 4000 gamblers collected unobtrusively for a relatively long period. Although gamblers' self-reported data could be used to test the theory comprehensively, such data bear a critical limitation attributable to the subjective characteristics of the respondents (Podsakoff et al 2003). Thus, in order to better understand online gamblers' betting behaviors, we recommend that IS researchers use similar datasets collected unobtrusively for a long time. Finally, we contend this study is the first to systematically examine the relationships between prior outcomes and gambling lifespan in the context of online gambling.

Our study has several limitations. First, the original dataset provides us with limited information regarding the incomes or starting wealth of online gamblers, both of which are factors that may affect the lifespan of their gambling (Thaler and Johnson 1990). Second, the variable TimeGap may not completely represent the internal motivation of an online gambler. Third, the generalizability of our study may be limited because the dataset was collected from a single Internet gambling website. Fourth, the majority of gamblers in our sample also played online sports betting on bwin. We did not account for this factor due to technical difficulties. Thus, the findings should be viewed with caution. Based on these limitations, several directions to extend our work can be identified. First of all, future studies may extend the Cox model to not only test the factors affecting gambling lifespan, but also to predict such lifespans for various kinds of gamblers. Last but not least, richer datasets of gamblers' online betting activities can be obtained from multiple online gambling websites in order to make estimations less sensitive to the design styles of a particular gambling website.

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