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Markers of unsustainable gambling for early detection of at-risk online gamblers

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In this work we propose novel markers for identifying at-risk gamblers based on the concept of sustainability. The first hypothesis here verified is that problematic gamblers oscillate between intervals of increasing wager size followed by rapid drops, probably because they exceed their economic sustainability limits. Due to the non-periodic nature of these fluctuations, the proposed marker detects a certain occurring feature, such as a rapid drop in wager size, over a wide range of fluctuation periods, drop sizes and shapes. The second marker, counting the number of games the gambler is involved in, aims at predicting possible consequences of an exceeding amount of time dedicated to gambling, that ultimately causes social and relational breakdowns. In the experimental phase we demonstrate how the adoption of these markers allows for identifying larger segments of high- and medium-risk gamblers with respect to previous research on actual betting behaviours.

Keywords: responsible gambling; classification; addictive behaviour; Internet gambling; screening

Introduction

The explosion of gambling activities and the increasing availability of Internet services are raising on the one hand serious concerns about gambling legality controls (against fraud, collusion, intrusions by criminal organizations, etc.), while on the other hand the same phenomenon solicits for new forms of protection for individual consumers, focusing particularly on underage gambling blocking and on the prevention of gambling-related addiction. Although pathological gambling is classified as an impulse-control disorder (American Psychiatric Association [APA], 2000), it nevertheless shares many features with addiction disorders due to substance dependence under the bio-psycho-social point of view (Potenza, 2006). The chronic and progressive nature of this disorder is often characterized by an inability to control or quit gambling, ultimately causing an overall decline in social and family relationships (Potenza, Fiellin, Heninger, Rounsaville, & Mazure, 2002; Shaw, Forbush, Schlinder, Rosenman, & Black, 2007), financial (Grant, Schreiber, Odlaug, & Kim, 2010) and legal consciousness (Abbott & McKenna, 2005; Abbott, McKenna, & Giles, 2005; Williams, Royston, & Hagen, 2005).

These gambling-related problems arise when betting activities of individuals become no longer sustainable. Derived from the Latin *sustinere* (*tenere*, to hold; *sus*, up), the word *sustainability* means the 'long-term maintenance of responsibilities', which in the

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gambling context encompasses the cognitive, economic and social dimensions. Under this lens, one of the most known instruments used to screen for probable pathological gambling behaviour, the South Oaks Gambling Screen (SOGS) developed by Lesieur and Blume (1987), can be interpreted as a method to assess the level of sustainability in its three different dimensions: the *cognitive* sustainability (regarding the level of self-awareness of the gambling problem), the *socio-relational* sustainability (concerning family and job disruptions deriving from disordered gambling behaviours) and the *economic* sustainability (e.g. default on debts, borrowing from illegal sources, committing an illegal act to finance gambling, etc.).

Concerning the *cognitive sustainability*, it is well known that gambling stimulates the brain areas that are responsible for analysis and predictive processes, as documented by van Holst, van den Brink, Veltman, and Goudriaan, 2010. When experiencing natural phenomena or social relationships, these processes help us elaborate behavioural rules that are useful in situations of uncertainty. In the case of aleatory phenomena typical of gambling, the cognitive effort of inferring rules is continuously frustrated by events, which are indeed governed by chance. These situations are sometimes referred to as the *cognitive distortions* (Clark, 2009; Toneatto, Blitz-Miller, Calderwood, Dragonetti, & Tsanos, 1997) which in some subjects evolve in progressive addiction characterized by increasing preoccupation with gambling, a need to bet more money more frequently, restlessness or irritability when attempting to stop, chasing losses, and loss of control manifested by continuation of the non-responsible gambling behaviour in spite of mounting, serious, negative consequences (Petry, 2004).

If the cognitive dependence is responsible for triggering non-responsible behaviours, heavy gambling activities continuously subtract time from other social and relational activities such as work, family and emotional relationships, often determining a breakup of the *socio-relational sustainability*; under this condition, relationships might become very conflicting (Petry, 2003; Potenza, Kosten, & Rounsaville, 2001), trigger a variety of psychiatric disorders (Crockford & el-Guebaly, 1998) and increase risks of suicidal behaviour (Bourget, Ward, & Gagne, 2003; Hodgins, Mansley, & Thygesen, 2006). Psychological treatments to overcome these pathological situations are usually long and no calculation of costs would be adequate to capture the intra-familiar costs of divorce and family disruption which are often associated (Shaw et al., 2007).

The need to increase the amount of wagers, which is often associated with pathological gamblers trying to achieve the desired excitement previously experienced at lower levels of wagering or trying to chase previous losses (APA, 2000), is the primary cause of exceeding the limits of the *economic sustainability* of gambling. This means that a constant increase in betting activities, especially when prolonged over time, unavoidably determine levels of economic non-sustainability – that is, the impossibility of facing present economic obligations (Grant et al., 2010).

In online gambling, betting activities and various factors which might be related to problem gambling can be monitored and logged by online operators at relatively little expense. These data could enable the operator to record gambling data and prevent problematic developments by the early detection of incipient problems. Previous work on early detection of high-risk online gamblers, such as the study by Braverman and Shaffer (2010), did not consider sustainability aspects to predict the development of gambling-related problems. They investigated whether several gambling characteristics cluster in a reliable way to identify bettors who will later close their accounts due to gambling-related problems. Nevertheless, since the employed data in Braverman and Shaffer (2010) describe the actual gambling behaviour of subscribers to the Internet service *bwin*

Interactive Entertainment AG (LaBrie, LaPlante, Nelson, Schumann, & Shaffer, 2007), these betting data likely contain the behavioural fingerprints of broken sustainability.

Using results shown in Braverman and Shaffer (2010) as a reference, in this paper we propose two novel markers based on the concept of sustainability for better segmenting different online gambling profiles. The hypothesis behind the first marker is that addicted gamblers fluctuate between intervals of increasing wager size followed by rapid drops, probably because they exceed their economic sustainability limits. Due to the non-periodic nature of these fluctuations, the proposed marker is obtained by detecting a certain occurring feature: a rapid drop in wager sizes, over a wide range of fluctuation periods, drop sizes and shapes. The second marker, counting the number of games the gambler is involved in, aims instead at estimating the total time spent in gambling and its possible consequences, in terms of social and relational breakdowns.

Ultimately, from this study we expect on the one hand new opportunities for researchers to better relate gambling issues from a clinical perspective to actual betting activities. On the other hand, the analysis of Internet gambling data relative to risk factors will provide online operators with concrete opportunities for giving players feedback on their gambling behaviour and helping at-risk bettors to make more informed decisions about their gambling.

This paper is organized as follows: initially we explore recent advances in protection against gambling-related problems, with a particular focus on early detection schemes on Internet data. After that, we present the overall methodology and recap previous findings and experiments that are preparatory to this work, as well as introducing two specific behavioural markers that relate to the initial emergence of addiction. Then we describe the performance of the proposed framework and discuss limitations and potentialities. Finally we gather concluding remarks and future research opportunities.

Previous Work

In the last few years, an increasing attention towards protection against gambling-related problems has emerged. On the one hand, public and private organizations are seeking new and validated approaches that could provide solutions to create awareness, mitigate and contrast gambling addictions at a very early stage, before problems become unsustainable. On the other hand, gamblers are starting to develop a higher level of consciousness about the problem, so that nowadays player protection seems almost to have become a competitive advantage within the gambling industry, especially on the Internet, where players can easily move from one operator to another (Haefeli, Lischer, & Schwarz, 2011; Wood & Williams, 2009). Common protection measures for online gambling encompass the practice of showing on-screen messages (Cloutier, Ladouceur, & Sevigny, 2006; Monaghan & Blaszczynski, 2010) and self-limitation (Veriplay, 2012; Haefeli et al., 2011).

The effectiveness of these protection procedures could benefit by introducing approaches able to single out possible gambling-related problems according to validated behavioural models which are adaptable to single gamblers. Along these lines, the first empirically validated model was introduced in Braverman and Shaffer (2010); it relies on a set of four behavioural descriptors that can highlight the presence of gambling-related problems at an early stage. In this study in collaboration with the online gambling company *bwin*, the authors analysed the first month of active play of 530 users who closed their account within two years, 176 of whom self-reported 'gambling-related problems' as a reason for closing their accounts. The authors clustered players according to four markers and found that one small group consisted mostly of individuals who declared that they had closed their account owing to gambling-related issues. These results and the markers used will be considered in the following sections of the paper, as they constitute the basis for our investigation.

The same indicators and clustering procedures were also used in Dragicevic, Tsogas, and Kudic (2011). Here the authors analysed two new datasets related to online casino and poker and found that the same methodology as in Braverman and Shaffer (2010) makes it possible to identify a small group of gamblers who showed markedly different gambling behaviours compared with other gamblers in their first month of activity.

However, the work illustrated in Haefeli et al. (2011) does not consider behavioural elements strictly related to gaming sessions, but focuses on communication-based indicators, looking at the interactions between users and the customer services of gambling operators. In particular, eight employees working in the customer service of three online gambling operators were surveyed to identify indicators in customer correspondence to be used as predictors for gambling-related problems. Once identified, the authors investigated to what degree these indicators were able to predict the presence of gambling-related problems in a prospective empirical design, thus obtaining a classification accuracy of 76.6% on identified cases. One point worth noticing is that in this study the authors analysed a sample of 300 users: 150 closed their accounts, self-reporting gambling problems, while the remainders did not declare any. For the control group, however, only 59 members actually contacted the customer service at least once (this may be too small a number from which to extract reliable statistics).

These aforementioned studies present alternative and complementary strategies for early detection of gambling-related problems; however, the same authors agree that some aspects should be further discussed in order to properly understand the proposed approaches. In Braverman and Shaffer (2010), for example, the authors notice that considerations are limited to one single gambling operator, not taking into account that a person could be involved in more platforms at the same time. Moreover, these studies consider as ground truth those declarations made by users when they de-register: in this sense, there could have been some users who did not declare the truth, or who, despite experiencing gambling problems, did not close their accounts. As such, to assess the real value of the reported findings, more rigorous approaches to the definition of a ground truth would be desirable. Further considerations, as well as possible operative strategies to overcome these limitations, will be discussed later in the paper.

Methodology

The work in Braverman and Shaffer (2010) is the first to analyse actual online gambling behaviour during the first month of play to predict gambling-related problems. Starting from these results and using the same data, our objective is to enlarge the set of behavioural markers to better segment and identify problematic gamblers.

Study by Harvard

The work in Braverman and Shaffer (2010) was carried out on live action sports bettors data, anonymized and publicly made available by *bwin*. Data describe the betting activities of 530 participants who subscribed to the service in February 2005 and who closed their accounts after at least one month of active playing, and no later than two years. When unsubscribing, 176 users reported gambling-related problems as the reason for closing their accounts and 98 claimed to be not satisfied with the service, while the 256 remaining declared that they were not interested in gambling.

The adopted behavioural parameters of players measured during their gambling activities are *frequency*, intended as the total number of active days for one month of betting; *intensity* – that is, the average number of bets per active day; *variability*, defined as the standard deviation of stakes; and *trajectory*, which is the slope of stake sizes.

Using these features in a *k-means clustering* algorithm with a Kappa degree of concordance procedure to verify the stability of the subdivision, participants are divided into four groups that are representative for different gambling behaviours. Results from this study, as reported in Table 1, highlight that one cluster of 15 gamblers, characterized by high intensity and high variability, contains a vast majority of gamblers (i.e. 11) who self-reported gambling-related problems as a reason for closing their account.

As admitted by Braverman and Shaffer (2010), this analysis identifies only a small portion of individuals with gambling-related problems. With the objective of better segmenting the gamblers' population, we propose to enlarge the previous set of markers by adding two indicators able to reveal unsustainable gambling (UG) behaviours.

UG marker: "sawtooth"

The hypothesis behind this marker is that problematic gamblers alternate between time intervals of increasing wager size followed by rapid drops, probably because they exceeded their economic sustainability limits, or their wish to control their impulse and stop or diminish the wagered money. This hypothesis is consistent with the clinical definition of problematic gambling as an impulse-control disorder (APA, 2000) as well as with the results of studies reporting that problematic gamblers often evidence periods of intensive activity interrupted by intervals of remission (LaPlante, Nelson, LaBrie, & Shaffer, 2008). The idea of periodic behaviour (fluctuations) in the context of socio-economic status has already been investigated in Baker and Marshall (2005), where the authors observe discrete periods of land-based gambling activity over the week. In our work, we observe that also for online gambling, problematic gamblers fluctuate from intervals of increasing wager size to rapid drops which prelude to inactivity periods. After a time interval of refraining from gambling, probably owing to the time needed to gather money to continue the betting activity, the process tends to repeat in time, resembling the shape of a *sawtooth* (as shown in the examples in Figure 1), even if over a wide range of fluctuation periods, drop sizes, pauses and shapes.

Further support for bet fluctuations as a risk factor can be found in Blaszczynski and Nower (2002) by analysing their pathways model. They identified three distinct groups of

Table 1. Composition (T_g: total number of gamblers, P_g: number of problematic gamblers) and centroids of the four clusters resulting from the study by Braverman and Shaffer (2010).

	Cluster 1 High activity, high variability	Cluster 2 Low first-month activity	Cluster 3 High activity, low variability	Cluster 4 Moderate betting
T_g	15	22	115	378
P_g	11	10	33	122
Frequency	2.635	−0.544	2.393	0.279
Intensity	1.787	0.039	1.9	0.004
Variability	4.409	0.156	0.262	−0.045
Trajectory	0.267	−2.486	0.143	0.223

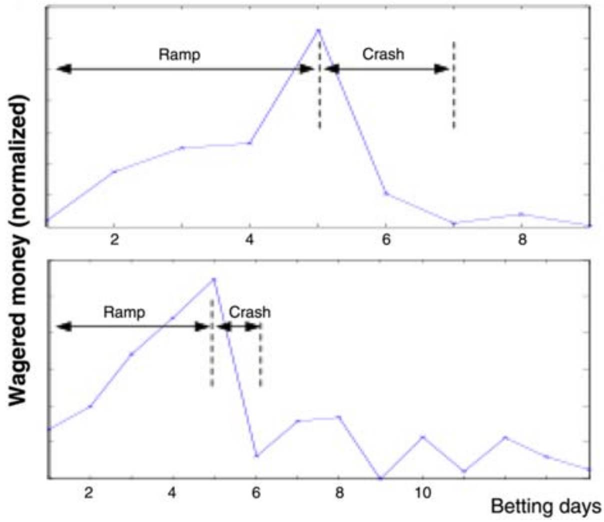

Figure 1. Wagered money over betting days for two gamblers of the *bwin* database (users 1369066 and 1394775). Sawtooth ramps and crashes present different values in terms of spread between samples.

gamblers: (a) behaviourally conditioned problem gamblers; (b) emotionally vulnerable problem gamblers; and (c) antisocial, impulsive problem gamblers. All distinct subgroups of gamblers identified in this study are invariably, due to the nature of gambling odds, characterized by a chase-losses phase through further gambling as debts rapidly escalate, followed by a 'losing more than expected' condition. It is rather obvious that this phase cannot last too long since it is *not economically sustainable*. This situation often ingenerates those behaviours (borrowing money from family, friends or illegal sources; committing an illegal act to finance gambling, etc.) when the gambler desperately tries to extricate himself/herself from a deteriorating financial predicament. Each of these operations for gathering money surely requires a certain amount of time and effort to fulfil, causing a temporary suspension from gambling activities.

The benefit of introducing the sawtooth marker with respect to, for example, the variability of stake fluctuations is evident when observing that this marker considers also the temporal aspect, which is conversely completely lost by the variability indicator. In fact, while variability describes the temporal series of stakes in statistical terms (so that we can have very different patterns of stakes that share the same standard deviation), a sawtooth event describes a very well-defined temporal pattern (i.e. a ramp followed by a crash) which happens in a very precise temporal instant. Therefore, as a first practical advantage of this marker, online operators could use the observation of a sawtooth pattern at a very specific time to responsively trigger automated personalized interaction with gamblers.

In addition to this, a sawtooth crash event, since it happens when a gambler exceeds his/her economic sustainability limits, is a more precise indirect clue to the individual's economic resources with respect to variability on stake fluctuations. As a consequence, the analysis of what happens in the correspondence of a crash event (how often this happens, the amount of last betting series, etc.) allows the building of statistics which are less dependent on the economic condition of individuals. This enables more accurate predictions on bettors belonging to different at-risk categories, and avoids using statistics built on all bettors such as general thresholds on indicators.

To allow the proposed analysis, sequences of wagers for each gambler in the *bwin* database are treated as discrete time signals. Specifically, gamblers' wagers constitute a class of aperiodic signals, since the period of these fluctuations is non-constant both within and across individuals. The presence of sawtooth shapes in gamblers' wagers is examined in the time domain by detecting an invariant repeating feature, such as the rapid drop in wager size, called sawtooth crash or drop. The algorithm is then able to reliably detect rapid drops over a wide range of fluctuation periods, drop sizes and shapes.

By looking at any sawtooth signal such as those shown in Figure 1, it is clear that the spread of the samples at the crash is higher than at the ramp part. Therefore, recognition of the sawtooth crash by use of the time-domain analysis can be established by investigating the difference in statistical dispersion of the samples along the sawtooth. The simplest method of performing this is to apply to the wager signal $x[n]$ a discrete difference filter:

$$y[n] = x[n-1] - x[n]$$

where a high positive value of $y[n]$ indicates a large difference between subsequent samples, which is the case at the crash part of the sawtooth signal. Indicating with $f_{Yi}(y)$ the probability function of the random variable Y for gambler i, the conditional probability density function $f_{Di}(d) = f_{Yi}(y|Y_i > 0)$ accounts for the statistics of the drops for gambler i, for whom the average μ_d^i and the standard deviation σ_d^i are determined. The crash detection algorithm distinguishes significant from non-significant drop events for each gambler i by imposing a positive-valued threshold t on the spread of the samples at the sawtooth crash. This means that a crash event at time n is detected if

$$y[n] > \mu_d^i + t \cdot \sigma_d^i$$

Our hypothesis is that the number of significant sawtooth crashes in the observation window, which in the following is referred to as *sawtooth* UG marker, is a potentially important characteristic, effective in identifying problematic gambling behaviour at an early stage.

UG marker: "games"

The hypothesis behind this second marker is that a gambler spending an elevated total time since involved in multiple gambling activities might ultimately bear an overall decline in social and family relationships. Baker and Marshall (2005) have already suggested that the total time spent in physical gambling venues is a proxy for problematic gambling behaviour; other studies highlight the fact that prolonged gambling ultimately causes an overall decline in social and family relationships (Potenza et al., 2002; Shaw et al., 2007). Moreover, for the offline scenario, several studies confirm that the involvement in multiple forms of gambling is a valid indicator of problem gambling (Cox, Enns, & Michaud, 2004; Risbeck & Romild, 2009). Concerning the online scenario, there is some evidence (Brosowski, Meyer, & Hayer, 2012) that the number of regularly used types of gambling is significantly associated with at-risk gambling.

Given this theoretical background, by counting the average number of different games per day that the bettor is involved in, we derive an indicator on the total time spent in gambling. In fact, in order to play multiple games, a gambler has to undertake a number of actions for each played game, so that the total number of attended games ultimately impacts on the total time spent in gambling activities. This indirect approach is also motivated by the nature of the *bwin* database, which does not provide direct information about total spent time, but only data related to single wagers on different games on a daily basis.

The computation of this marker, called *games*, which we related to a risk of harming the socio-relational sustainability, is made possible by combining, by an inner join clause on users' IDs, the records from the dataset 'How Do Gamblers Start Gambling: Identifying Behavioural Markers for High-risk Internet Gambling' (Division on Addiction, 2009a) which is the one used in Braverman and Shaffer (2010), with the dataset 'Actual Internet Sports Gambling Activity: February 2005 through September 2005' (Division on Addiction, 2009b), which contains betting information about eight different betting products (*Sports book fixed-odd, Sports book live-action, Poker BossMedia, Casino BossMedia, Supertoto, Games VS, Games bwin, Casino Chartwell*). Since there is a slight mismatch between databases, due to the fact that out of the 530 gamblers investigated in Braverman and Shaffer (2010) only 482 of them are present in the second database, only for these last ones it is possible to compute the average number of games played per day. As a consequence of this reduction, the number of people who when closing their account reported gambling-related problems diminishes as well, specifically from 176 to 160. More detailed specifications about the samples can be found in the related dataset descriptions provided by the Division on Addiction as part of the Transparency Project.

Data analysis

In this study we employ the four markers introduced in Braverman and Shaffer (2010) plus the two UG markers previously described, and work on the joined *bwin* databases discussed above. Our first goal is to uncover new perspectives and highlight new information buried in the data. Secondly, we aim at increasing the ability for early detection of problematic gamblers (P_g) with respect to the results obtained in Braverman and Shaffer (2010), thanks to the adoption of the two markers of unsustainable: sawtooth and games.

We adopt the following procedure: first, we extract all the aforementioned markers, to which we apply a z-normalization. After verifying that the Spearman's correlation coefficient among all features is moderate (excluding an isolated peak of 0.75 found between variability and sawtooth, as expected), we apply a k-means clustering algorithm. By means of a Kappa degree of concordance procedure with $k = \{3,4,5,6,7\}$ and repeating over 100 trials, we find that the optimal number of groups in terms of clustering stability is $k = 5$. As a result of the clustering process, we thus identify five different gambler groups, which are reported in the following for further analysis and discussion.

Results

The adoption of the two UG markers allows for a finer segmentation of the gamblers' population into five resulting groups (against the four in Table 1), each of them associated with a different gambling behaviour, as described in the following. In Table 2 centroids and composition of the five resulting groups are reported.

Cluster A is the smallest one: it contains only 16 members whom we can refer to as heavy bettors (HB), since they present significant positive values for all markers. Cluster B consists of users who did not play very often during the observation period (low frequency), but when playing they gamble very intensively (high intensity, HI) with a high

Table 2. Centroids and composition (T_g: total number of gamblers, P_g: number of problematic gamblers) of the five clusters obtained by using k-means on six markers.

	Cluster A HB	Cluster B HI-MV	Cluster C HF-HS	Cluster D MF-LV	Cluster E MB
T_g	16	43	72	114	237
P_g	9	20	20	40	71
Frequency	1.012	−0.252	1.665	0.196	−0.623
Intensity	1.118	1.952	0.671	−0.2242	−0.526
Variability	4.338	0.183	0.195	−0.183	−0.297
Trajectory	1.334	−0.546	−0.011	−0.013	0.019
Sawtooth	0.955	0.242	1.741	−0.141	−0.569
Games	0.185	0.056	0.580	0.806	−0.587

number of bets, a medium variability (MV) of wagered money, and a medium value of sawtooth crash events. Players in Cluster C showed interest in a number of different games, gambling very frequently (highest frequency, HF), with medium intensity and variability, and with a gambling style showing a profusion of sawtooth events (highest sawtooth, HS). Cluster D contains individuals who take part fairly often (moderate frequency, MF) in several online games (high games) and who are characterized by a low variability of wagered money (LV). Cluster E, the most populous one, refers to moderate bettors (MB), with low values for all considered markers.

Clusters' association with levels of disordered gambling

A chi-square analysis considering T_g (total members of the cluster) and P_g (problematic gamblers in the cluster) in Table 2 reveals an important relationship between cluster membership and reason for closing the account ($x^2 = 13.53$, $P < 0.05$).

It is interesting to draw a parallel between our results and the findings in Braverman and Shaffer (2010). As a first consideration, it clearly emerges that Cluster A isolates a small group of addictive gamblers with high precision. Such result is coherent with findings in Braverman and Shaffer (2010), where in Cluster 1, among a group of 15 heavy bettors, 11 people declared that they suffer from gambling problems (see Table 1). As a further confirmation, we experimentally verified an almost total correspondence between users' IDs in Cluster A and Cluster 1.

Another correspondence between groups in the two experiments relates Cluster 4 (378 users) in Table 1 and Clusters D and E (114 and 237 gamblers, respectively) in Table 2. If Cluster 4 is described by Braverman and Shaffer (2010) as composed of moderate bettors (MB), Clusters D and E in our results are characterized by a vast majority of negative markers. Recalling that values in Table 2 are z-normalized, this means that members of Clusters D and E are below the average value (computed on the whole gambler population) for most markers. Since positive marker values are associated with an increased probability of developing gambling problems, it is clear that Clusters D and E (one and two positive markers only, out of six) describe gamblers with low probability of developing disordered gambling behaviours.

In Braverman and Shaffer (2010) no conclusive remarks were drawn on the remaining two clusters, namely Cluster 2 (low first month activity, $T_g = 22$, $P_g = 10$) and Cluster 3 (high intensity, low variability, $T_g = 115$, $P_g = 33$). For Cluster 2 this was due to the fact that, although a significant portion of players actually closed their account for gambling-related problems ($P_g = 10$ out of 22), most indicator centroids showed negative or close to zero values (see Table 1), thus not supporting for this group any correspondence between self-reporting and gambling behaviour. However, regarding Cluster 3 despite the positive values for frequency and intensity centroids, the presence of near zero scores for variability of wagered money and trajectory, combined with a not-so-high percentage of self-reported problematic gamblers in the group ($P_g = 33$ out of a total 115), suggested that the authors should not draw any conclusion on the level of disordered gambling behaviours among bettors.

The real advantage brought by this work is the ability of the new marker set to segment two new groups, namely Clusters B and C, which did not clearly emerge from the study in Braverman and Shaffer (2010), and the possibility of advancing conclusions on their gamblers' behaviour and the connected risk level.

Although Cluster B does not present such high centroid values for every marker as Cluster A does, it nevertheless shows positive scores of cluster centres on most behaviour characteristics (see Table 2), with a peak on intensity marker. The disordered gambling behaviour suggested by the positive values of centroids are further confirmed by the fairly good precision achieved by this cluster in identifying problematic gamblers: Cluster B contains 20 self-declared problematic gamblers out of a total 43 bettors.

Cluster C is another small group of gamblers that has become evident for the first time in this study. Although having similar values of precision as Clusters D and E (20 Pg out of a total 72), as for Clusters A and B (and differently from Clusters D and E), Cluster C shows positive scores of cluster centers on most gambling behaviours characteristics (see Table 2) and a peak on the sawtooth marker. This evidence on this segment of the population, which was missing in previous studies (no conclusions could be drawn by observing centroids of Clusters 2 and 3 in Braverman & Shaffer, 2010), suggests the presence of signs of disordered gambling behaviour even in this group.

To conclude, users in Cluster A (all positive markers) are players at high risk – like the bettors in Cluster 1 studied by Braverman and Shaffer (2010). Gamblers in Clusters D and E (one or two positive markers only) are bettors with a low probability of developing gambling-related problems – like Cluster 4 in Braverman and Shaffer (2010). Finally, people in Clusters B and C are those who developed, if not a high risk, at least a *medium risk* of disordered gambling behaviour (majority of positive markers and non–trivial number of self-reported problematic gamblers in both groups).

Although we do not have clinical evidence about the participants' level of pathological gambling, as we employed only account closers' self-reports as an indication of actual gambling-related problems, in any case the proposed subdivision into *high/medium/low* levels of risk finds a supportive correspondence in the theory introduced by Shaffer, Hall, and Vander Bilt (1999), which divides problematic gamblers into different categories according to the seriousness of their disease. The scheme in Shaffer et al. (1999) is based on five levels: Level 0 is reserved for non-gamblers, Level 1 for non-problematic gamblers, Level 2 for gamblers with sub-clinical levels of gambling problems, and Levels 3 and 4 for those who show the most severe level of gambling problems (Level 4 gamblers are a subset of Level 3 gamblers, those who present themselves for treatment). While it is still not feasible to establish a final mapping between our categorization and the levels expressed by Shaffer et al. (1999) (thing that could be done only with some clinical or collateral evidence), nevertheless our findings lead to a better understanding of the phenomenon, and stimulate further research in the creation of better correspondences. These considerations are summarized in Table 3, where clustering results and level subdivisions are listed for easy comparison.

Table 3. Cluster groups obtained with six markers, their associations with gambling seriousness levels as defined by Shaffer et al. (1999), plus their corresponding behavioural types.

Cluster subdivision with 6 markers	Levels of gambling by Shaffer et al. (1999)	Corresponding behavioural types
Cluster A: high risk	Levels 3 and 4: severe gamblers	Disord. gambling accord. to diagnostic criteria
Clusters B and C: medium risk	Level 2: sub-clinical gamblers	From mild to moderate gambling problems
Clusters D and E: low/no risk	Level 1: non-problematic gamblers	Recreational gambling

Identifying larger portions of at-risk gamblers

When aiming at identifying problematic bettors, recall should be somehow privileged with respect to precision in order to identify as many problematic gamblers as possible. By considering only Cluster A, it is possible to isolate only a very small group of addictive gamblers ($P_g = 9$, corresponding to 5.6% of the population) with a fairly good precision. As already pointed out, this result reproduces the one obtained in Braverman and Shaffer (2010) (Cluster 1 in Table 1, $P_g = 11$, recall 6.25%). However, when the goal is to identify as many problematic gamblers as possible, having such low recall values is penalizing. As an answer to this limitation, the ability of the new marker set to segment two new subgroups of subjects characterized by a medium risk of developing gambling-related behaviours (Clusters B and C), makes it possible to obtain larger recall values on identified problematic bettors.

Considering first the members of Cluster A as high-risk gamblers, and then adding in an incremental fashion those at medium risk, who are bettors in Clusters B and C, the ability of the system to segment the at-risk population significantly increases. In this sense, when considering Clusters A and B together, recall rises from 6% to 18.01%, while maintaining a fairly good precision (49.2%). When adding the population of Cluster C, recall reaches the score of 30.6%, still with an acceptable level of precision (37.4%). The precision-recall curve accounting for the three segments of at-risk population (high, medium, low/no risk) is shown in Figure 2.

Drawing a similar curve for findings in Braverman and Shaffer (2010) would be inappropriate, because with that set of descriptors, the authors could draw no conclusions on the level of gambling disorder for bettors in Clusters 2 and 3. In any case, even combining Cluster 1 with Cluster 3 (assuming that the latter could correspond to a medium-risk level due to the positive values of its centroids), recall would reach a maximum of 25% (with a precision of 33.8%), thus remaining much lower than in our procedure when considering at-risk clusters (recall 30.6%, precision 37.4%). Therefore, for levels of precision comparable to those obtained in the Harvard study, our method scores higher values of recall, meaning that the introduction of the two UG markers is significantly effective – sign significance test on recall $P < 0.05$, as suggested in Yeh (2000) – in better segmenting the gambler population in different risk categories for early detection of problematic gambling behaviours.

Discussion

In this work we propose a new method, ultimately aiming at the protection of online consumers by an early prevention of gambling-related addiction. In fact, while preventive

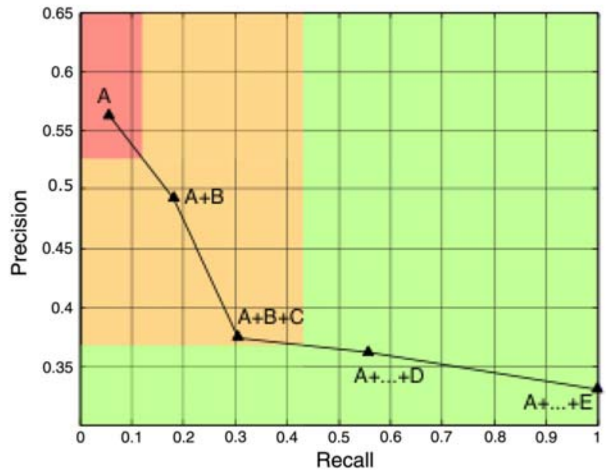

Figure 2. Precision-recall curve for segmenting gambler population in risk categories (high/medium/low–no risk) for early detection of addictive behaviours.

measures are to some extent difficult to implement in land-based gambling, for online games the availability of behavioural player data allows research into effective protective measures.

In particular, we propose a segmentation strategy based on the analysis of behavioural player data aiming at identifying at-risk gamblers during the early period of active betting. To do this, we employ a combination of the risk factors already proposed by Braverman and Shaffer (2010), with two new descriptors related to aspects of unsustainable gambling. The new set of indicators, beyond including variability of bet size, intensity and frequency of betting, and trend of wagered money, now encompasses a first marker for highlighting fluctuations between intervals of increasing wager size followed by rapid drops, and a second one accounting for the total number of different games played per day by the same gambler.

As a result, we segmented the gambler population into five resulting groups, each of them associated with a different gambling behaviour. The high-risk subgroup that we identified includes 3.3% of all gamblers (Cluster A), a result that is comparable to the 2.8% in the high-risk subgroup in Braverman and Shaffer (2010). Nevertheless, the real advance brought by this work is the ability of the new marker set to segment two new groups of bettors (Clusters B and C) which include gamblers who likely developed a medium risk of disordered gambling behaviour, a category not identified in previous studies.

The positive values of marker centroids in these segments of population, and the non–trivial number of self-reported problematic gamblers, suggest that these two groups belong to a more diverse group with respect to their high-risk counterpart. In particular, some of the behaviours exhibited in Clusters B and C provide evidence suggesting a certain consistency with Level 2 gambling suggested by Shaffer et al. (1999). While extremely diverse, Level 2 gamblers experience a wide range of problems because of their gambling. Most importantly, since Level 2 gamblers are much greater in number than their Level 3 counterparts (Shaffer et al., 1999), the ability of the proposed methodology to identify a portion of Level 2 gamblers allows for a significant increase of the total number of isolated at-risk gamblers.

Referring to the work by Blaszczynski and Nower (2002) on a pathways model, we observe that the high trajectories exhibited by bettors in Cluster A could relate these gamblers to pathway 3 (antisocial, impulsive problem gamblers), while some of the behaviours exhibited in Clusters B and C could find consistent correspondences with pathway 1 (behaviourally conditioned problem gamblers, notably heavy or excessive gambling and loss chasing). At the moment, no evidence suggests the possibility of linking any found cluster with pathway 2 (emotionally vulnerable problem gamblers), for which gambler data on betting patterns seem at the moment insufficient, if not accompanied by data derived from gambling screens.

Ultimately, the provided segmentation opens up, on the one hand, new opportunities for researchers to better relate gambling issues from a clinical perspective to actual betting activities, and, on the other hand, opportunities for gambling operators for providing feedback to their players, at least helping at-risk players to take more informed decisions about their gambling choices. Common protection measures for online gambling, which encompass the practice of showing on-screen messages and self-limitation, would significantly benefit from an approach able to classify each single gambler according to a validated behavioural model. It has already been demonstrated that on-screen messages, for example, are able to raise the level of self-consciousness of the user (Cloutier, Ladouceur, & Sevigny, 2006), but their effectiveness depends on the type of message and timing (messages are more effective if shown during the game rather than at the beginning). So far, the usage of on-screen messages has many different implementations, but experimentations mainly use general warnings or informative notes regarding only the amount of time spent playing or the number and entity of bets (Haefeli et al., 2011). The possibility of delivering messages at the exact moment when the gambler is violating a certain threshold on a specific marker of unsustainable gambling behaviour would increase the overall effectiveness of the protection system. Regarding the general effect of such message content about responsible gambling on regular gamblers, Monaghan and Blaszczynski (2010) showed that these message effects impact subsequent gambling sessions even following brief exposure and last at least two weeks.

Limitations

Our work continues and takes inspiration from the study presented in Braverman and Shaffer (2010), and as such inherits all its general limitations, especially those regarding the *bwin* database and the level of uncertainty related to users' self declarations. The database considers only players who unsubscribed from the service within a two-year period, so we are able to evaluate results using only users' self-declarations about the motivation for closing their accounts as a ground truth.

In addition to this, by adopting this database, we can theoretically distinguish only between self-declared problematic gamblers and self-declared non-problematic ones. However, this subdivision of the population does not consider possible intermediate levels of pathology which are supported by clinical evidence (Shaffer et al., 1999) and that could constitute an important target for early detection of gambling problems. In our study we try to push the model proposed by Braverman and Shaffer (2010) a step further, suggesting that the introduction of two markers related to unsustainable gambling, beyond improving the validity of prediction, provides a set of composite indicators of adequate sensitivity and specificity able to target individuals at both high and medium risk of gambling-related problems. Nevertheless, the presented results require further evidence in order to be fully validated; the absence of clinical evidence limits the general value of the database and raises some questions about the applicability of the proposed system in real-world cases. Our expectation is that researchers could find the proposed markers inspirational for their work.

Other limitations regarding *bwin* data consist in the fact that it is possible that some players played on different gambling websites and other land-based gambling venues, thus not providing a completely reliable view of the player's full gambling profile.

Finally, even though k-means clustering has been adopted in many studies on Internet gambling (Braverman & Shaffer, 2010; Dragicevic et al., 2011), its unsupervised nature has some limitations: for example, in case of the presence of outliers with non-normally or skewed distributed populations, that could be overcome, for example, by adopting winsorization methods on data.

Conclusions and implications for further research

The outcome of this paper demonstrates that adding sustainability-based indicators for gambling-related problems increases the hit-rate for early detection of high-risk individuals as well as for the identification of a larger class of medium-risk subjects. By counting the recurring presence of intervals of intensive activity interrupted by periods of remission, and by an indirect measure of the amount of time dedicated to gambling and likely subtracted from social and family relationships, we improve the validity of prediction and provide composite markers of adequate sensitivity and specificity with respect to previous state-of-the-art indicators.

A possible solution to overcome the limitations of this study, derived from the nature of the *bwin* data, which have been discussed above could be represented by the introduction of validated data corpora integrating gambling data with psychological studies using structured interviews in order to determine the level of gambling problems, such as the SOGS questionnaire, the NORC DSM Screen for Gambling Problems (NODS) (Gerstein et al., 1999) or the newer Canadian Problem Gambling Index (CPGI) (Ferris & Wynne, 2001), to mention only a few. The usage of such questionnaires, related in turn to the actual gambling habits of players, could reveal a sufficient number of clues able to better distinguish different levels of addiction consistent with the study in Shaffer et al. (1999), or to isolate different pathways, as identified in Blaszczynski and Nower (2002). The identification of different phases, pathways and levels of problematic gambling would also be useful to generate specific messages and feedback mechanisms helping players to regulate their gambling behaviour. Furthermore, the availability of such screens would allow for the analysis of data in relation to problem-gambling risk factors by using different statistical methodologies. For example, an alternative approach could entail the usage of supervised learning techniques, by using the six risk factors as variables in order to assess whether they can predict which players self-exclude themselves from gambling or self-declare themselves as having experienced gambling-related problems.

Even though the need for clinical evidence could be confirmed only by the adoption of adequate screening programmes and questionnaires, online operators might already use the monitoring of these aspects of player behaviour experimentally. For example, the presented findings indicate that the number of different games the bettor is involved in may be an important predictor of an at-risk status. As a consequence, the self-exclusion option – as one protection measure – could limit, for example, the maximum number of products the gambler can play, or all gambling products of one gambling website, or again, all gambling providers in one jurisdiction. In a similar manner, observations of multiple sawtooth patterns in the stakes of a bettor could be used by online operators to trigger automated personalized interactions (e.g. display of informative messages) and assess whether the provision of such specific feedback could be perceived as useful by bettors belonging to different at-risk categories, at least for planning more specific interventions.

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