

Usage of a Responsible Gambling Tool: A Descriptive Analysis and Latent Class Analysis of User Behavior

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Published online: 11 January 2016
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Abstract Gambling is a common pastime around the world. Most gamblers can engage in gambling activities without negative consequences, but some run the risk of developing an excessive gambling pattern. Excessive gambling has severe negative economic and psychological consequences, which makes the development of responsible gambling strategies vital to protecting individuals from these risks. One such strategy is responsible gambling (RG) tools. These tools track an individual's gambling history and supplies personalized feedback and might be one way to decrease excessive gambling behavior. However, research is lacking in this area and little is known about the usage of these tools. The aim of this article is to describe user behavior and to investigate if there are different subclasses of users by conducting a latent class analysis. The user behaviour of 9528 online gamblers who voluntarily used a RG tool was analysed. Number of visits to the site, self-tests made, and advice used were the observed variables included in the latent class analysis. Descriptive statistics show that overall the functions of the tool had a high initial usage and a low repeated usage. Latent class analysis yielded five distinct classes of users: self-testers, multi-function users, advice users, site visitors, and non-users. Multinomial regression revealed that classes were associated with different risk levels of excessive gambling. The self-testers and multi-function users used the tool to a higher extent and were found to have a greater risk of excessive gambling than the other classes.

Keywords Responsible gambling tool · Decrease gambling · User behavior · Latent class analysis · Initial high usage · Low repeated usage

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Introduction

Gambling is a common activity throughout the world that is often done in pursuit of entertainment or leisure. The gambling activities available today have varying degrees of risk and sizes of possible winnings to accommodate different individual needs and preferences. The majority of individuals that gamble are able to manage the risk of overspending money and time on gambling activities. However, there is a minority of gamblers that cannot appropriately manage their gambling, which results in negative financial, social and emotional consequences (Kalischuk et al. 2006; Kourgiantakis et al. 2013).

In Sweden, approximately 70 % of the population gambles at least once a year, roughly 44 % of the population gambles every month, and according to a national prevalence study, about 2.2 % of population is considered “problem gamblers.” The study classified “problem gamblers” as those who score at least three points on the Problem Gambling Severity Index (Holtgraves 2009) and this included both at-risk gamblers (1.9 %) and problem gamblers (0.3 %). Adding to this, the incidence rate of at risk and problem gamblers in Sweden is high. Half of the participants in the national prevalence study that were problem gamblers at a screening conducted in 2008/2009 were no longer at risk when tested again during a 1-year follow-up, but they were replaced by new problem gamblers. Some of these new problem gamblers reported having gambling problems before the initial survey in 2008/2009 (Swedish Institute of Public Health 2012). This suggests that problem gamblers can alternate between periods of non-problematic and excessive gambling.

The incidence rate of at-risk and problem gamblers, along with the fact that the population is constantly changing, can be understood in light of the results from studies showing that some problem gamblers self-recover (Hodgins and El-Guebaly 2000; Slutske 2006). Less cognitive distortions and performing better on decision making tasks are factors associated with self-recovery from at-risk and problem gambling (Rossini-Dib et al. 2015). Problem gamblers that self-recovered had less severe issues with gambling than problem gamblers that sought treatment (Toneatto et al. 2008). This might also be one reason for self-recovery among gamblers.

Self-recovery among gamblers might explain why some problem gamblers were less likely to endorse treatment than non-gamblers and social gamblers (Cunningham et al. 2011). Only about 7–18 % of problem gamblers seek treatment (Slutske 2006; Suurvali et al. 2008). One of the main reasons problem gamblers report for not seeking treatment is the belief that they could handle their problem on their own without outside help (Gainsbury et al. 2013a; Suurvali et al. 2009). However, even if the gamblers at risk have the ability to self-recover, there is a need to limit excessive gambling in simple, efficient, and accessible ways in order to limit the negative consequences. Strategies may include interventions that help gamblers learn to manage their gambling, and prevent their habit from becoming harmful.

Different tools aiming to promote responsible gambling (RG) may be one way to target gamblers of varying levels of risk, and prevent them from becoming excessive gamblers and experiencing the negative consequences of excessive gambling. RG is defined as “policies and practices designed to reduce and prevent potential negative consequences associated with gambling.” (p. 308) (Błaszczynski et al. 2004). These policies and practices cover a wide range of interventions, such as promotion of consumer protection, community/consumer awareness and education (Błaszczynski et al. 2004). RG strategies for both land based and internet gambling include limit setting, self-exclusion, maximum

bet limits, limiting hours of availability, mandatory breaks, and pop-messages during gambling sessions (Wood et al. 2014). In recent years, the field of RG expanded due to the onset of internet gambling. This provides new ways of implementing prevention strategies, like behavior tracking, and online RG programs (Gainsbury et al. 2013b).

Studies focusing on RG features have researched different types of strategies to limit excessive gambling for different gambling activities. Ways of reducing spending on electronic gambling machines (EGM's) has been one focus in RG research. In a review of 17 studies investigating limit setting and EGMs (Ladouceur et al. 2012), occluded that findings were mixed with some studies showing that limit setting for time and money was effective for this type of gambling activity and others showing that the impact of limit setting was more modest. Also, one study investigated the implementation of win limits to decrease excessive gambling. Gamblers playing on EGM's improved their performance and limited spending when gambling with a win limit (Walker et al. 2014).

Limit setting and Internet gambling have also been researched. Limit setting in internet gambling seems to have an effect in limiting spending (Auer and Griffiths 2012; Broda et al. 2008; Nelson et al. 2008). Also, offering Internet gamblers the ability to set spending limits would increase trust toward the gambling sites among those who gamble online (Gainsbury et al. 2013b).

One innovative study used employees at a gambling site to analyze complaint e-mails from users and successfully managed to identify future excessive gamblers (Haefeli et al. 2011). This study was replicated using software to analyze the same type of communication. A combination of manual rating (performed by employees) and automated text analysis was the most effective way to detect future excessive gamblers (Haefeli et al. 2014).

Another study focused on behavior tracking found that adding sustainability markers (intervals of intense activity and rapid drops in wagering) increased hit-rate when identifying individuals at risk (Adami et al. 2013). Also, improving detection algorithms to analyze an individual's gambling history could lead to better ways of identifying at-risk gamblers (Philander 2013). A cluster analysis successfully identified a subgroup characterized by high intensity, high frequency gambling, and high variability of wager sizes. This subgroup was found to be at a higher risk for problems related to gambling when closing their account than the other subgroups of gamblers included in the study (Braverman and Shaffer 2012).

Different types of brief interventions with personalized feed-back were effective in decreasing different aspects of gambling behavior (Martens et al. 2015; Neighbors et al. 2015). Most of the studies presented here underline, in different ways, the importance of monitoring, giving feedback on gambling behavior and tailoring and providing feedback. However, even though some studies have researched RG strategies, more research is needed (Blaszczynski et al. 2011; Shaffer et al. 2010).

The need for more research holds true when it comes to the emerging field of RG tools. These tools are designed to decrease and prevent excessive gambling for individuals at risk by means of behavior tracking (recording gambling history), feedback on gambling behavior, and supplying strategies to limit excessive gambling behavior. However, two studies have investigated the effect of these types of tool on gambling behavior. Users that received personalized feed-back spent less time and money on gambling than matched controls that did not receive any feed-back (Auer and Griffiths 2015). The effect of the RG tool Playscan has been evaluated. Non-risk users and at-risk users that used the tool reduced their spending on gambling compared to non-risk and at-risk users that did not use

the tool. However, for the two groups of high risk users (both Playscan-users and non Playscan-users) this effect was not present (Wood and Wohl 2015).

Playscan is the focus of our study. Playscan contains a risk assessment that is communicated to the users. The tool employs a 3-step scale from low to high risk of developing gambling problems. The risk assessment is based on gambling history, self-reported negative consequences due to gambling, and if the user exceeded a limit concerning what was considered adequate time and money to spend on gambling per week. The users at risk received advice on how to cut back on their gambling. The tool communicated with the users via messages that were visible in a mailbox on the start page of the tool (a more detailed description of Playscan can be found in the “[Method](#)” section).

Usage of Playscan has been the focus of one previous study (Griffiths et al. 2009). Users at a Swedish gambling site were surveyed (an inquiry to participate in the study was sent to 10,412 users) on their use of the site and of Playscan. In total, 2332 answered the questionnaire and 594 of these participants had activated a Playscan account. High frequency players were more likely to activate a Playscan account (Griffiths et al. 2009). One way of interpreting this is that high frequency players are more at risk of developing gambling problems, so they begin using the tool to decrease their risk. However, the main reason reported for joining Playscan was curiosity (Griffiths et al. 2009). A majority of the gamblers (89 %) had not changed their risk level since joining Playscan. The authors interpret this as the consequence of low risk ratings among the participants; the ratings may have given them the impression that they had no need to use the tool to change their behavior (Griffiths et al. 2009). This was one of the first studies about users of a RG tool, but it was based on self-reports and was not entirely focused on Playscan. In contrast, the current study is focused on exploring actual usage of the different functions of Playscan. We consider this to be an important first step in evaluating the effects of RG. Similar tools and programs in other areas of health management had a low overall usage (Wangberg et al. 2008; Wanner et al. 2010). There is a need to investigate if this low usage pattern holds true for tools targeted towards gambling.

The overarching aim of this article was to describe user utilization of Playscan from two different perspectives. First, to explore usage of the different functions of the tool, such as the proportion of members that visited Playscan, how many members received and read the messages sent by Playscan, how many members answered the self-test, and how many members used the advice-function supplied by Playscan. Second, a Latent Class Analysis (LCA) based on individual usage was performed to further explore the usage of tool. LCA is a method that focuses on identifying unobserved subpopulation, i.e., latent classes, based on individual response patterns on observed variables. Previous studies have successfully been able to validate 3–5 classes of gamblers, ranging from low to high frequency gamblers, using LCA (Carragher and McWilliams 2011; Dufour et al. 2013; Goldstein et al. 2012; Lloyd et al. 2010; McBride et al. 2010; Studer et al. 2015; Tackett et al. 2014). In addition to the LCA, a multinomial regression will be carried out with risk of excessive gambling as variable to explore if there is a difference in risk between the different classes. This study will continue to explore gamblers’ behavior in a new context. We believe that these two perspectives on usage will further enhance the knowledge about RG tools.

Method

Description of the Responsible Gambling Tool

Participation was voluntary and open for all users of Svenska Spel's gambling website. Svenska Spel is a company owned by the Swedish state that provides gambling services to the inhabitants of Sweden. The tool was free of charge and users could stop their participation at any time without impacting their membership of the gambling site. The aim of the tool was to prevent users from the risk of becoming excessive gamblers both in terms of time and money spent. The definition used concerning the risk of developing an excessive gambling pattern is an escalation of time and/or money spent on gambling over time, and if the gambler reports greater negative consequences of gambling or spends a much greater amount of time and/or money gambling compared to an average user. The tool is designed to detect and support gamblers at different levels of risk. The tool was partly based on the Stages of Change Model (Prochaska et al. 1993) and Motivational Interviewing (Miller and Rollnick 2002). The communication and advice available are formulated using techniques from these two models to promote behavior change.

Playscan consists of three parts: risk assessment, communicating the risk of excessive gambling, and advice/strategies on how to decrease gambling activities. The risk assessment contains three levels ranging from no risk (symbolized by a green light), moderate risk (yellow light) and high risk (red light) of developing excessive gambling behavior. The risk assessment is, in turn, based on three parts. One part is the user's gambling history (spending, frequency and duration), as well as the user's choice gambling activities (e.g., poker). The second part is a self-test focused on the negative consequences of gambling for both the user and the user's family and friends. The self-test contains of sixteen items. Fifteen items focus on how the user experiences the current negative consequences of gambling, and one item focuses on problematic gambling behavior during the past 3 months. The self-test covers the following areas: general problems due to gambling, problems with/for close family and friends due to gambling, mental health, and physical problems. Every question has a range from 1 to 10 with ten indicating the most severe problems. The user also has the option to set a limit to reflect what he/she considers to be adequate money and time to spend on gambling per week. If this limit is exceeded, it will lead to higher calculated risk level (e.g., changing from a green risk level to yellow). The different parts of the risk assessment are weighted. Gambling history and the result of the self-test can lead to a yellow or red light. If the limit of what is considered to be adequate time and money spent on gambling is exceeded, the risk assessment will automatically be yellow (no matter how much the limit is exceeded). It is only necessary for one part of the assessment to be yellow or red to yield a higher risk assessment. Clinical expertise was used to determine the levels of gambling that are considered risky. Risk is assessed on a weekly basis and communicated to the user, as well as personalized written information on their gambling behaviors. If the risk level has not changed, no information is presented to the user during that week.

In conjunction with the presented risk assessment, advice on how to prevent excessive gambling is available to the user. The user can choose to click on different advice to get more information about strategies on how to decrease gambling behavior. The advice available was presented as headlines within the message. The advice includes the following suggestions: "you need a break from gambling," "oversee your weekly budget," "keep track of your deposits," and "learn about problem gambling from a support hotline".

Procedure/Data Collection

Data collection started on December 12, 2011 after the launch of an updated version of the tool. Data from the Playscan system was extracted on October 30, 2013. The variables used were: the numbers of times a user logged in, the number of self-tests the user started to answer and completed, how many users received and read messages from the RG tool, and how many users clicked the advice available. Demographic information regarding age and sex was also used.

A risk assessment based on gambling data during a 5 week-period before the user joined the RG tool was included in the analysis (the risk assessment was only based on the participant's gambling history and was made available to Playscan when the participant joined the tool).

Participants

In total, 10,252 users began using Playscan during the 23-month inclusion period. 724 users were excluded because they actively left the tool during the inclusion period, leaving 9528 users. Of the 9528 participants, 235 (2.5 %) participants did not disclose their sex or age. Of the remaining 9293 there were 7823 males (84.2 %) and 1470 females (15.8 %). The mean age of the 9293 participants was 41.80 years ($SD = 15.42$). The mean age of the men in the sample was 41.41 years ($SD = 15.58$) and the mean age of the women was 43.94 years ($SD = 14.36$).

Of the 724 users that actively left the tool, 704 disclosed their sex and age. The gender distribution was 617 men (87.6 %) and 87 women (12.4 %). The mean age of this sub-sample of 724 participants was 49.29 ($SD = 15.39$). The mean age of the men was 48.84 ($SD = 15.61$) and the mean age of the women was 52.54 ($SD = 13.34$).

Statistical Analysis

As a first step, usage of the different functions was analyzed by means of descriptive statistics. The second step of the analysis was to explore the possibility of unobserved subpopulations, i.e., latent classes, using LCA (Hagenaars and McCutcheon 2002; McCutcheon 1987). Number of visits, self-tests and number of advice read were included in the LCA. A categorization of different user levels was done prior to performing the LCA. Categorization was based on the results from the descriptive statistics (number of log ins, started self-tests and advice used). The results were analyzed to determine an adequate categorization. If the user had not utilized a function, it was categorized as “non-usage.” If a function was used once, it was categorized as “low usage,” two times was labeled “moderate usage,” and three or more times was considered “high usage” (for self-tests there was no “high usage” category). Messages received and read were not included in the LCA. The reason for this was that some of the messages sent to the users did not contain feedback on their gambling behavior, only information about updates and general information about the tool. Therefore, the messages read might not contain any information that would necessarily promote RG, so reading them is likely not a useful way to prevent excessive gambling.

To determine the optimal number of classes, several criteria were used: Akaike's Information Criterion (AIC; Akaike 1974), Bayesian Information Criterion (BIC; Schwarz 1978), the sample-size adjusted Bayesian Information Criterion (SSABIC; Sclove 1987)

and a measure of entropy (Ramaswamy et al. 1993). BIC is viewed as a reliable indicator for model fit (Nylund et al. 2007a) and lower BIC-values are seen to reflect a better fit (Nylund et al. 2007b; Pears et al. 2008). The level of classification accuracy, entropy, will also be important for assessing model fit. Entropy values will be assessed on the basis of unity (Croudace 2003). The closer the entropy number is to 1, the better the fit. As a last step to assess model fit, the different class solutions were judged based on coherence, distinction, and meaningfulness.

To examine whether gambling could discriminate between different classes, risk of excessive gambling was used as a covariate in the LCA. Employing this method is equivalent to a multinomial regression in which the probability of class membership is regressed on the covariate. Both the LCA and multinomial regression was fitted to the data simultaneously (Vaughn et al. 2011).

The software used for the descriptive statistics was IBM SPSS 22. The LCA was performed using Mplus 5.2 (Muthén and Muthén 1998–2011).

Ethical Considerations

The study was approved by the regional Ethical Board in Stockholm, Sweden (Dnr 2014/545). The data files used were based on ID-tags created at random, guaranteeing the anonymity of the participants.

Results

The first part of the results section focuses on user utilization of the different functions of the tool, and the second part presents the results from the LCA, the distribution of age and gender among the classes, and the result of multinomial regression.

Usage of the Tool

As illustrated in Table 1, the different functions of the tool have an initially high usage. However, usage decreases for every repeated use of a function. Also noteworthy was the discrepancies between started and completed self-tests, and between messages received

Table 1 Usage of different of the different features in Playscan (*N* = 9528)

	Visits		Self-test (started)		Self-test (completed)		Advices used		Messages sent		Messages read	
	<i>n</i>	%	<i>n</i>	%	<i>n</i>	%	<i>n</i>	%	<i>n</i>	%	<i>n</i>	%
No usage	1320	13.9	1906	20.0	3297	34.6	5374	56.4	864	9.1	6195	65.0
One time	8208	86.1	7622	80.0	6231	65.4	4154	43.6	8664	90.9	3333	35.0
Two times	4188	44.0	1679	17.6	1220	12.8	1246	13.1	7658	80.4	2189	23.0
Three times	2144	22.5	476	5.0	341	3.6	427	4.5	5516	57.9	1598	16.8
Four times	1160	12.2	173	1.8	131	1.4	211	2.2	3730	39.1	1072	11.3
Five times or more	696	7.3	79	0.8	58	0.6	122	1.3	2959	31.1	722	7.6

and messages read. Additionally, 43.6 % of the participants use the advice function with a decline in usage. However, the high initial usage of the advice function indicates that many users wanted to change their gambling behavior, and 80.8 % of the first advice used was taking a break from gambling (additional information regarding the different advices, what types of messages that were and read and also the level of self-reported negative consequences can be requested from the first author).

Results from the LCA

Class Solutions for the LCA

The different class solutions from the LCA are presented in Table 2. Based on the selected criteria, a 5-class model was chosen. The main reason for this choice was the drop in entropy between the 5-class and 6-class solution. There was also a steady decrease in AIC, BIC and SSABIC from a 3-class to 5-class solution, and only a small change on these criteria between 5-class and 6-class solution. In addition, comparing the 5-class solution to the distribution of usage (see Table 1), a 5-class gave the most coherent picture of individual usage compared to the 4- and 6-class solution.

Description of the Five Classes and the Distribution of Age and Gender

In Fig. 1, the different classes are presented based on the probability that the users have very high usage of a function. The five classes were assigned labels. The five different classes were: “self-testers”, “multi-function users”, “advice users”, “site visitors” and “non-users”. The self-testers are characterized by a high utilization of the self-test and the advice-function. While they did not visit the site many times, they were active when they did visit. The multi-function users visited the site several times and used advice to potentially decrease their gambling. These users also answered the self-test, but to a lesser extent than the self-testers. However, they have a pretty even use of the functions incorporated in the tool. Advice-users were low frequency visitors and did not use the self-test to a high extent. However, the users in this group used several pieces of advice. Site visitors logged into the site several times, but did not use any of the functions. Non-users did not use any of the functions of the tool (non-users are not represented in Fig. 1).

Table 3 presents mean age and gender distribution for the five classes. The mean age and gender distribution were similar across all groups. The mean age and gender distribution were based on the 9293 participants that disclosed their age and sex.

Table 2 Fit indices for a three-class to a six-class model

Model	Fit statistics			
	AIC	BIC	SSABIC	Entropy
3-class	46,534.065	46,734.601	46,645.621	0.905
4-class	45,744.147	46,016.147	45,895.544	0.849
5-class	45,591.326	45,935.102	45,782.565	0.846
6-class	45,502.319	45,917.715	45,733.400	0.818

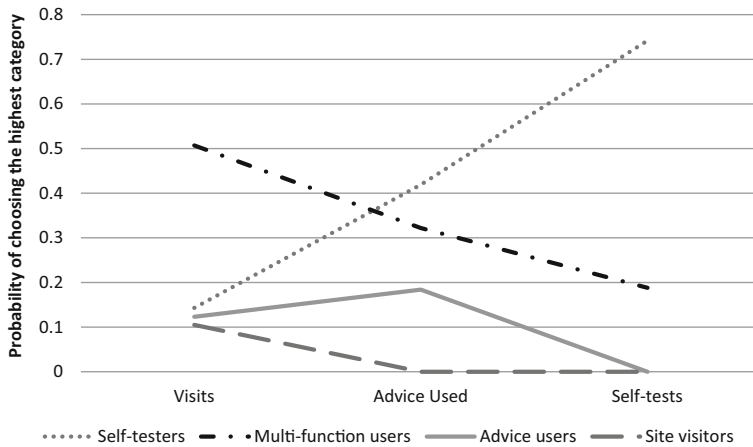


Fig. 1 User groups based on the LCA-result

Table 3 Socio-demographic characteristics of the five classes

Class	Number		Mean age (SD)	Gender distribution			
	n	%		Male		Female	
			n	%	n	%	n
Self-testers	308	3.3	45.77 (16.00)	268	88.2	36	11.8
Multi-function users	884	9.3	45.13 (16.09)	772	88.0	105	12.0
Advice users	3037	31.8	41.15 (15.09)	2433	83.1	494	16.9
Site visitors	4541	47.7	40.86 (15.26)	3752	82.6	709	17.4
Non-users	758	7.9	44.70 (15.50)	598	84.1	126	15.9

Table 4 Multinomial regression of the five user groups in relation to risk category serving multi-function users as reference group

	β	SE	Z	p
Self-testers	0.163	0.104	1.567	0.117
Advice users	-0.643	0.152	-4.227	0.000
Site visitors	-0.739	0.100	-7.372	0.000
Non-users	-0.343	0.094	-3.646	0.000

Risk Associated with Class

As can be seen in Table 4, there was a significant difference in risk level between multi-function users (used as reference category) compared to site visitors, advice users, and non-users, indicating that the probability of belong to these classes were associated with lower odds of having a high risk of excessive gambling. The self-testers and the multi-function

users had no significant difference in risk. In conclusion, higher risk rating predicted a higher degree of usage of the tool.

Discussion

Overall, Playscan had a high level of first time visitors, single self-test takers, and one-time advice users. However, repeated visits and usage were low and continued to decrease rapidly with every repeated use of a function. Consistent with this, the LCA yielded five distinct classes, and two of these (site visitors and advice users) were characterized by low usage of one or several functions, while two classes were characterized by higher usage of one or several functions (self-testers and multi-function users). Also, one group was characterized by non-usage. This is the first study exploring usage of a RG tool so determining if the results are a general trend or a one-time result is not possible. More studies that explore the usage of other RG tools and that analyze user behavior from different Playscan user populations are needed to establish overall user patterns. However, other types of internet interventions have been more extensively researched. The same low utilization of functions can be found in other areas (Wangberg et al. 2008). The underutilization of functions in these types of interventions has led researchers to try to explain low usage. The term “Law of Attrition” was coined for this type of user behavior (Eysenbach 2005), and it is an accurate description of user behavior in the current study. The low amount of repeated visits, the decrease in started and completed self-test and the decrease in repeated advice can be seen as a result of this “law”. Window shopping (Donkin and Glozier 2012) might be another plausible explanation for the low level of repeated usage. Users just try the tool with no intention of using it. Users of Playscan might just want to experience the tool to understand what participation entailed. Another explanation is that users might have acted on their curiosity (Griffiths et al. 2009). Another hypothesis for the low repeated usage is that the users collected the information they needed to continue their behavior change during their first visit. Also, if a user received a low risk rating (green) and continued to gamble in the same way, there would not be a reason for the gambler to return. In conclusion, the users with low adherence might not have an actual need to use the tool, and therefore have a low usage or another agenda for using joining the tool.

One interesting class of users is the advice users. They do not have a higher risk rating than the low usage groups, but use a specific function in the tool. One hypothesis regarding the usage in this group is that they understand that they have increased the amount of time and money they spend on gambling, and so they decide to take advice on how to decrease their gambling. These users probably took the advice to take a break from gambling because that was the first piece of advice chosen by 80.8 % of first time advice users.

Approximately 12.6 % of the users use the tool to a high extent. A plausible explanation for the users’ utilization might be “perceived need” (Andersen 1995). Perceived need is when an individual feels a subjective need to utilize health care or other interventions. In this case, risk might be an indicator of excessive gambling, which in turn makes the users more prone to using Playscan. The element of need might be present among the users that who used the tool to a high extent. Additionally, users that used the tool to a lesser extent (advice users and site visitors) had a lower risk assessment during the 5 weeks before

joining than the high frequency users, meaning that the high usage-classes were more at-risk of developing an excessive gambling behavior over time.

The different profiles of the two groups that use the tool to a higher extent could reflect their different “needs.” The self-testers appear to check how their gambling is progressing by using self-tests, while the multi-function users appear to both check how their gambling is progressing and use advice to find ways to regulate their gambling. This might result in different trajectories when trying to limit excessive gambling behavior. The self-testers could be using the self-tests as a way of determining how their gambling is affecting their well-being and everyday life. They seem to do this during specific periods since they do not visit the tool very frequently. Maybe in periods when they increase the time and money spent on gambling. The multi-function users log in frequently and use several pieces of advice suggesting that they are aware of their spending and employ strategies to gamble less. This class can be seen as a more extreme version of the advice users.

One important question that needs to be raised based on the results from this study is if a RG tool should cater to every user at a gambling site or just users at-risk. One argument for repeated visits and/or usage for low risk users is that they might not acknowledge increasing spending on gambling activities. Losing might make the gambler see the gambling activity as something increasingly positive and thus be prone to spend more (Rachlin et al. 2015). If higher usage is important for all user classes, there are different methods to employ to achieve that. For example, e-mails to users have been found to increase retention to member sites (Jolley et al. 2013), and might be a way to increase usage of the tool. Hence, alternative ways of communicating with the participant could be a way of adherence and retention. E-mails and messages can contain gambling feedback, changes in risk rating and additional information regarding gambling in general. The users can receive other gambling related content via e-mail, messages, in a smartphone application, or on the website. For example, a study showed that a short 3 min video had an effect on limit adherence when gambling on EGMs (Wohl et al. 2013). Psychoeducational videos focused on other aspects of gambling could be beneficial to limit risk behaviors among users.

There were small differences in age and gender distribution among the different classes. The biggest difference in mean age was approximately 5 years, and the biggest difference in gender distribution was 5.6 %. Even though there were differences, they were very slight and should not have any influence on gambling behavior. The similarities between the classes in terms of age and gender suggest that there were not any systematic differences between the five classes other than risk level and usage.

Limitations

The most important limitation pertains to the execution of the LCA and the multinomial regression analysis. Two issues need to be addressed. The first issue is that categorization of user utilization was based on how many times a function was used. This categorization was made on the basis of the descriptive result. This means of categorization might have impacted the final result, and a different categorization method might have yielded different classes. The other issue is about the use of risk assessment as a variable in the multinomial regression analyses. The risk assessment was made by Playscan and was based on gambling history, and variables related to time (e.g., frequency, duration and when the user gambled). Using another type of risk evaluation or a different algorithm to calculate risk might have yielded a different result. However, individuals that engage in

gambling and spend a large amount of time and money would probably have received a high-risk assessment regardless of how the assessment was carried out.

Another important limitation to address is that the tool underwent minor changes during the time of the data collection. As a consequence, some of the functions included in the tool were displayed and organized in different ways, depending on when the user accessed them. This might have influenced the way the participants used the tool. It is not possible to ascertain how these changes have influenced user behavior, but one speculation is that it has not influenced it to a high degree. This is because 56 % of the users only logged in once and would not have encountered the changes made to the tool.

An additional limitation is that the participants in this study were volunteers, so we cannot be certain if the reasons why a user chose to participate had any influence on the study outcomes. Forty-seven percent of the participants reported using Playscan because of their curiosity (Griffiths et al. 2009). This could have influenced users in our study regarding their behavior and willingness to use the tool. If the tool was mandatory for gamblers on the site, the user patterns might be different. The overall usage would probably be lower than in the current sample.

Another limitation is that there is no information (risk level) about the other members on the gambling site that do not use the tool. This knowledge would further increase the understanding of the need for a system that targets excessive gambling behavior.

There is also no information about whether or not users of the tool gambled on other sites. The risk assessment and advice function has the potential to limit gambling behavior at Svenska Spel's site, but this potentially positive effect might not influence gambling behavior on other gambling sites. However, it was reported that about half of the population surveyed in a previous study did not gamble on other websites (Griffiths et al. 2009). This supports the validity of the tool's risk assessment and the notion that the tool was potentially useful for those who used the tool in our study.

A final possible limitation was that the users who have been a part of the tool for a longer time use the tool more than recent members of the tool. However, usage seems to be related to risk and can therefore potentially be explained by "perceived need" (Andersen 1995) rather than how long a user has been a part of the tool.

Conclusions

The two perspectives on usage uncovered two trends in the data. "Law of Attrition" and "window shopping" best explain one trend; why approximately 87 % of the users are low frequency users of the tool, have a low risk level before joining, and why they do not repeatedly use the functions. These users might not feel a subjective need to use the tool, and therefore do not visit the tool or use the functions.

The other trend might be explained by "perceived need." Users feel the need to change their gambling behavior and therefore utilize the tool. The two classes of high frequency users might be more prone to change due to the negative consequences associated with higher risk of excessive gambling.

This exploration of Playscan has answered some questions regarding the usage and users, but questions remain that warrant further exploration. One overall important conclusion from this study is that when evaluating the effects of a tool, the usage of the tool needs to be taken into account. The study by Wood and Wohl (2015) showed an decrease in spending for some users, but if usage had been taken into account, the results might have

been different and more nuanced. Such an analysis should focus on the approximately 12.6 % that use the tool to a high extent and the advice users.

Further analysis should be carried out to answer when users utilize the different functions; when the users visit the site (at what time of day and which days) and in what order they use the different functions. This could help to further understand the behavior of the users and provide points on how to build a more effective tool. Finally, further inquiries need to be made regarding the risk assessment in the tool, and how this relates to the user's gambling behavior over time.

Acknowledgments The current study was made possible thanks to a Grant from the Svenska Spel's independent research council to the last author. The granting source was not involved in the preparation or execution of the current study, and was not a part of the statistical analyses or drafting of the manuscript. The authors of the current study would like to thank Playscan for supplying the data for the study (Playscan was also not involved the statistical analyses and drafting of the manuscript).

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