Disrupting Unwanted Habits in Online Gambling Through Information Technology

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ABSTRACT: The instant access to gambling anytime, anywhere, has made online gambling highly habitual for some people. As a result, some online gamblers choose to volitionally enable the website-provided disruptive information technology (IT) features to control their gambling routines. The objective of this study is to examine the role of these features in regulating online gambling behavior. It is worthwhile to note that in this research, we do not make the assumption that habitual or regular online gambling is a bad thing; nor does the development of our conceptual framework — which focuses on the effect of disruptive IT features and moderating roles of individual regularity and game type in modifying gambling routines — depend on such an assumption.

Drawing on theories of habitual automaticity and habit disruption, the conceptual framework theorizes the efficacy and mechanism of disruptive features while taking into account heterogeneity in individual regularity and game type. We tested the model using data collected over 10 years from 3,526 users of a gambling website. First, we found that individuals' repetitive gambling patterns weakened as the duration of exposure to disruptive features increased. Second, the behavior of more regular gamblers was more resistant to the disruptive features, because more regular gamblers exhibited a stronger habitual pattern. Third, disruptive features were less effective on sports games compared with casino games, because sports gamblers tended to exhibit stronger gambling routines. Overall, the present study contributes to the information systems (IS) literature by clarifying how simple IT features may disrupt unwanted and difficult-to-break online gambling habits as judged by the gamblers. Our findings are likeliest to apply to broader areas of online services in which the application in question is integrated into everyday life and the system can offer a disruptive mechanism.

KEY WORDS AND PHRASES: online gambling, habit disruption, online habits, automaticity, individual regularity, casino games, sports games, online games, negative online habits.

Introduction

Online gambling is a form of entertainment that involves gambling activities over the Internet. The instant access to online gambling at one's convenience anytime and anywhere has made it easier for online gambling to become habitual [16]. In New Jersey alone, where Internet gambling has been legalized, 350,000 residents are known to engage in routine gambling [21]. Habitual use of an information technology (IT) application has been attracting the attention of researchers in the field of information systems (IS) [3, 38, 40, 46]. This research suggests that conscious decisions initially drive IT use, but with repeated use, its use becomes routine and requires no deliberation. A variety of forms of IT use have been shown to exhibit habitual patterns. Examples include organizational computing [52, 78], online news [42], and online collaboration [46, 62]. Likewise, a recent IS study of an online gambling service shows that online gambling can be highly habitual [50].

For most individuals, habitual online gambling is a healthful entertainment, for example, gambling every Friday night to unwind from the work week. Still, some gamblers seek ways to better control their gambling routines. Indeed, an important issue related to habitual use, although incurred by only a small portion of the population [50], is how to help control habitual behaviors. For those that do incur gambling-related problems, however, the potential benefits of an effective countermeasure can be immense. Many online gambling operators have adopted such IT features that enable gamblers to set up customized restrictions on their gambling activities. Some online gamblers choose to set up these disruptive IT features *volitionally*, with the knowledge that these features are designed to help manage their gambling routines. To them, gambling routines are said to have become *unwanted*[1] and hoped to be changed, all judged by these gamblers themselves. Despite the ease and promise of implementing these features, a minimal amount is understood regarding the effectiveness of disruptive IT features in helping these online gamblers regulate their unwanted online gambling routines.

The objective of this paper is to examine the role of disruptive IT features in regulating habitual online gambling. Disruptive IT features are defined in our context as system-imposed functions or programs designed to help online gamblers control unwanted gambling habits as judged by the gamblers themselves, by means of interfering with their gambling routines.[2] We develop a conceptual model by drawing on the literature on online gambling and habit disruption. Specifically, we argue that simple IT features disrupt unwanted online gambling habits by imposing a change in the routine IT environment and making individuals continually conscious of their decisions. Additionally, drawing on the recent literature on online gambling [16, 50], we propose that individuals' regularity of online gambling behavior can influence online gambling habits and, hence, affect the effectiveness of disruptive strategies. Finally, we maintain that game type can have an impact on online gambling habits as well as on the efficacy of disruptive features [73]. Overall, we assemble an integrated model of modifying unwanted habits of online gambling by simultaneously taking into account its routine nature, disruptive mechanism, individual regularity, and game type.

Our central argument is that IT features may help gamblers better resist a continuous but unwanted gaming pattern following their explicit consents to the IT features. While this study adopts a more observational field-study approach than a highly controlled experimental setup, it offers one of the first pieces of evidence that IT-based disruptive strategy, which utilizes three technological features, can effectively help those online gamblers who want to change their gambling routines. This research makes important contributions to the IS field. First, we theorize and demonstrate that unwanted habitual patterns in online gambling can be modified over time through exposure to disruptive IT features. Second, we further examine the differential effectiveness of disruptive strategies based on two key IT-related factors, namely, individual regularity of gambling activities and game type. Third, using large-scale data from 3,526 users' gambling activities over the course of 10 years, this study empirically confirmed disruptive features' impact on controlling unwanted gambling patterns in an online setting.

Conceivably, our findings could have broader implications beyond the immediate context of online gambling and into other compulsive computing behaviors, such as overuse of social media, compulsive video-game play, and obsessive smartphone use. Moreover, our study context is similar to a growing industry of companies, technologies, and websites offering help and support *for individuals who want to help themselves* into less phone app use, away from procrastination, or into a more productive life. For example, in 2018 Apple offered new features (e.g., "Screen Time") that allow users to set a specific amount of time to be in an app. The purpose is that for users who want to better control their app usage, these IT features can help them achieve their goals. Similar features have been implemented by Facebook[3] and Google.[4] Our findings are hoped to shed lights on the effectiveness of these IT features.

Study Context and Merits of Disruptive IT Features in Online Gambling

The context of this study is online gambling use. Our data is about a large cohort of online gamblers using the services operated by bwin.party (henceforth "bwin"), a European Internet gambling facility (more details can be found in the Method section). Roughly half of them volitionally enabled the disruptive IT feature. Before enabling the feature, their gambling routines somehow became unwanted and were thus hoped to be changed, as judged by the gamblers themselves. In the present study, we focus on whether the disruptive feature can change what these gamblers would themselves choose to change. Such unwanted gambling routines typically consist of overly repetitive engagement in gambling activities online [51] and are often performed habitually enough to render self-control ineffective [60]. In other words, it is reasonable to say that these gamblers found it difficult to change habit all by themselves and had to explicitly seek external help from the operator [51, 95].

The 24/7 availability of online gambling services coupled with their great ease-of-use may have facilitated formation of strongly habitual online gambling. Narayanan and Manchanda [56] examined the use of traditional gambling over two years and found that prior behavior did not affect subsequent behavior significantly, and only 8% of the offline gamblers exhibited repeated gambling patterns. In contrast, Ma et al. [50] found that 45% of online gamblers exhibited repetitive behavioral patterns. These inconsistent findings can be attributed to the contextual difference — that is, to the routine nature of online gambling versus sporadic incidents of offline gambling [16]. The findings also hint that online gambling can be more likely to become routine than offline gambling. Indeed, both anecdotal and research evidence has shown that a vast number of gamblers worldwide engage in habitual online gambling (e.g., [32, 91, 96]). That said, we *do not assume* regular online gambling to be a bad habit.

Hing et al. [31] found that online gamblers are less likely to seek help from peers and experts, which has been a common practice among offline gamblers. This suggests the need to provide online gamblers more readily available and less costly measures than group meetings [31]. Customized applications of disruptive features have the potential to help those gamblers achieve their goals. Once a customized feature is activated by a user, it is effective 24/7. Furthermore, it is conceivably more effective to implement these techniques in online gambling because of the availability of detailed individual activity data and the ease of customizing restrictive settings on each account. Thus, from a cost-effectiveness point of view, disruptive strategies that utilize changes of IT features has striking advantages [33]: IT features are relatively simple to implement and maintain; these features potentially provide timely, customized, and enduring assistance to gamblers, and can be easily scaled to help millions of users.

Some initiatives have taken on measures to address unwanted gambling. A leading online gambling operator in Europe has joined the "Responsible Gaming" movement and implemented disruptive IT features. This gambling operator offers several features: providing online feedback on how to control gambling use (a type of disruptive features called "training-in-context," according to [63]), allowing temporary exclusion of a user account ("physical access changes"), and partially restricting certain gaming or payment option ("modified routines"). IT-based strategies like these present opportunities for IS researchers to examine how technology artifacts can be devised as a habit-breaking mechanism once habit is deemed unwanted by the gamblers. Table 1 summarizes the difference between online and offline gambling as well as the difference in disruptive features between the two contexts.

Moreover, we advocate that an online gambling operator should optimally take a combinatorial approach to leveraging the multiple IT disruptive features. Our proposition is based on the following considerations. For one, powerful habits of IT use are particularly difficult to break because they are deeply embedded in a user's daily routines and tend to be automatically triggered and performed. As such, any IT features that are unidimensional may not provide a large-enough dissimilar trigger to suppress an old habit and to promote a new, more desirable habit. Indeed, as emphasized in Polites and Karahanna [63], "any given method of encouraging behavioral change, when used as the sole method of promoting such change, tends to possess weaknesses" (p. 243), because each "intervention strategy only directly addresses particular incumbent or new system habit dimensions … if enough similarity remains [between the old and the modified environments due to multiple remaining situational cues], the behavior in question may continue to be practiced" (p. 243). Thus, employing a mixture of disruptive IT features is a desirable and/or even necessary approach in our context. For another, as we

Table 1. Comparison between Online and Offline Gambling

Characteristics	Offline gambling	Online gambling
Accessible anytime, anywhere	Low	High
Routine gambler (%)	Low	High
Problem gambling (%)	Low	High
Help-seeking by problem gambler	High	Low
Ease of behavior tracking by service provider	Low	High
Ease of individual-specific control	Low	High

will explain later, in theory the different IT features all work under the same fundamental mechanism, that is, they disrupt online gamblers' unwanted routines by altering the IT environment. To date, a minimal amount is known about the effectiveness of *any* of these existing IT disruptive features in the online gambling context. Our research aims to address this notable gap. To our knowledge, this study is among the first to investigate the impact of IT-based disruption, which combines the three IT features, on mitigating unwanted habits of online gambling.

The bwin has been a leading operator in Europe to offer several state-of-the-art disruptive IT features empowering self-identified problem gamblers in the self-help process. The bwin is a suitable study site for the present research because it applied a mixture of the abovementioned disruptive IT features. This approach is in line with our advocated combinatorial approach. Specifically, for any gambler voicing a will, bwin immediately activated the *training-in-context* feature, which embodies such a notion in Polites and Karahanna [63]. At bwin, this feature embedded contextual reminders, i.e., pop-up dialogues and messages, at various decision points on the gambling interface. The main purpose of this feature is to slow down the automatic execution of a sequence of gambling decisions (i.e., right-at-the-moment when the user clicks menu items and buttons), explain the reason for the interruption, and prompt gamblers to take a moment and think twice about their next choice. In addition, the pop-ups may embed links to additional posts curated by bwin that contain tutorials on how to implement self-disruption measures. The detailed content was unfortunately not available to the researchers.

Besides training-in-context, bwin also applied one of the following two features to the gamblers: physical access changes or modified routines [63]. By *physical access changes*, bwin allowed a volitional user to temporarily self-exclude from the betting function in the gambling interface; thus, during the affected time-window, a gambler was unable to place any bet on any game, although the gambler could still visit and browse the website. By contrast, *modified routines* did not entirely disable the betting function; instead, it blocked a gambler from accessing and betting on his or her favorite game type(s) as well as buying tokens with the favorite payment option. The idea behind both of these features is also to slow down the usually automatic firing of habituated mental scripts and prompt gamblers a moment to think twice, while they still allow gamblers to browse the site or bet on other options. Thus, the basic working mechanism of all three features is fundamentally the same, despite their differences in the extent of blockage and their technical representations in the system. Again, the researchers did not have access to bwin's underlying decision process of deciding on which combination of disruptive features to implement strategically on a specific gambler.

Theoretical Background

Previous Research on Habit

In everyday explanations of human behavior, habits feature one's routine ways of behaving. In empirical studies, a well-documented relationship holds that frequency of past behavior, a standard indicator of habit strength [74], is the best predictor of future behavior [57]. To understand the past-behavior–future-behavior link, habit has been extensively studied in a variety of behavior domains (e.g., exercise, eating, smoking) and across different fields. Major and earlier work has been conducted in social psychology (e.g., Ouellette and Wood [57] and Wood [92]), wherein the origin of habit research can be traced back to William James [36], who believed that "habit covers a very large part of life" and urged the field to "define clearly just what its limits are" (p. 104). Recognizing the importance of habit in guiding daily activities, psychologists have developed different accounts of habit, incorporating the concept of automaticity [69] and theories of dual information processing [86].

Notwithstanding the variety of research approaches in the prior literature, habit is most commonly referred to as a process whereby contexts prompt responses automatically via activation of mental context-response associations acquired through repeated prior practices [80]. Drawing on the theory of automaticity [69], habit theory basically proposes that frequently performed behaviors tend to become habitual and, thereby, become automatic over time. Automatic responses, as opposed to deliberately-controlled and cognitively-effortful actions, typically occur quickly with minimal thought and effort. From a functional perspective, habitual behavior is nonreflective [47], effortless, and efficient, freeing up limited cognitive resources.

Importantly, a stable context that supports repeated practices is important for habit formation. Once a habit is formed, perception of contextual cues might trigger habit performance, such as attributes of physical environments, social context, internal states, and preceding actions in a sequence [92]. As a behavior becomes more habitual, it becomes more directly driven by the stimulus context, and thereby tend to be relatively more detached from motivational or intentional control. Even when it is in conflict with their interests or intentions, people often act out of habit, and as a result, the behavior becomes difficult to change [93].

Habit in IS Research

The concept of habit has sparked IS scholars' interests primarily as an effort to understand repeated and continued use of information systems [37, 41, 46, 50, 62, 63, 79]. IS researchers found that while technology acceptance models (e.g., the TAM, the Unified Theory of Acceptance and Use of Technology or UTAUT) have explained well on factors leading to the initial acceptance (or nonacceptance) of a particular IT, they do not sufficiently capture what happens over time. To better understand the effect mechanisms in the postadoption stage, researchers have incorporated the habit theory. Adapting the habit construct to the context of IT usage, *IS habit* is generally defined as the tendency to use an IT automatically as a result of learning in the past [41, 46, 62, 79].

One main research stream has studied how IS habit influences technology use [37, 41, 46, 50, 79]. In general, research on continued use of IS — or IS continuance — suggests that past IT use predicts future IT use at the postadoption stage [41, 46]. At an early stage, IT users deliberately evaluate the benefits and costs of using an IT application. However, as the IT application is repeatedly chosen for specific tasks, its use becomes a routine part of everyday life. Thus, IT use behavior becomes increasingly habitual. Eventually, IT use at the postadoption stage is developed into a stable state in which conscious evaluations are unnecessary. Approaching IS habit as a positive driver of continued usage of an IT, this body of work has expanded prior models that focus on conscious and intentional processes of technology use [79]. The positive impact of habit on IT use has been evidenced in empirical research across contexts of various technology applications, such as using web-based academic portals [41] and mobile Internet [79], reading online news [42], gambling over the Internet [50], and shopping on e-commerce websites [29]. Across usage domains, the research has improved our understanding of how habitual IT use may develop and lead to increased and sustained future use.

Another research stream examines how ingrained habitual use of a system can influence people's perceptions of the system. For example, Kim and Malhotra [41] have found that past use of a personalized web portal positively affects user perceptions of the system — perceived ease of use and perceived usefulness — and these effects persist over time. Furthermore, adopting the perspective of status quo bias [67], Polites and Karahanna [62] have shown that habitual use of an incumbent system can develop inertia or persistence of the existing use patterns of the old system. Inertia negatively influences attitudes toward a newly introduced system, produces less favorable perceptions of its ease-of-use and other advantages, and further attenuates intentions to use the new system [62]. Advancing IS habit research, this body of work has demonstrated that habitual use can modify user cognition of and bias toward an incumbent IT artifact to the extent that it may further inhibit acceptance of a new system [62, 63, 75].

Altogether, IS habit research has greatly improved our understanding of the role of habit in technology use and perception. Nevertheless, comparatively few studies have investigated ways to counteract IS habit [63]. In their theory and review article, Polites and Karahanna [63] have proposed potential methods for breaking the habitual use of an incumbent system. Their strategies have primarily focused on manipulating work routines within an organizational environment [63]; that is, changing some aspect of the user's performance context to inhibit automatic use of the incumbent IT. For example, organizations are recommended to establish such new policies that disrupt sequences of work activities that make up the existing daily routines, modify access to the incumbent system, and mandate training of new system use [63]. However, empirical evidence on the effectiveness of these strategies to disrupt habits has been lacking. In addition, to our knowledge, a relatively minimal amount of empirical research has examined how IS functions themselves can serve as disruptive strategies. To advance IS habit research, our study theorizes and tests disruptive IT features as a habit-breaking mechanism that could potentially counteract the habit of technology use.

Previous Research on Breaking Habits

As discussed earlier, individuals sometimes perform habits that are in conflict with their interests, and many would want to change their habitual practices. However, changing unwanted habits can be difficult. The central challenge lies in the fact that despite people's desire to control their unwanted behaviors, the old habits continue to be activated automatically by recurring environmental cues [84, 92]. Various disruptive strategies have been suggested to help control unwanted habits in psychology, marketing, public policy, and organizational science. In traditional research of habit disruption, a major strategy to overcome habit is through brief disruptions, which emphasize motivating individuals to deliberately reconsider their habitual actions [28, 43, 63, 77]. Verplanken et al. [80, 82] explain that automatically activated behaviors can be disrupted by making information salient and individuals attentive. For example, offering free bus tickets was found to reduce drivers' use of personal cars [25]. Moreover, some disruptive strategies have centered on motivating and involving individuals. From alcoholism to drug use and offline gambling, prevention programs have focused on support from friends and family, professional consultants, or peers in a group meeting [45, 87]. Based on comparisons between successful and unsuccessful participants in open meetings, Petry [60] reported that more involved gamblers showed better results. Indeed, a low level of involvement has been shown to slow the process of changing habit [23, 28], and strongly habituated gamblers were least involved in seeking help and showed the most resistance to change [80, 81].

However, belief or motivation-oriented disruptive strategies were shown to have limited effect [92]. Particularly when habits are deeply ingrained, the strong and direct context-response associations in memory impede change regardless of how much people are determined to control their responses. A commonly preferred approach to break habit has maintained that modifications in the supporting environment can derail the automatic cuing and execution of old habits, because when habit cues are changed or controlled, they are less likely to trigger habitual responses via activation of the context-response associations. As such, people no longer have a ready response in the modified context and are freed up to respond more deliberately [92]. For example, when people relocate or switch jobs, their routine behaviors of exercise and newspaper reading can change to the extent that performance contexts of the old habits alter with the new life transitions [93]. In the context of changing unwanted habits, studies on habitual offline gambling have shown that banning credit card use, limiting ATM withdrawal amounts, or even removing ATMs from gambling venues [26, 48, 90] are somewhat effective in limiting gambling behavior, although they have been criticized for inconveniencing casual gamblers [53].

Disruption of Habits in IT Contexts

Research on disruptive strategies for modifying habits has been predominately carried out in non-IT contexts in which the classic focus is on the control of overeating, smoking, drinking, using drugs, and delaying exercise. As far as our extensive literature review has shown, relatively little empirical research has investigated whether and how technology artifacts can support disruptive strategies to break habits of technology use [63]. This review has also uncovered that the several IT-based strategies proposed in the literature (i.e., training-in-context, physical access changes, and modified routines) essentially operate under the same fundamental mechanism. That is, these features disrupt users' unwanted routines by modifying the IT environment [92]. This view is consistent with that of [63] who denote that "each of the intervention strategies … is highly dependent on changing (or stabilizing) some aspect of the user's performance context" (p. 224). Based on this view, we theorize and empirically test the fundamental mechanism by which disruptive IT features may be effective in controlling unwanted gambling habits online.

Technologies today constitute many of the contexts in which user behaviors take place [33]: playing games online, gambling over the Internet, and surfing on social media, just to name a few. In this sense, technologies can be conceptualized as a stable supporting environment in which users repeat IT usages, and technological features might trigger habit performance that users acquire in the technological environment. The central challenge is that old habits continue to be activated by recurring environmental cues when technology use is intensive, pervasive, and ubiquitous. In response to this challenge, it has become almost inevitable to leverage new technological features to interfere with routine behavior. Meanwhile, disruptive strategies that leverage technological features can be a promising avenue toward fighting unwanted habits of IT misuse. Because shifts in the supporting context and the presence of behavior barriers can mute the impact of habits [57, 92], changing or controlling certain technological features might also help suppress unwanted habitual activities.

As the habits of IT misuse have received much discussion in our society (e.g., overuse of social media, compulsive video-game play, obsessive smartphone use, and problematic online gambling), IS scholars are being called upon to better understand them. The present study theorizes and empirically tests whether and how disruptive IT features could mitigate unwanted IS habit in the context of online gambling.

Hypothesis Development

It is worth emphasizing again, as it is also clear from the Theoretical Background section above, that the theorization of this work and the development of our hypotheses below *do not* rest on an assumption that regular or habitual online gambling is bad for the gamblers. We made no such assumption. Meanwhile, though regular online gambling is healthful entertainment for the majority of people, some gamblers could be more vulnerable to the negative consequences of unwanted gambling habits and thus hope to better control them. This section will develop five hypotheses on the effects of disruptive IT features on online gambling routines by considering simultaneously the routine nature of online gambling, disruptive mechanism, individual regularity, and game type.

Disruptive IT Features and Online Gambling Habits

Despite the desire to better manage gambling activities, many gamblers find it difficult to change their habitual patterns without appropriate assistance [71, 88]. As discussed earlier, a successful approach of changing habits lies in disrupting the context cues that trigger the habitual response, because this disruption pushes its recipients to deliberative decision-making [93]. Following this reasoning, disruptive IT features use new rules to diminish automatic activation of gambling. In the case of online gambling, for example, limiting a gambler's favorite credit card use can change the condition of the online gambling environment (e.g., by forcing the user to find another way — another credit card or bank wire transfer — to reload money) and thus mitigate continuation of gambling. Whenever a gambler accesses the website, the changed environment remains in force. Conscious effort and new decision-making contribute to the establishment of an individual's new mindset, and these impacts are cumulative [5, 64].

We note here again that we propose a combinatorial approach to leveraging disruptive IT features. Our approach is in line with the proposition of [63], who have emphasized that "we argue for a multi-pronged approach to disrupting incumbent system habits (and encouraging new system habits)" (p. 232). Thus, in our hypothesis development, we hypothesize the impact of a mixture of disruptive IT features. Despite the technical differences in their implementation, these disruptive features function under the same working mechanism. That is, they are designed to disrupt the IT context that triggers the online gambling routine.

The literature in cognitive psychology provides a theoretical explanation for the persistent impact of disruptive strategies. A brief interruption turns an old environment into a new one in which people invest conscious effort in evaluating the pros and cons of actions and potential outcomes [85]. If corrections are repeated over time, the old routines will vanish because of the weakening of the mental context-response association [93]. This discussion also notes that during the disruptive period, an individual's attitude is also being consistently updated by ongoing learning and experience [40]. As a result, disruptive effects are progressively accumulated, eventually affecting subsequent behavior. Thus, longer exposure to constant disruption increases individuals' conformity with designated behaviors [1, 2]. With repeated interruptions, people are more likely to perform the preferred action [11]. Thus, the longer the exposure to disruptive strategies, the less likely the automatic behavior occurs. Applying this to online gambling, we expect that with an increase in the duration of exposure to the disruptive IT features, the correlation between current and subsequent gambling is likely to weaken.

> *Hypothesis 1: Time since using disruptive IT features decreases repetitive online gambling behavior (i.e., the relationship between current and subsequent online gambling).*

Roles of Gambler Type: Regular Use

Some people gamble sporadically on a special occasion such as during a vacation, but others play regularly as part of their daily routine. Thus, the degree of regularity is likely to vary across individuals. According to the psychology literature, regular and irregular behaviors differ in the strength of habitual repetition. Ouellette and Wood [57] regarded behavioral regularity — defined as how consistently a specific action is performed over a certain period — as a key factor in characterizing the nature of habitual behavior. Their meta-analysis research identified two groups of existing studies that examined the relationship between past and future behavior [57]. The first group looked at behaviors performed mostly irregularly (e.g., blood donations); the second consisted of behaviors performed regularly (e.g., seat belt use). The results showed that the effect of past behavior on future behavior was significantly stronger in regular contexts than in irregular ones. When applied to online gambling, these general findings imply that gamblers who visit online gambling website in a regular basis are more likely to be habitual gamblers. Accordingly, we anticipate that the relationship between current and subsequent gambling will be stronger for more regular online gamblers than for those who gamble less regularly.

> *Hypothesis 2: Repetitive online gambling behavior (i.e., the relationship between current and subsequent online gambling) is stronger for more regular gamblers than for less regular gamblers.*

We earlier predicted in H1 that the duration of exposure to disruptive IT features negatively affects repetitive online gambling. However, some research suggests that the disruptive impact on behavior varies with respect to the regularity of events [17, 82]. Specifically, this stream of research suggests that the disruptive effect on habitual behavior is weaker for regular events than for irregular events. The rationale is that in a more routine environment people tend to ignore new information, which delays the magnitude and speed of changes in their behavior. For example, in Polites and Karahanna [62], regular use of an incumbent IT system was shown to discourage people's intention to adopt a new IT system. In Turel et al. [75], regular use of online auctions made individuals disregard new information about the cons of using the auctions, eventually causing them to continue to use the same auctions. Put simply, people tend to stick with their prior beliefs in a regular context because they unconsciously ignore the need to assess valuable information [41].

The psychology literature also argues that in a routine environment, people often skip conscious effort in evaluating new situation. Instead, their decision-making follows a heuristic process mainly driven by prior behavior [8]. As a result, habit disruptions are not as effective as they should be, especially not as would be expected in an irregular context [83]. For example, in an irregular context (e.g., compliance with medical recommendations), even a single disruption has been shown to be effective in overcoming patient inertia, leading patients to avoid inferior medical options [72]. In contrast, in a regular context such as commuting, disruptive programs designed to promote public transportation were found to be less effective for people who had routinely used their cars [43]. Overall, these findings collectively suggest that for more regular online gamblers, the negative impact of the duration of exposure to disruptive IT features on gambling repetition is weaker than for gamblers who are less regular.

Hypothesis 3: The decrease of repetitive online gambling behavior (i.e., the relationship between current and subsequent online gambling) because of disruptive IT features is smaller for more regular gamblers than for less regular gamblers.

Roles of Game Type: Sports Games vs. Casino Games

Online gambling providers offer customers numerous game options. These options include casino games (e.g., slots) and sports gambling. An important characteristic of habitual behavior is that it is triggered by a situational cue, such as an external event. Polites and Karahanna [63] mentioned that repeated use of a certain IT tool is triggered by external business events that regularly occur but not necessarily at the exact same time each day. Similarly, Becker [6, 7] suggest that IS habits are primarily event-driven rather than time-driven. Extending this perspective into our context of online gambling, we argue that casino gambling rarely has external triggers, whereas sports gambling is largely triggered by regular public events prevalent in professional sports. In a traditional setting, people may have to attend a sports event to gamble, but in the context of online gambling, location is no longer a constraint. Thus, these recurring triggers are expected to play a more important role in online gambling than in offline gambling. This discussion leads us to believe that at least *in the online context, sports games induce a stronger behavioral regularity than can casino games*; furthermore, it implies that online gamblers may be likelier to become habituated to sports than casino games.

Research on gambling behavior suggests that individuals' reactions differ considerably with respect to games of skill and those of chance [10, 44, 55]. Whereas a random process regulates outcomes in games of chance, a person's expertise plays a role in games of skill [10, 55]. In our particular context, sports games are considered skill-based, and casino games are considered to be based on random chance, with the odds strategically chosen by the provider [44]. The literature on gambling indicates that the two types of gamblers are expected to differ considerably in how they react to gambling. For example, Bonnaire et al. [10] argued that those preferring games of skill tend to seek the arousal from the game, whereas those preferring games of chance play to avoid unpleasant feelings such as anxiety, boredom, or depression. Meanwhile, in a study comparing gamblers of skill and chance games, Myrseth et al. [55] showed that those preferring skill games exhibit a greater level of cognitive distortions than those preferring chance games. These findings collectively imply that skill games, more than games of chance, engage people more and make them more involved in gambling. Thus, all things being equal, people would find it more difficult to stay away from games of skill than from games of chance.

Because of the difference between games of skill and those of chance, we expect that sports gambling is generally more conducive than casino gambling to habitual behavior. And this prediction is consistent with our earlier argument that routine patterns are more evident in online sports games than in online casino games because of the difference in behavioral regularity between the two types of games. All things considered, we propose the following hypothesis:

Hypothesis 4: Repetitive online gambling behavior (i.e., the relationship between current and subsequent online gambling) is stronger for sports games than for casino games.

We previously predicted in H1 that exposure to disruptive features will weaken the routine nature of online gambling and in H3 that the effect of disruptive features on routine gambling would be weaker for more regular gamblers than less regular gamblers. Similarly, we expect that the effect of disruptive features on online gambling will be weaker for sports games than for casino games. As described earlier, in sports gambling external triggers are more prevalent than they are in casino games because sports events are held regularly. Additionally, given the difference between skill and chance games, sports games are likely to be more conducive to habitual behavior than casino games. Taken together, disruptive features are expected to be less effective for sports gamblers than for casino gamblers. Thus, we contend that the impact of the exposure to disruptive IT features on habitual gambling (i.e., the positive relationship between current gambling and subsequent gambling) is weaker for sports games.

Hypothesis 5: The decrease of repetitive online gambling behavior (i.e., the relationship between current and subsequent online gambling) because of disruptive IT features is smaller for sports games than for casino games.

Method

Sample and Measures

We used data from bwin.party (bwin), a global online gaming corporation headquartered in Gibraltar. bwin offers a range of Internet-based betting services including sports, casino, poker, and bingo games. From May 2000 to November 2010, the data recorded complete betting histories of a cohort of 4,113 gamblers mainly in online sports and casino games, which excludes poker. The original data consisted of two groups: 2,068 gamblers who volitionally activated disruptive IT features ("Study" group) and 2,045 gamblers with no such features ("Comparison" group). In addition to offering educational materials on how to self-control gambling use (training-in-context), disruptive IT features included: temporary suspension (physical access changes), or partial restrictions on certain gaming or payment option (modified routines). After removing unusable data[5] from the original sample, we arrived at a final sample consisted of 3,526 gamblers (1,970 in the Study group and 1,556 in the Comparison group; Appendix A includes more details of the two groups). Care was taken to strictly observe Institutional Review Board regulations in protecting the participants' privacy.

Table 2 includes the variable definitions. The original data summarized gambling activities into daily records such as the amount of betting and amount of winning, both converted to euros. Subsequent online gambling was measured by aggregating the daily amount bet into a weekly amount ($\ln(\text{STAKES}_{j,\ i,\ t+1})$), because a week is the preferred time unit of aggregation for online gambling behavior, and doing so produces results that

Table 2. Variable Definitions

Measures	Definitions
Research Variables	
$\ln(\mathrm{STAKES}_{j,\ i,\ t+1})$	Euros staked during period t+1 by gambler i from country j, with natural log transformation
$\ln(\mathrm{STAKES}_{j,\ i,\ t})$	Euros staked during period t by gambler i from country j, with natural log transformation
$\mathrm{DUR\_DIS}_{j,\ i,\ t+1}$	Number of days on a scale of 100 days passed since the first exposure to disruptive features for gambler i from country j until either the current week or the week that those features were removed, whichever happened first
$\mathrm{RU}_{j,\ i,\ t}$	Number of active gambling weeks during the past six weeks before the subsequent period for gambler i from country j
Control Variables	
$\mathrm{STUDY}_{j,\ i}$	Dummy variable equal to 1 if gambler i from country j belonged to the Study group
$\mathrm{CUMUGAIN}_{j,\ i,\ t}$	Net cumulative gain in 1,000 euros if there was a net positive balance from this gambler's account start time until period t (0 otherwise) for gambler i from country j
$\mathrm{CUMULOSS}_{j,\ i,\ t}$	Net cumulative loss in 1,000 euros if there was a net negative balance from this gambler's account start time until period t (0 otherwise) for gambler i from country j
$\mathrm{GAIN}_{j,\ i,\ t}$	Net immediate gain in 1,000 euros if there was a net positive balance during period t (0 otherwise) for gambler i from country j
$\mathrm{LOSS}_{j,\ i,\ t}$	Net immediate loss in 1,000 euros if there was a net negative balance during period t (0 otherwise) for gambler i from country j
$\mathrm{AGE}_{j,\ i}$	Age of gambler i from country j upon registration of account
$\mathrm{GENDER}_{j,\ i}$	Dummy variable equal to 1 if gambler i from country j is a male

are quite reliable [50]. Accordingly, current online gambling was measured by its lagged term ($\ln(\mathrm{STAKES}_{j,\ i,\ t})$). The duration of exposure to disruptive features ($\mathrm{DUR\_DIS}_{j,\ i,\ t+1}$) was measured by the number of passed days (rescaled to 100-day units to be consistent with conventional gambling-control programs) since the activation of disruptive features. We created a variable "Regular Use" that measured how regularly a gambler had gambled online in recent weeks ($\mathrm{RU}_{j,\ i,\ t}$). This variable was measured by the number of weeks during the previous six weeks in which the gambler was actively betting online [50]. Thus, Regular Use is a unique variable that primarily measures how persistently and regularly a user had gambled online during an extended period in the recent past.

Control Variables

We created a dummy variable to identify members of the Study group ($\mathrm{STUDY}_{j,\ i}$). Consistent with previous research, we included four control variables that captured prior gambling outcomes: net cumulative gain ($\mathrm{CUMUGAIN}_{j,\ i,\ t}$), net cumulative loss ($\mathrm{CUMULOSS}_{j,\ i,\ t}$), immediate gain ($\mathrm{GAIN}_{j,\ i,\ t}$), and immediate loss ($\mathrm{LOSS}_{j,\ i,\ t}$). It should be noted that net cumulative gain ($CUMUGAIN_{j,\ i,\ t}$) and net cumulative loss ($CUMULOSS_{j,\ i,\ t}$) tracked all previous gambling balances from each gambler's unique starting time. Descriptive statistics of the final sample are in Table 3. There were in total 145,582 weekly observations.

Empirical Model Development

In the panel data, each gambler is tracked for multiple periods. The unique behavioral characteristics of a particular gambler may be a confounding factor. There may be serial correlation in the error term, the order of which is unclear. Moreover, testing of theory requires us to estimate the dynamic effect of current gambling on the subsequent, which may be biased. The equation in Table 4 is the basic functional form of our model. To properly deal with the above issues, we considered using a random effects model (e.g., Hierarchical Linear Model or HLM) or a fixed effects model (i.e., standard fixed effects panel data model) to control for the time-invariant individual- or higher-level unobserved effects. We conducted a Durbin–Wu–Hausman [28, 30] test of the null hypothesis that the random effect estimator is consistent and preferable to the fixed effects estimator. The chi-squared test significantly rejected the null hypothesis ($p < .001$), indicating that a random effect estimator in our context is not consistent. Therefore, we chose the fixed effects model (i.e., within-transformation) to specify the unobserved gamblers' effect (i.e., the α_i in the equation).

Next we examined the existence and orders of serial correlation (i.e., autocorrelation or AR) by first conducting a Wooldridge test of serial correlation [94] under the within-transformation fixed effects model without including time fixed effects. The test rejected the null hypothesis that the error is serially uncorrelated ($p < .05$). We then used the System GMM estimator to test for any higher orders of serial correlation [4]. The results indicated that AR(1) is significant ($p < .01$) while AR (2) is largely insignificant ($p > .05$).[6] Thus, we concluded that our data has first-order serial correlation. Because including time fixed effects (i.e., time dummies, the δ_t in the equation) may effectively control for first-order autocorrelation [28], we ran the Wooldridge test of serial correlation again under the fixed effects model with time dummies. The result under the new model failed to reject the null hypothesis that the error is serially uncorrelated. As such, a fixed effects model with time dummies is able to properly control for first-order autocorrelation existent in our data.[7]

Results

Table 5 presents model results of the final sample. Model 1 shows a baseline model that excluded the effect hypothesized in H1. Model 2 added the interaction between $DUR\_DIS_{j,\ i,\ t+1}$ and $\ln(STAKES_{j,\ i,\ t})$ (i.e., β_1). Adding the interaction term barely altered the other effects in the model.

Table 3. Descriptive Statistics

	Variables	Mean	s.d.	Min	Max	1	2	3	4	5	6	7	8	9	10
1	$\ln(STAKES_{j,i,t+1})$	4.81	2.45	0	13.95	1									
2	$\ln(STAKES_{j,i,t})$	3.96	3.41	0	13.5	.59	1								
3	$DUR\_DIS_{j,i,t+1}$	.50	1.23	0	7.36	.04	.02	1							
4	$RU_{j,i,t}$	4.03	2.00	0	6	.29	.58	.03	1						
5	$STUDY_{j,i}$	.77	.42	0	1	.36	.29	.22	.22	1					
6	$CUMUGAIN_{j,i,t}$	.07	.91	0	49.58	.07	.05	.02	.02	.01	1				
7	$CUMULOSS_{j,i,t}$	4.78	10.63	0	157.68	.37	.30	.23	.19	.19	-.03	1			
8	$GAIN_{j,i,t}$	.03	.28	0	42.14	.15	.15	.01	.05	.04	.19	.06	1		
9	$LOSS_{j,i,t}$	.1	.31	0	19.3	.32	.37	.03	.17	.13	.03	.34	-.04	1	
10	$AGE_{j,i}$	30.45	9.54	17	90	.07	.08	-.01	.12	$0^{\dagger}$	$-0^{\dagger}$	.10	.01	.06	1
11	$GENDER_{j,i}$	.06	.23	0	1	.01	$-0^{\dagger}$	$0^{\dagger}$	-.03	-.02	$0^{\dagger}$	$-0^{\dagger}$	$0^{\dagger}$	.01	.07

Notes: No. Obs. = 145,582. No. Gamblers = 3,526. Coefficient is significant with $p < .05$ unless marked with †.

Table 4. Empirical Model

$$
\begin{aligned}
In\left(STAKES_{j,i,t+1}\right)
&= \beta_1 DUR\_DIS_{j,i,t+1} \times \ln\left(STAKES_{j,i,t}\right) + \beta_2 \ln\left(STAKES_{j,i,t}\right) + \beta_3 DUR\_DIS_{j,i,t+1} \\
&\quad + \beta_4 CUMUGAIN_{j,i,t} + \beta_5 CUMULOSS_{j,i,t} + \beta_6 GAIN_{j,i,t} + \beta_7 LOSS_{j,i,t} + \beta_8 RU_{j,i,t} + \alpha_i \\
&\quad + \gamma_j + \delta_t + \varepsilon_{i,j,t+1}
\end{aligned}
$$

Notes:
1. t indicates the week; i indicates the gambler; j indicates the country of residence.
2. $\varepsilon_{j,i,t+1}$ is within-gambler error term in week t +1 of gambler i from country j. It may include up to k orders of serial correlation.

Table 5. Model Results of Final Sample

	Models	
Variables	1. Nested model	2. Full model
$DUR\_DIS_{j,\ i,\ t+1} \times ln(STAKES_{j,\ i,\ t})$ [β_1]		−.010(.002)***
$ln(STAKES_{j,\ i,\ t})$ [β_2]	.179(.004)***	.180(.004)***
$DUR\_DIS_{j,\ i,\ t+1}$ [β_3]	−.131(.013)***	−.132(.013)***
$CUMUGAIN_{j,\ i,\ t}$ [β_4]	.004(.007)	.005(.007)
$CUMULOSS_{j,\ i,\ t}$ [β_5]	.008(.003)**	.009(.003)**
$GAIN_{j,\ i,\ t}$ [β_6]	.371(.105)***	.371(.105)***
$LOSS_{j,\ i,\ t}$ [β_7]	.283(.038)***	.281(.037)***
$RU_{j,\ i,\ t}$ [β_8]	.021(.005)***	.021(.005)***
Model features		
No. of observations	145,582	145,582
No. of gamblers	3,526	3,526
R-sq (overall)	.373	.378
Max VIF	1.26	1.27
Gambler fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
Serial correlation checked	Yes	Yes

Notes: Robust standard errors are in parentheses. †p < .1. *p < .05. **p < .01. ***p < .001.

H1 stated that time since using disruptive IT features decreases repetitive online gambling behavior (i.e., the relationship between current and subsequent online gambling). β_1 in Table 5 was used to test H1, and it was supported ($\beta_1 = -.010$, $p < .001$). This result means that every additional 100 days after the first exposure to disruptive features will decrease the repetitive online gambling use by .010, or 5.6% from the base level of $\beta_2 = .180$ (percent change = −.010/.180 = -.056). Figure 1a illustrates this effect difference by showing that the relationship between current and subsequent online gambling before exposure to disruptive features (solid line) was reduced to where it was after 100 days into the first exposure to disruptive features (dashed line).

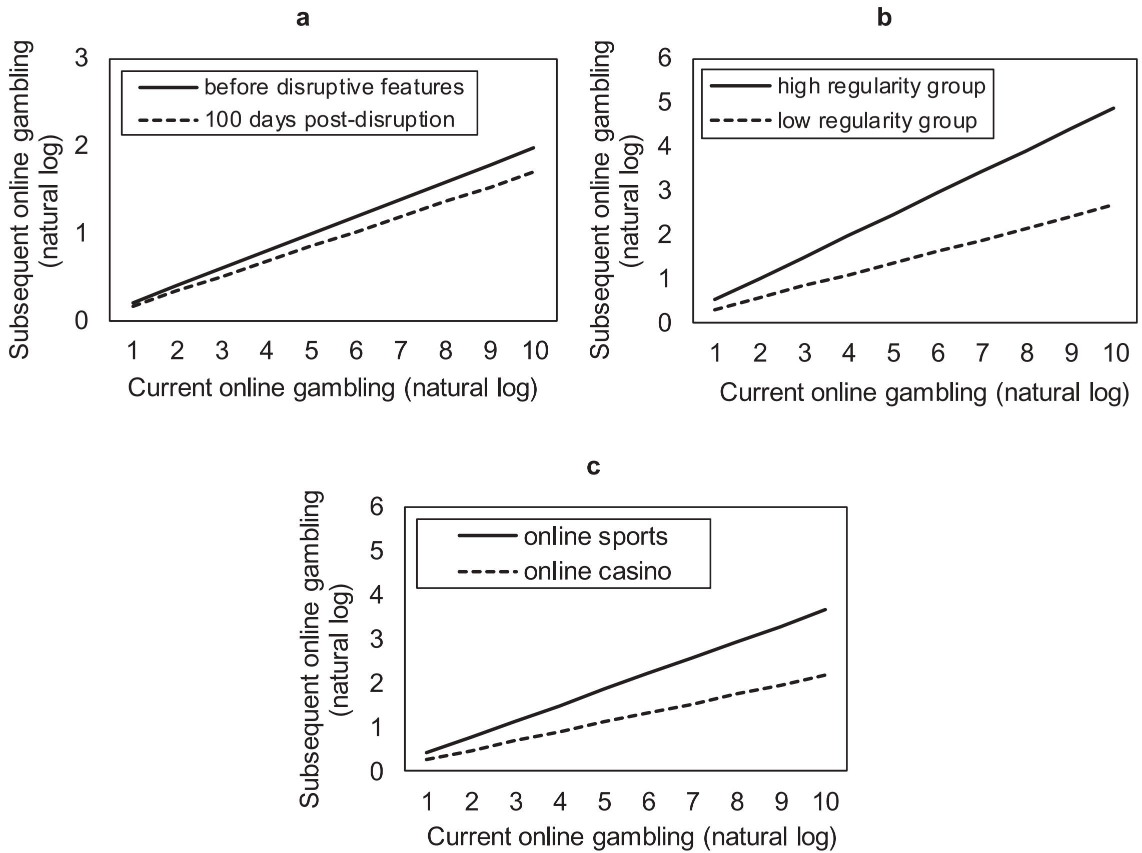

Figure 1. The Effects on the Relationship Between Current and Subsequent Online Gambling by (a) Disruptive Features, (b) Gambling Regularity Levels, and (c) Gambling Types

Because H2 and H3 required comparisons of the gambling behavior and disruptive effect between gamblers who gambled online at different regularity levels, we divided the full sample into two groups: those who gambled more regularly overall (i.e., average Regular Use is above the sample mean, or mean($RU_{j,\ i,\ t}$) > 3) and those who gambled less regularly (i.e., mean($RU_{j,\ i,\ t}$) < 3).[8] As a result, the High Regularity sample includes 1,575 (45% of all) gamblers. Then we applied the final model on each sample separately. Table 6 shows the results and how the two samples compare. H2 stated that repetitive online gambling behavior is stronger for more regular gamblers than for less regular gamblers. We compared β_2 in Models 3 and 4 to test H2. β_2 was significant in both samples (ps < .001). The difference was also significant [15, 59], thus supporting H2 (Diff$\left(\beta_2^{High}, \delta_2^{Low}\right)$ = .115, z = 16.69, p < .001). The repetitive online gambling in Model 3 was more than twice as strong as in Model 4. Figure 1b shows this difference visually. The slope of the high regularity gamblers (solid line) was significantly steeper than the one for the low regularity gamblers (dashed line).

H3 stated that the decrease of repetitive online gambling behavior is smaller for more regular gamblers than for less regular gamblers. $|\beta_1|$ in Table 6 was used to test H3, and it was significant in both models (ps < .001). Their difference was negative as predicted (i.e., $\left|\beta_1^{High}\right| < \left|\beta_1^{Low}\right|$) but not significant (Diff$\left(\left|\beta_1^{High}\right|, \left|\beta_1^{Low}\right|\right)$ = -.005, z = −1.06, p > .10), implying that the absolute disruptive effect was equal. Nonetheless, the *relative* effect of duration of disruptive features should be evaluated relative to their respective base levels of the repetitive online gambling (i.e., β_2). H2, which was strongly supported, stated that

Table 6. Comparing Model Results of High vs. Low Regularity Samples

Variables	Models: 3. High regularity sample	Models: 4. Low regularity sample
$DUR\_DIS_{j,\ i,\ t+1} \times \ln(STAKES_{j,\ i,\ t})$ [β_1]	−.012(.002)***	−.016(.004)***
$\ln(STAKES_{j,\ i,\ t})$ [β_2]	.209(.005)***	.094(.005)***
$DUR\_DIS_{j,\ i,\ t+1}$ [β_3]	−.129(.014)***	−.156(.027)***
$CUMUGAIN_{j,\ i,\ t}$ [β_4]	.005(.006)	.050(.091)
$CUMULOSS_{j,\ i,\ t}$ [β_5]	.009(.003)**	−.021(.017)
$GAIN_{j,\ i,\ t}$ [β_6]	.352(.113)**	.290(.176)†
$LOSS_{j,\ i,\ t}$ [β_7]	.247(.037)***	.062(.129)
Model features		
No. of observations	116,609	28,973
No. of gamblers	1,575	1,951
R-sq (overall)	.382	.117
Max VIF	1.26	1.74
Gambler fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
Serial correlation checked	Yes	Yes

Notes: Robust standard errors are in parentheses. †p < .1. *p < .05. **p < .01. ***p < .001.

repetitive online gambling is stronger for more regular online gamblers than for less regular online gamblers. Thus, given that the baseline was significantly stronger for more regular online gamblers, we conclude that the relative effect of duration of exposure to disruptive features is significantly weaker for this group, hence H3 was supported.

Recall that earlier we predicted that online sports games induce a stronger behavioral regularity than can online casino games. To test this assertion, we first aggregated the weekly measure of $RU_{j, i, t}$ into $MEAN\_RU_i$ across all time periods to create an individualized regularity measure. Then, we used the independent samples t test on this individual-level measure to test the equality of group means between the two samples of different gambling types (i.e., Sports vs. Casino). Model 5 in Table 7 shows that the t test result confirmed the level of gambling regularity in online sports is significantly higher than in online casino ($t = 21.52$, $p < .001$). The bias-robust bootstrap t test also confirmed this result ($t^{bootstrap} = 20.89$, $p < .001$).

Some gamblers in our sample played both gambling types (hereafter "dual gamblers," $n = 1{,}105$). To examine whether the above result pertaining to the regularity of gambling types is consistent even for the same user, we subjected the dual gamblers group to a paired sample test for the equality of group means between the two game types. The result in Model 6 shows high consistency with the previous result ($t = 23.77$, $p < .001$; $t^{bootstrap} = 24.95$, $p < .001$). Therefore, our prediction was supported with strong evidence.

To test H4-H5, we did separate analyses of the final model on the different types of gambling samples. In Table 8, Model 7 presents the Sports sample results, and Model 8 presents the Casino sample results. H4 stated that repetitive online gambling is stronger for online sports games than for online casino games. β_2 in Table 8 was significant in both sports and casino games (ps < .001). The difference in β_2 between two samples was statistically significant [15, 59], and hence H4 was supported ($\text{Diff}\left(\beta_2^{Sports}, \beta_2^{Casino}\right) = .074$, $z = 10.45$, $p < .001$). The repetitive gambling behavior in online sports was almost twice as strong as that in online casino. Figure 1c shows

Table 7. Comparing Usage Regularity of Online Sports vs. Casino Samples

	Models			
	5. Independent samples test		6. Paired sample test	
	Sports	Casino	Sports	Casino
No. of gamblers	3,455	1,176	1,105	1,105
Group mean ($MEAN\_RU_i$)	2.682	1.662	2.961	1.680
Group mean difference	1.020		1.281	
t test of equal means [1]	21.52***		23.77***	
Bootstrap t test of equal means [1,2]	20.89***		24.95***	

Notes: †$p < .1$. *$p < .05$. **$p < .01$. ***$p < .001$.

1. Under Model 5, equal variances of measure between groups are not assumed.

2. Bootstrap results are based on 1,000 bootstrap samples.

Table 8. Comparing Model Results of Online Sports vs. Casino Samples

Variables	Models: 7. Online sports	8. Online casino
$DUR\_DIS_{j,\ i,\ t+1} \times \ln(STAKES_{j,\ i,\ t})$ [β_1]	−.011(.002)***	−.009(.005)†
$\ln(STAKES_{j,\ i,\ t})$ [β_2]	.180(.004)***	.106(.006)***
$DUR\_DIS_{j,\ i,\ t+1}$ [β_3]	−.092(.012)***	−.055(.038)
$CUMUGAIN_{j,\ i,\ t}$ [β_4]	.011(.012)	.024(.011)*
$CUMULOSS_{j,\ i,\ t}$ [β_5]	.013(.002)***	.004(.006)
$GAIN_{j,\ i,\ t}$ [β_6]	.631(.080)***	.173(.123)
$LOSS_{j,\ i,\ t}$ [β_7]	.372(.037)***	.207(.060)***
$RU_{j,\ i,\ t}$ [β_8]	.036(.004)***	.047(.013)***
Model features		
No. of observations	138,378	21,047
No. of gamblers	3,455	1,176
R-sq (overall)	.415	.246
Max VIF	1.32	1.21
Gambler fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
Serial correlation checked	Yes	Yes

Notes: Robust standard errors are in parentheses. †$p < .1$. *$p < .05$. **$p < .01$. ***$p < .001$.

this difference visually. The slope in online sports (solid line) was significantly sharper than the one in online casino (dashed line).

Finally, H5 stated that the relative effect of duration of exposure to disruptive features on the repetitive online gambling is weaker for online sports games than for online casino games. $|\beta_1|$ was highly significant in Model 7 ($p < .001$) and marginally significant in Model 8 ($p < .10$), but the absolute difference between the two samples was not significant (Diff $\left(\left|\beta_1^{Sports}\right|, \left|\beta_1^{Casino}\right|\right) = .002$, $z = .45$, $p > .10$). As for the *relative* effect of duration of exposure to disruptive features on the repetitive use, recall that H4 was strongly supported and implied that the base level was much stronger in online sports. Therefore, we concluded that H5 was supported.

We conducted numerous robustness analyses to gauge the rigor of our results. These included using the number of bets as an alternative measure of gambling behavior, removing gamblers who might have switched to a different site, using alternative thresholds for splitting high vs. low regularity samples, and replicating all the analyses mentioned in Ma et al. [50]. We obtained consistent findings.

Alternative Explanations and Test for Self-Selection

An alternative explanation of our main findings, that is, the repetitive online gambling behavior is weakened by the duration of exposure to disruptive features, can simply be a self-selection bias. In other words, the same gamblers who enabled the disruptive IT features were the same people who might eventually have their gambling pattern weakened, regardless of the technology. This is a critical concern because, if it were true, the self-selection bias could introduce a substantive amount of bias into our model and hence our results might not be consistent. From a technical standpoint, our findings about the duration effect of disruptive features on the repetitive online gambling behavior could be overestimated because those who self-selected for the benefits of disruptive functions might be more self-prepared for the behavioral change.

To formally address this concern, we adopted Propensity Score Matching (PSM) as a robustness analysis to correct for any bias that self-selection could produce. The basic idea is, assuming that the gamblers in the Study group exhibited certain unique properties or behavioral characteristics that made them better able to self-control their repetitive gambling behavior online regardless of whether they activated any disruptive IT features, it would make the model robust and the effect estimation consistent if the gamblers in the Comparison group exhibited the same properties or behavioral characteristics such that they too were more likely to self-control their repetitive gambling behavior. In our study, the essential behavioral characteristic of the gamblers in the Study group is that they self-selected to have the disruptive IT features enabled at the online gambling facility. Thus, in order to construct a Comparison group that is comparable to the Study group, PSM used the estimated probability that a gambler in the Comparison group might have also self-selected to enable the disruptive IT features [19, 65]. PSM has been used extensively in economic research and has become a popular method in IS research to deal with confounding factors such as self-selection or endogeneity (e.g., Chan and Ghose [13], Chang and Gurbaxani [14], Jabr et al. [34], and Smith and Telang [70]). This technique has been shown to be effective in reducing the bias that could remain in an estimate that is obtained by simply comparing outcomes among users who received an intervention versus those who did not.

We first used PSM to re-test the main hypothesis (H1), that is, the duration effect of disruptive features on the repetitive online gambling pattern. It should be noted that our data did not directly measure the latent repetitive gambling pattern, which was only testable under the econometric model. Thus, we created a proxy variable to represent this latent behavior. Specifically, we used the first-differenced value of online gambling amount (DELTA_LN_STAKES $_i$) as a proxy for the repetitive online gambling. The rationale is, the more repetitive one's gambling behavior was, the more positive (or less negative) such a first-differenced value of gambling amount would be. After controlling for self-selection bias,[9] PSM analysis confirmed H1, that is, disruptive features significantly reduced the repetitive online gambling behavior (Diff$\left(DELTA_LN_STAKES_{adj}^{aft\ ITV}, DELTA_LN_STAKES_{adj}^{bfr\ ITV}\right)$ = -.207, z = -5.95, $p < .001$). Figure 2a illustrates the dramatic change in repetitive gambling behavior attributed to the disruptive features, even after controlling for the self-selection bias.

To investigate the moderating roles of behavioral regularity and gambling type, we used the proxy variable (DELTA_LN_STAKES $_i$) created above to focus PSM analyses on repetitive gambling behavior. To test the effect of individual regularity

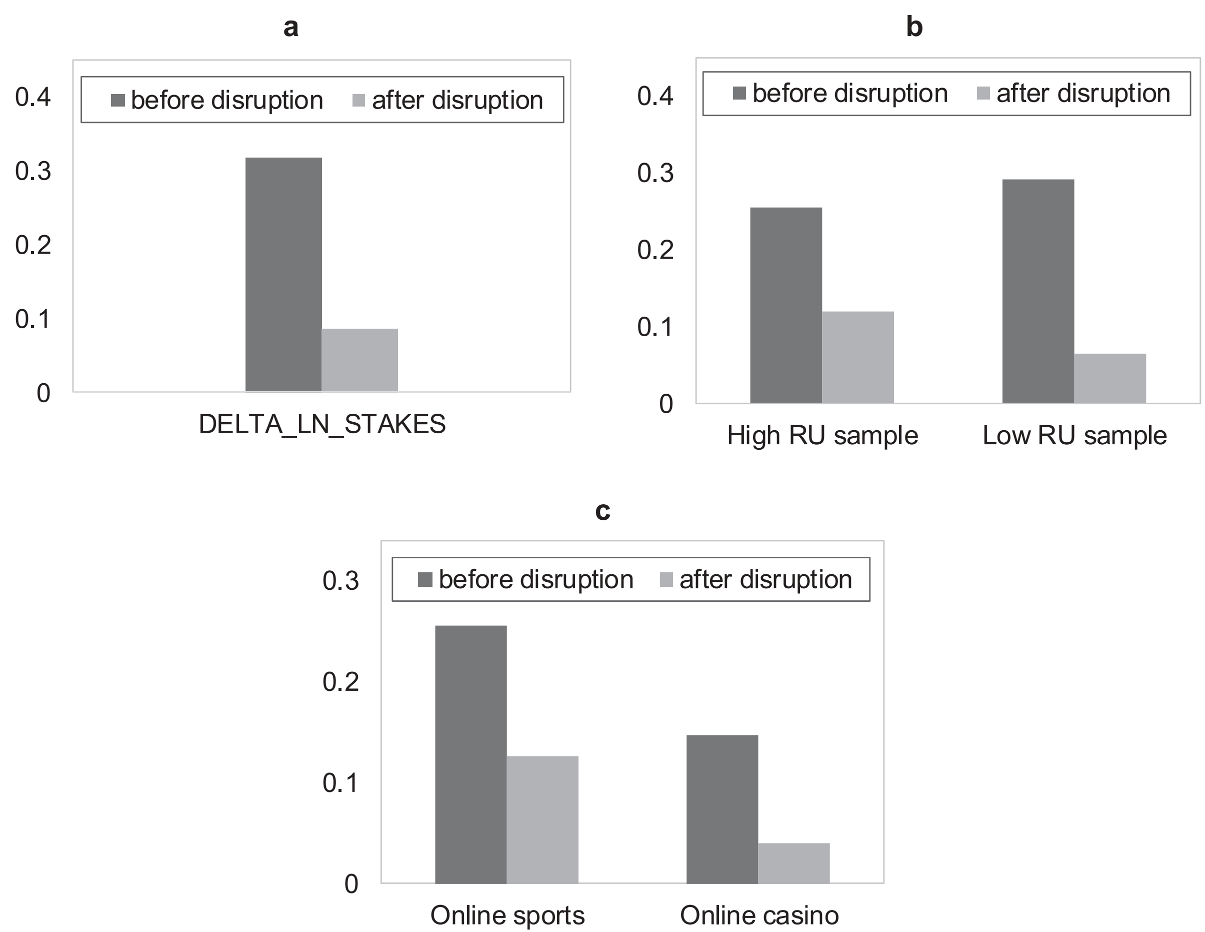

Figure 2. Robustness Tests of Alternative Explanations for the Effects of Disruptive Features on Repetitive Online Gambling Behavior and the Moderating Roles of Regularity and Game Type*Notes*:1. Propensity score matching (PSM) was used to correct for the self-selection bias of the Study group when testing the comparison between two adjacent bars. All comparisons illustrated were significant at least at the .05 level.2. A proxy measure for the latent repetitive online gambling behavior (i.e., DELTA_LN_STAKES) was used in a, b, and c.

(H3), we divided the sample into high and low regularity groups, just as we did earlier in testing H2-H3. Using PSM, the effect of disruptive features on repetitive gambling behavior was significant in the high regularity group (Diff $\left(DELTA\_LN\_STAKES_{adj}^{High,aft\ ITV},\ DELTA\_LN\_STAKES_{adj}^{High,bfr\ ITV}\right) = -.134$, $z = -2.66$, $p < .01$) and the low regularity group (Diff $\left(DELTA\_LN\_STAKES_{adj}^{Low,aft\ ITV},\ DELTA\_LN\_STAKES_{adj}^{Low,bfr\ ITV}\right) = -.227$, $z = -5.44$, $p < .001$). Moreover, such an effect was stronger for the latter group, that is, the effect of disruptive features on repetitive gambling behavior was significantly stronger in less regular online gamblers, thus supporting H3 again. To see this comparison visually, we graphed the effects in the two groups separately in Figure 2b. The behavioral change is much more noticeable for the low regularity group ("Low RU sample") than for the high regularity group ("High RU sample").

Lastly, to analyze the differential effects of disruptive features under different game types (H5), we divided the data into sports and casino groups. The result of comparing the repetitive gambling behavior before and after disruptive features were implemented, while adjusting for self-selection bias, again confirmed H5. Specifically, disruptive features reduced this behavioral pattern roughly by half in online sports games (change $^{\text{Sports}} = -50.8\%$, Figure 2c, "Online sports"). Meanwhile, they resulted in an even greater reduction in online casino games (change $^{\text{Casino}} = -73.1\%$, Figure 2c, "Online casino"). Furthermore, whereas the repetitive gambling pattern after disruptive features were enacted was still significant in online sports ($DELTA\_LN\_STAKES_{adj}^{Sports,aft\ ITV} = .125$, $t = 4.68$, $p < .001$), such a measure was not significant in online casinos ($DELTA\_LN\_STAKES_{adj}^{Casino,aft\ ITV} = .039$, $t = .32$, $p > .10$). All in all, these results clearly confirmed that the disruptive technology was more effective in online casino games than in online sports games.

DISCUSSION

Theoretical Contributions

Although the conceptual framework by Polites and Karahanna [63] suggests several disruptive strategies to modify IS habit, the effectiveness of such strategies has not been empirically tested in the context of online gambling. The present study is particularly meaningful because it develops and tests a conceptual framework on the differential effects of disruptions to help regulate unwanted gambling pattern online. Our findings are expected to apply to broader areas in which (1) the application in question is integrated into everyday life and (2) disruptive features can be offered by an IT-driven technique. In addition to online gambling, such areas can also include online social networks and social casino games. The use of online social networks (OSN) has attracted growing attention of the IS community. Billions of people nowadays access various OSN applications regularly [24].

Research has found the use of OSNs could become a strong habit because for many users, such usage is deeply embedded in the daily routine [35, 76].

Meanwhile, with the proliferation and market penetration of OSN services, social casino games have become more popular and influential. Social casino games simulate an online casino site in which players interact with their social network-enabled friends when engaging in the gambling activities. Although such games are free to play, research has found that a nontrivial proportion of players are highly likely to become routine gamblers of online casinos, primarily because regularly playing social casino games has made the virtual casino environment — conveniently accessible on smartphones — a routine and familiar setting for the players' entertainment needs [39]. Altogether, in light of the habitual use of online services such as social networks and casino games in association with the growing use of smartphones in recent years [12, 49], we believe that our model will serve as a sound basis for research not only on online gambling but also on other online services.

Drawing on the psychology literature in habitual automaticity, we used the notion of regularity [57] and showed that more regular gamblers exhibited a stronger repetitive pattern than those who gambled less. Our findings indicate that regular use of online services plays a crucial role in habit formation, and thus the effectiveness of disruptive features is likely to vary according to individual regularity [18]. In fact, this study demonstrates that disruptions were less effective in correcting unwanted habitual gambling by more regular gamblers than with less regular users. These findings support the suggestions in the recent gambling literature that the role of disruptions in gambling behavior is best understood by taking into account individual idiosyncrasies [22, 73]. We believe that the notion of regularity will provide valuable insights into online behavior given that individuals' use of online services can be performed on a highly regular basis without restrictions on time and location.

Another notable part of this study is the way we distinguish two different game types. A previous study in online gambling did not assume any systematic difference across the game options [50]. However, Toneatto and Ladouceur [73] emphasized a need to analyze gambling behaviors by specific game types to account for heterogeneity in each game. Drawing on the notion of an external trigger as a critical factor in disrupting habit [62, 63], we categorized games into sports and casino gambling according to the existence of external triggering events. In particular, sports games tend to be held regularly (e.g., weekly), and such regularity embedded in the games stimulates people's regular visits to the sites. Consistent with this prediction, our empirical results indicate stronger habitual patterns in sports games than in casino games. These results appear to contradict the literature in offline gambling that suggests that casino games (e.g., slots) are the most continuous and hard-to-control [20, 31, 44, 89]. However, we believe that these findings do not necessarily conflict but rather imply the powerful impact of the contextual differences between online and offline gambling. Overall, our study emphasizes the importance of investigating the characteristics of game type with contextual specificity accounted for. Such a nuanced understanding is essential to better understand the complex dynamics underlying behavioral changes caused by disruptions in the context of online gambling.

Practical Implications

This research demonstrates that disruptive strategies aimed at helping gamblers and administered by online gaming providers can be effective. The findings reveal that the duration of exposure to disruptive features continues to have penetrative effect on routine online gambling behavior. In light of this finding, online gaming providers may want to consider continuing disruptive features, once activated, for as long as necessary. A major advantage of online gambling, compared with its offline counterpart, is its superb ability to implement personalized control over what and when a gambler can or cannot do. Thus, online providers can relatively easily launch an individualized gambling procedure as requests from a gambler arrive. Subsequently, they can easily extend such a feature for as long as deemed appropriate to achieve the best result for this particular gambler. Furthermore, to facilitate such customized process and to further improve efficacy, online providers should find innovative ways to leverage their rich data about past and present personalized measures, possibly building an intelligent information system that automatically manages the optimal length of disruptive process for each individual gambler.

Moreover, online gambling providers should focus on disrupting the *regularity* rather than on simply decreasing the amount or duration of gambling activities. Our findings unveil that the underlying mechanism of forming unwanted gambling habits is through engaging with the behavior highly regularly, and the immediate utility of disruptive IT features decreases on more regular gamblers. In order to target the behavioral regularity of gamblers, designers or policymakers of online gambling need to develop creative models to more accurately measure the level of regular use of those who need help. Certainly, using our regular use measurement is a good starting point; we nevertheless encourage practitioners to derive and test more sophisticated measurements.

Last but not least, this research discovers that disruptive IT features are less capable of regulating unwanted gambling routines when online gamblers engage in sports games than when they engage in casino games. This novel finding provides important insights into what policymakers could do to combat persistent and unwanted habits in online sports gambling. Policymakers may want to inject some randomness into online sports gambling so that it can be made less regular. For instance, though schedules of professional sports may not be altered, the availability of the games that can be wagered on can be made less regular and less predictable — by using a simple randomization process — for certain problem gamblers, or even for the entire online gambling industry with respect to certain professional sports. Just as we find that behavioral regularity is weaker in online casino than in online sports games and that disruptive IT features work better in the former, policymakers should expect to see a weaker behavioral regularity of this somewhat *randomized* version of online sports gambling and a more effective result of disruptive features.

Limitations and Future Research

This research has some limitations. Even though we used PSM technique to largely mitigate the self-selection bias, the same or other types of self-selection bias could still remain in the model. Thus, our findings may still be biased. Readers should exercise caution when they generalize our findings to other disruptive IT features in curbing unwanted gambling habits. Besides, we did not have access to other background information about the gamblers in the sample, for example, income, occupation, and years of education attained. This has limited our ability to conduct more nuanced comparisons of unwanted gambling behavior online across different demographic groups. Furthermore, the fixed effects model used to test the hypotheses has precluded the time-invariant effects from being estimable, for example, age, gender, and country effects. Last, but not least, we did not have access to additional details as to how bwin strategically chose physical access changes over modified routines, or vice versa, at the individual level; should there be any systematic mechanism by which bwin preferred one feature over the other for different groups of gamblers, our findings could potentially be biased.

Future research may extend our work in several promising directions. In this study, we have examined how habitual use is disrupted by a mixture of disruptive features *as a whole*, such as modified routines, physical access changes, and training-in-context. Polites and Karahanna [63] argue that in addition to these types of disruption, a technique named monitor-and-feedback can also be used to break habits. We believe that this technique would be particularly effective in the online context because of the ease of tracking and reporting individuals' usage through the power of IS. For example, to help control unwanted gambling, the system could provide online gamblers with a warning sign following certain time limit or monetary loss. Thus, we encourage researchers to examine how monitor-and-feedback could be leveraged as an IT-related technique in the context of online gambling.

In addition, investigation is warranted into other types of online gambling and what effects disruptive features may have. Specifically, online poker and online bingo continue to grow more popular. It is worth checking whether the existing models of disruptive features also work effectively there. If not, what can be done to improve its efficacy? Our study reveals the critical role that the type and regular nature of the games play in forming gambling habits and in affecting the efficacy of disruptive features. Because online poker involves player-to-player interactions, this type of gambling may be more subject to certain social effects; thus, it is unclear whether standard means of disruptive features will be effective.

Furthermore, it is worthwhile to examine how generalizable our theoretical framework of habitual automaticity and disruptive IT features is beyond the immediate context of online gambling. As discussed earlier, there has been growing attention on the use of OSNs in recent years [35]. IS researchers may want to examine the validity of this study's framework in the OSN context. Specifically, future studies could examine whether habitual automaticity works similarly in forming and intensifying unwanted habits of using OSNs. Given that it is extremely difficult for researchers outside large OSN companies (e.g., Facebook) to trace and collect longitudinal individual-level usage data, we suggest researchers affiliated with these companies to leverage their rich data and our framework to better understand the formation process of unwanted habits and to innovate effective ways of disrupting them.

Particularly, there are interesting avenues for future research to explore how to break unwanted habits around OSNs. Studies have shown that teenagers are at the highest chance of habitual OSN use [54, 61]. It is possible that this demographic group feels particularly rewarded from socializing with peers [68], and such a reward-driven motivation might aggravate OSN use. Future research could take a closer look at these relevant individual differences. Even more, considering that smartphones have become an indispensable part of people's lives, social networking on smartphones can be uncontrollable [66]. Some scholars have attributed unwanted smartphone use to the habit of checking the phone upon hearing a notification [58]. News feed updates may also keep users preoccupied with using OSNs [58]. Future studies could look at how technological features, such as push notifications and news updates, might interact and co-contribute to unwanted usages.

Conclusion

This research has proposed an IT-based habit-disruption framework for intervening in unwanted online gambling habits, and it is largely confirmed empirically. Drawing upon the literature of IS habit, habit disruption, behavior regularity, and different gambling types, the five proposed hypotheses provide novel insights into the phenomenon. In addition to theorizing the mechanisms by which IT-based strategies disrupt and reduce gambling habits, this research underscores the key role that individual idiosyncrasies in behavior regularity plays in facilitating habit formation and thereby lessoning the efficacy of IT-based disruption. Moreover, perhaps for the first time in IS, this paper differentiates between two popular online gambling types (online sports vs. casino gambling) in terms of gamblers' behavioral regularity, and thus innovatively formulates their interactions with the impact of disruptive IT strategies. We believe that our findings and insights can be extended and applied into other contexts, such as use of online social networks and smartphone use, in which the behavior in question is easily habitual, and disruptive features can be offered by an IT-driven technique.

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Notes

1. In terms of why some gamblers wanted to change or better control their gambling routines, we have no way to determine. While using the term "unwanted," we neither assume nor imply that habitual online gambling is a bad habit. Our focus is on whether disruptive features can change what these gamblers would themselves want to change.

2. A typical disruptive IT feature is called "modified routines," for example, placing a partial or temporary restriction on certain gaming or payment option in order to make it inconvenient (but not impossible) for an online gambler to execute an established gambling routine. More examples and details on the applications of disruptive IT features will be discussed later in the Study Context and Method sections.

3. https://newsroom.fb.com/news/2018/08/manage-your-time/

4. https://wellbeing.google/

5. Among the original sample of 4,113 users, 587 users had unusable data. Specifically, 263 users had records of gambling amounts that the dataset source advised us not to use (i.e., missing or zero-valued betting amounts); 96 users did not bet anything on online sports or online casinos; and 228 users stopped playing shortly after opening an account. These and more details regarding the final sample are reported in Appendix A.

6. Because of the large sample size (both N and T are large in our data), running System GMM on the entire dataset was not feasible. Therefore, we took numerous random subsets of data (N' = 500 and T' = 10) and ran the model on each subset. We found a consistent pattern across all of these results.

7. Although autocorrelation seemed to be properly specified with time dummies, we still used the robust standard errors to ensure that they are robust for any remaining serial correlation as well as for possible heteroscedasticity in the error across time [94].

8. We also used alternative threshold values for separating these two groups to ensure our results are robust to different specifications.

9. The difference of the first-differenced gambling amount between the Study and the Comparison groups became smaller after we used PSM. Thus, PSM effectively corrected for the self-selection bias.

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APPENDIX A. CLEANING AND PREPARING THE DATASET

Among the 4,113 gamblers in the original data, 96 (or 2.3%) did not bet anything on online sports or online casinos; 263 (or 6.4%) had missing or zero-valued betting amounts. These gamblers were excluded from further analyses. We excluded 228 (or 5.5%) gamblers from the Comparison group who remained active for no more than a week after considering both types of games. As a result, our final sample consisted of 3,526 gamblers (the “Full” sample), 55.9% (or 1,970) of whom were in the Study group. The rest (or 1,556) were in the Control group. In this final sample, 3,455 (or 98.0%) gamblers had bet on online sports (the “Sports” subsample), and 1,176 (or 33.4%) had bet on online casinos (the “Casino” subsample). Table A1 shows the demographic information for these two samples. The two samples of gamblers were quite comparable in terms of the spread of locations (“countries of residence”) and demographic information (i.e., gender and age). We normalized the betting and winning amounts by removing inflation from the data because our data covered a long period in which inflation was expected to have affected gambling behavior.

Table A1. The Online Sports Sample vs. Online Casino Sample

Variables	Statistics	Online Sports	Online Casino
Gamblers	Count	3,455	1,176
Unique countries of residence	Count	46	38
Percent of females	Count	9.49	7.99
Age	25th percentile	22	24
	50th percentile	27	30
	75th percentile	34	36
	Mean	29.44	31.26