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Prevalence and characteristics of addictive behaviors in a community sample: A latent class analysis

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ABSTRACT

While addictions to substances such as alcohol, tobacco, and other drugs have been extensively investigated, interest has been growing in potential non-substance-related addictive behaviors (e.g., excessive gambling, buying or playing video games). In the current study, we sought to determine the prevalence and characteristics of a wide range of addictive behaviors in a general population sample and to identify reliable subgroups of individuals displaying addictive behaviors.

Seven hundred seventy participants completed an online survey. The survey screened for the presence and characteristics of the main recognized substance and behavioral addictions (alcohol, tobacco, cannabis, other drugs, gambling, compulsive shopping, intensive exercise, Internet and mobile phone overuse, intensive work involvement, and overeating) in a three-month period. Key aspects of addiction were measured for each reported behavior, including negative outcomes, emotional triggers (positive and negative emotional contexts), search for stimulation or pleasure, loss of control, and cognitive salience.

Latent class analysis allowed us to identify three theoretically and clinically relevant subgroups of individuals. The first class groups problematic users, i.e., addiction-prone individuals. The second class groups at-risk users who frequently engage in potentially addictive behaviors to regulate emotional states (especially overinvolvement in common behaviors such as eating, working, or buying). The third class groups individuals who are not prone to addictive behaviors.

The existence of different groups in the population sheds new light on the distinction between problematic and non-problematic addiction-like behaviors.

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1. Introduction

A growing interest is emerging in the study of addictive behaviors in everyday life. This interest is reinforced by the fact that a significant part of the population is concerned with such problematic behaviors, given their variety and widespread prevalence (e.g., Linskiy et al., 2012). Moreover, the consequences of addictions on health and psychological well-being (e.g., social exclusion, invalidity, physical illness), as well as on global social and economic concerns (e.g., reinsertion programs, health-related costs), are heavy (Peleteiro, Castro, Morais, Ferro, & Lunet, 2015; Rehm et al., 2009).

Negative consequences resulting from the frequent consumption of alcohol and drugs have been widely investigated and constitute a crucial public health concern (UNODC, 2012; World Health Organization, 2010). Beyond substance-related disorders, the concept of addiction has recently been widened with the inclusion of addictive disorders that are unrelated to substance use, namely, "behavioral" addictions. Currently, the only recognized behavioral addiction is "disordered gambling", although "Internet gaming disorder" has been proposed as a new tentative condition in Section 3 of the *Diagnostic and Statistical Manual of Mental Disorders* (5th ed.; *DSM-5*; American Psychiatric Association, 2013).[1] Diagnostic criteria of behavioral addictions have been aligned with those of Substance Use Disorders (SUDs) (Ko et al., 2014; Petry & O'Brien, 2013; Petry et al., 2014), mostly including symptoms of withdrawal, tolerance, cognitive salience, unsuccessful attempts to quit, and risks of relapse (American Psychiatric Association, 2013). In the last decade, a growing number of data established psychological and neurobiological similarities between Internet gaming disorder and SUDs (e.g., Achab, Karila, & Khazaal, 2014; Grant, Brewer, & Potenza, 2006; Grant, Potenza, Weinstein, & Gorelick, 2010; Ko et al., 2013; Vanes et al., 2014; Wareham & Potenza, 2010). Nowadays, the excessive practice of, or involvement in, a wide range of other activities (e.g., shopping, sex, sport, mobile phone use) has been associated with addictive patterns of use (e.g., Billieux, Van der Linden, & Rochat, 2008; Landolfi, 2013; Mentzoni et al., 2011), although the evidence regarding their psychological and neurobiological similarities to SUDs remains scarce (Billieux, Maurage, Lopez-Fernandez, Kuss, & Griffiths, 2015).

Elevated comorbidity has been identified in past studies across SUDs (Sintov et al., 2010) and between SUDs and gambling disorder (Wareham & Potenza, 2010), suggesting common and transdiagnostic factors such as neurobiological alterations (Grant et al., 2006), heightened impulsivity and reduced executive control (Groman, James, & Jentsch, 2009), or maladaptive dysfunctional metacognitive beliefs (Spada, Caselli, Nikčević, & Wells, 2015). In recent years, a wide range of behaviors has been conceptualized as addictive behavior, such as exercise addiction (e.g., Berczik et al., 2014), excessive social networking (e.g., Griffiths, Kuss, & Demetrovics, 2014), and overinvolvement in work (e.g., Andreassen, 2014). Nevertheless, their co-occurrences and similarities have received little attention.

The objective of the current study was to fill this gap by screening for the prevalence of a wide range of behavioral and substance addictions in order to analyze their co-occurrences and characteristics in a sample of volunteers from the community. To this end, we created a comprehensive questionnaire to assess (1) the prevalence and frequency (in a three-month period) of a wide range of potentially addictive behaviors (use of alcohol, tobacco, cannabis, other psychoactive substances; gambling; shopping; exercising; working; eating; Internet use; mobile phone use) and (2) the presence of addiction symptoms (negative outcomes, emotion triggers, search for stimulation or pleasure, loss of control, cognitive salience) for each behavior in which participants had been involved during the last three months. After having considered the prevalence of each behavior, a latent class analysis (LCA) method was applied to identify the existence of subgroups on the basis of the addictive behaviors that participants reported themselves to be involved in. The identified subgroups were then compared for their potential addictive involvement in the assessed behaviors. This innovative analysis allowed us to identify both addiction-prone and non-addiction-prone individuals, as well as to explore the type of behavior and substance uses in which they were involved.

2. Methods

2.1. Participants and procedure

Participants were recruited through announcements sent on the intranets of the Universities of Geneva (Switzerland) and Louvain-la-Neuve (Belgium) and through their dissemination on social networks and specialized health-related forums. The entire survey was delivered by using the online services of the "Survey Monkey" website. Anonymity of the participants was guaranteed (no personal data were collected, including Internet Protocol addresses). The informed consent of the participant was required before starting the online survey. The study protocol was approved by the ethical committee of the Psychology Department of the University of Geneva.

Inclusion criteria were being over 18 years of age and a fluent French speaker. A total of 819 individuals were included in the study. Forty-nine participants were excluded because they did not complete the entire questionnaire ($n = 22$) or because of too many missing data therein ($n = 27$). A final sample of 770 participants (534 females, 69.3%) completed the entire survey. Their age ranged from 18 to 72 years ($M = 30.36$, $SD = 10.68$, median $= 27$). Years of schooling ranged from 4 to 29 ($M = 17.04$, $SD = 3.19$). At the time of the survey, the participants reported being employed (54.2%), undergraduate students (38.4%), unemployed (5.7%), or retired (1.4%), or they did not specify their occupation (0.3%). Most participants (93%) were native French speakers and the remaining were fluent French speakers.

2.2. Online survey

The online survey[2] was composed of a short section assessing demographic variables, followed by a comprehensive questionnaire designed to screen for a wide range of potential addictive behaviors (use of alcohol; tobacco; cannabis; other drugs; gambling; shopping; exercising; working; eating; use of Internet; use of mobile phone). One item was left free for respondents wishing to report any other potential addictive behavior. Each behavior was addressed sequentially and non-relevant behaviors were skipped (i.e., if the participant did not consume a

[1] Online games, however, reflect only one aspect of the cyberaddiction spectrum. Indeed, several other types of Internet-related disorders have been identified, including excessive involvement in cybersex, in online gambling, and in social networks (Griffiths & Pontes, 2014; Kuss, Griffiths, Karila, & Billieux, 2014).

[2] The English and French versions of the questionnaire used, called the Comprehensive Inventory of Substance and Behavioral Addictions (CISBA), are available on request from the corresponding authors.

substance or was not involved in a specific activity). Importantly, common or "everyday" activities that almost everyone is involved in, such as shopping, exercising, working, eating, and using a mobile phone, were screened for their corresponding excessive or intensive manifestation (compulsive shopping; binge eating; intensive exercise, work, and use of the mobile phone). For these behaviors specifically, the respondents were asked to take into consideration only the excessive episodes to avoid the measurement of regular, non-excessive, everyday behaviors. For example, excessive shopping was assessed with the following item: "*During the last three months, how often did you make excessive shopping (e.g., unnecessary purchases, significant expenses)*", and excessive working was assessed with the following item: "*During the last three months, how often did you work in an excessive way and beyond your obligations (e.g., overtime, during the week-end, at home at night)*".

Several behaviors also required further disentanglement, particularly drug consumption (type of drug used), gambling (type of gambling activity practiced), and Internet use (type of online activity practiced). For these activities, after participants had indicated whether they were concerned or not, an additional list of subtypes was proposed: cocaine, amphetamines, solvents, sedatives, hallucinogens, and opiates (for drugs); lotteries, both online poker and casino, poker and cards, casino games, slot machines, scratch cards, and bets (for gambling activities); multiplayer games, other games, social networking, chatting, online pornography, and searching or downloading (for online activities). For these multifaceted activities, participants could also indicate a subtype that was not proposed and were eventually asked to indicate their preferred subtype among those proposed.

For each behavior that the participant was concerned about, the frequency of involvement during the last three months was addressed with a five-point Likert scale (1 = "never," 2 = "less than once per month," 3 = "a few times per month," 4 = "a few times per week," and 5 = "every day or almost every day"). The three-month period was chosen to cover as many occurrences of behaviors as possible among individuals over a sufficient period: not too short to miss any less frequent behaviors, and not too long to avoid reporting behaviors that were no longer relevant to the current and recent habits of the individual. This approach reduces the risks of biased and/or imprecise memories, with a better accuracy than for a 12-month period or for lifetime prevalence. Six items targeting key features of addictions were then proposed. These items measured (1) negative outcomes, (2) emotion triggers (one item for each positive and negative emotional context), (3) the search for stimulation or pleasure, (4) loss of control, and (5) cognitive salience. Each item was assessed with a four-point Likert scale (1 = "I strongly agree," 2 = "I somewhat agree," 3 = "I somewhat disagree," and 4 = "I strongly disagree"). The labeling of each item was adapted to the related behavior.

2.3. Data analysis

Descriptive analyses were used to determine the three-month prevalence and endorsement of addiction symptoms for each type of behavior. Scores for frequency and addiction symptoms were reversed when necessary so that a positive answer indicated a higher score ("I strongly agree" = 4).

LCAs were performed by using the software *R* (Development Core Team, 2008) with the package poLCA (Linzer & Lewis, 2011). LCA is a multivariate method, similar to cluster analysis, which allows identification of discrete multivariate variables (called "latent classes") in the population on the basis of multivariate categorical data. The advantage of LCA over cluster analysis is that it can be conducted on nominal and categorical variables (including binary variables). Therefore, frequencies of potential substance and behavioral addictions were recoded into binary codes on the basis of a three-month prevalence (1 = presence of the behavior; 0 = absence of the behavior). LCA was performed on all behaviors to determine the probability of involvement in each addictive behavior per latent class, as well as co-occurrence of addictive behaviors within latent classes. The class assignment was based on the maximum posterior probability.

As our study was exploratory and we had no a priori hypotheses regarding the number of subgroups in our sample, several models (ranging from 1 to 10 classes) were computed and compared. The number of latent classes to choose from was determined by relying on two criteria: the Akaike information criterion (AIC) and the Bayesian information criterion (BIC). Both are measures of the relative quality of a model, penalizing the number of estimated parameters in order to find the most parsimonious model. The best solution is chosen based on the smallest index. An additional index of entropy was calculated for accuracy, with values close to 1 meaning better homogeneity of the classes.

Latent classes were then compared for frequency of involvement and addiction symptoms (for all addictive behaviors, and then separately for substance vs. behavioral addictions). To perform these analyses, we created three types of scores: (1) scores of frequency and addiction symptoms for all potential addictive behaviors reported by participants, (2) scores of frequency and addiction symptoms for potential substance addictions reported by participants, and (3) scores of frequency and addiction symptoms for potential behavioral addictions reported by participants. Each score was computed by averaging the relevant items to obtain a global score for each participant (e.g., if a participant reported being involved in four types of addictive behaviors, his or her global "loss of control" score was obtained by averaging the answers provided for these four behaviors). Analyses of variance with Newman–Keuls post hoc tests were then used to compare latent classes on demographical variables with external correlates (addiction symptoms). Chi-square tests were used to test gender differences among latent classes. All analyses were conducted with a significance threshold of $\alpha = .05$, two-tailed.

3. Results

3.1. Descriptive and exploratory analyses

Prevalence and frequencies of involvement for each type of behavior (substance use, gambling, online activities, and excessive behaviors) for a three-month period are reported in Table 1.[3] We determined the proportion of individuals who endorsed addiction symptoms (at least once per month in a three-month period) for each potential addictive behavior. These data are summarized in Table 1.

Table 2 shows the proportion of individuals who were positively concerned about each type of addiction symptom. The lack of respondents per subtype of drug and gambling games led us to consider both behaviors as a whole (i.e., not distinguishing their subtypes). For Internet activities, the use of social networks, chatting, and both categories of video games were chosen for their particular salience.

3.2. Latent class analysis

An LCA was performed on the basis of the three-month prevalence (1 = presence of the behavior; 0 = absence of behavior). Table 3 shows the two fit indices (AIC and BIC) for the various models computed, as well as a measure of class homogeneity (entropy). The fit indices follow the rule of the smaller the better. According to the AIC, the best fit is the seven-class model. However, the AIC constantly decreases as the

[3] Ninety-two participants responded to the supplementary item provided at the end of the questionnaire. The more frequent answers were watching television/movies/series ($n = 13$); sexual behaviors, including sex, masturbation, or voyeurism ($n = 25$); and leisure activities such as reading/music/games ($n = 8$). Several other behaviors (e.g., biting nails, controlling assets or the stock market) were reported by only one or two participants. These additional answers were provided by a very small proportion of the participants and grouped heterogeneous problematic behaviors that were not necessarily considered to be potential addictions. For these reasons, they were not taken into account in the analyses.

Table 1
Prevalence and frequency of use.

Behavior	Three-month prevalence	Less than once per month	A few times per month	A few times per week	Every day or almost
Alcohol use	83.36	6.88	38.83	30.77	6.88
Tobacco use	39.07	1.42	3.37	4.80	29.48
Cannabis use	16.86	4.54	5.71	2.59	4.02
Excessive shopping	59.07	42.07	15.32	1.68	–
Excessive sport	68.55	17.01	22.85	23.63	5.06
Excessive work	59.07	11.42	21.94	16.49	9.22
Excessive eating	60.23	20.38	25.45	10.51	3.89
Excessive mobile phone use	49.45	7.27	10.38	11.03	20.77
Drugs	5.94	3.63	1.29	0.25	0.77
Cocaine use	1.28	0.90	0.38	–	–
Antidepressant use	0.26	–	–	–	0.26
Hallucinogen use	1.02	0.77	0.25	–	–
Amphetamine use	0.63	0.38	0.25	–	–
Opiate use	0.37	–	–	0.12	0.25
Others	0.12	–	–	–	0.12
Involvement in gambling	29.84	16.49	10.38	2.20	0.77
Lottery	10.76	4.67	4.54	1.55	–
Poker	2.19	1.55	0.64	–	–
Online poker	1.91	0.64	0.64	0.25	0.38
Casino	1.41	1.16	0.25	–	–
Scratch cards	9.46	6.49	2.85	–	0.12
Bets	0.88	0.25	0.51	–	0.12
Slot machines	0.24	0.12	0.12	–	–
Others	0.51	0.51	–	–	–
Involvement in online activities	84.52	1.03	4.02	14.93	64.54
Multiplayer games	1.79	–	0.12	0.64	1.03
Other games	4.13	–	0.25	1.29	2.59
Social networks	32.58	–	1.16	4.02	27.40
Chatting	4.9	0.12	0.25	0.77	3.76
Pornography	0.88	–	0.12	0.38	0.38
Searching/downloading	16.34	0.77	1.16	4.41	10
Forum	1.29	–	–	–	1.29
Others	3.22	–	0.12	0.38	2.72

Note. Numbers are expressed as a percentage of the total sample. "Others" = answers corresponding to other behaviors reported by the participants.

number of classes increases. Therefore, in this case, it becomes uninformative. The BIC reaches its minimum at the three-class solution, which is a more suitable solution. On the other hand, the measure of entropy shows better homogeneity of the classes with a two-class model. Still, entropy must be cautiously used to select a model (Collins & Lanza, 2013). Indeed, as more classes are considered, entropy is expected to

Table 2
Frequency of each addiction symptom per behavior.

		NC	NEG	POS	STI	LC	CS
	n	%	%	%	%	%	%
Alcohol use	642	8	18.5	70.7	58.7	9.9	14.2
Tobacco use	301	20	68.9	59	63	74.1	42.2
Cannabis use	130	17.1	30.8	65.4	91.6	27	29.5
Drug use	46	19.5	26	50	71.7	23.9	41.3
Gambling involvement	230	2.6	6.1	38.7	63.3	3.9	10
Excessive shopping	455	13.4	38	50	56.3	24.2	25.4
Excessive sport	528	5.2	34.7	53.1	69.7	9.7	36
Excessive work	455	44.1	21	26	22.4	32.3	46.9
Social network use	251	14.7	32.3	39.7	44.8	52.3	14.1
Chat use	38	21	39.5	50	43.2	34.2	15.8
MMO use	14	57.1	42.9	42.9	85.8	64.3	50
Use of other games	32	25.1	34.4	31.2	83.9	50	37.5
Excessive eating	464	25.1	61.9	42.2	62.6	54.2	38.1
Excessive mobile phone use	381	9.7	36.2	48.3	21.4	16.5	8.2

Note. Proportions are based on the total number of individuals (n) who consume/practice the reported behavior. NC = negative consequences in everyday life; NEG = negative emotional context; POS = positive emotional context; STI = search for stimulation; LC = loss of control; CS = cognitive salience; MMO = massively multiplayer online game.

Table 3
Fit indices for the latent class analyses.

Number of latent classes	AIC	BIC	Entropy
2	15,319.27	15,565.52	0.7815
3	15,147.76	15,519.47	0.6536
4	15,083.52	15,580.68	0.6886
5	15,034.38	15,657	0.6958
6	14,998.74	15,746.81	0.7156
7	14,977.95	15,851.47	0.7435
8	–	–	–
9	–	–	–
10	–	–	–

Note. The maximum likelihood was not found beyond the seven solutions because of the lack of convergence. AIC = Akaike information criterion; BIC = Bayesian information criterion.

decrease because of the growing risks of assignment errors, as evidenced by the drop between the two-class and the three-class models. Conversely, entropy progressively increases after three classes, making it unreliable.

Although the various models were considered, we ended up retaining a three-class model. This choice was motivated by the principle of parsimony, which was further supported by the latent class comparisons (see below) that emphasized the theoretical and clinical relevance of the three-class model. Indeed, choosing a model with two classes would potentially lead to a binary interpretation of the results (e.g., addicts vs. non-addicts), which excludes profiles expressing risks or tendencies toward addictions. In contrast, a model composed of too many classes would be difficult to conceptualize and interpret. Fig. 1 depicts the three classes in terms of the probability of endorsing each specific behavior item, knowing that the subject belongs to one of the classes.

The identified classes were then compared for key addiction symptoms. For this analysis, we first compared the classes for all addiction symptoms (i.e., without distinguishing substance and behavioral addictions), and then separately for substance and behavioral addictions. Comparisons between classes emphasized the following results (see Table 4). Regarding frequency, members of the first class were more involved in the targeted behaviors, followed by those in the second class. If we consider only substance addiction, members of the first class were significantly more involved than those in the other classes, with no differences between those in the second and third classes. When we consider only behavioral addictions, those in the second class reported more involvement than those in the other classes. Negative outcomes associated with the behavior were more important in members of both the first and second classes, as compared with those in the third class. Negative emotional contexts more frequently triggered the assessed behaviors in members of the first class, and positive emotional contexts more often triggered the targeted behaviors in members of the first and second classes, as compared with members of the third class. If we consider only substance abuse, it appears that those in the first class more often consumed substances in response to negative emotions. If we consider only excessive behaviors not related to substance use, they were more frequently triggered by negative emotional contexts in members of the second class and by positive emotional contexts in members of both the first and the second classes. When we consider the search for stimulation and pleasure (hedonic aspects), those in the first class more often consumed substances for this purpose. Compared with those in the third class, members of both the first and second classes were more involved in non-substance-related behaviors to search for pleasure and stimulation. Finally, regarding both loss of control and cognitive salience, it appears that these two key aspects of addiction were more pronounced, specifically with regard to substance use, only in those in the first class. Regarding demographics, no differences between classes were found regarding level of education, whereas members of the third class were older than members of the two other

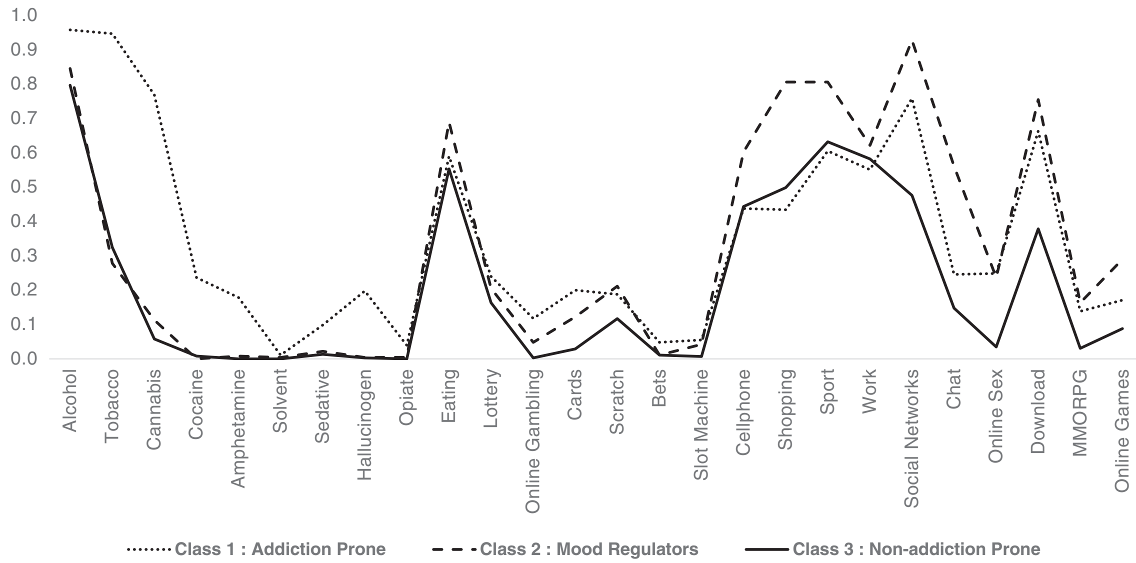

Fig. 1. Latent classes. The Y-axis indicates the conditional probability of item endorsement by latent class membership. The number for the latent class solution is based on the Bayesian information criterion and index of entropy.

classes. It also appears that the third class comprised a higher proportion of females.

From these findings, the first class (12.2% of the participants) appears to group individuals with high addiction proneness and therefore was labeled "addiction-prone individuals." The second class (31.6%) comprises individuals who are involved in targeted behaviors to regulate their emotional states; hence, we labeled the class "mood regulators." Lastly, the third class (56.2%) appears to comprise individuals who are less involved in the targeted constructs, and we labeled the class "non-addiction-prone individuals."

Table 4
Descriptive statistics for the three classes.

Type of behavior		Range	Class 1 (N = 94, 12.2%) "Addiction Prone" M (SD)	Class 2 (N = 243, 31.6%) "Mood regulators" M (SD)	Class 3 (N = 433, 56.2%) "Non-Addiction Prone" M (SD)	F	p	η^2
Mean scores	FR	1–5	2.67 (.41)	1.90 (.48)[a]	1.60 (.47)[a,b]	204.4	.00	.34
	NC	1–4	1.61 (.46)	1.51 (.46)	1.42 (.46)[a]	7.0	.00	.01
	NEG	1–4	2.03 (.56)	1.97 (.63)	1.84 (.68)[a]	5.2	.00	.01
	POS	1–4	2.43 (.57)	2.48 (.61)	2.23 (.65)[a,b]	13.4	.00	.03
	STI	1–4	2.69 (.56)	2.47 (.60)[a]	2.24 (.70)[a,b]	21.7	.00	.05
	LC	1–4	2.06 (.51)	1.80 (.53)[a]	1.79 (.63)[a]	8.6	.00	.02
	CS	1–4	1.90 (.66)	1.73 (.58)[a]	1.61(.63)[a]	9.2	.00	.02
Substance	FR	1–5	2.98 (.58)	1.17 (.79)[a]	1.10 (.77)[a]	246.6	.00	.39
	NC	1–4	1.62 (.57)	1.39 (.59)[a]	1.31 (.59)[a]	10.1	.00	.02
	NEG	1–4	2.16 (.69)	1.82 (.87)[a]	1.80 (.92)[a]	6.5	.00	.01
	POS	1–4	2.74 (.73)	2.75 (.80)	2.54 (.85)[a]	5.6	.00	.01
	STI	1–4	3.02 (.61)	2.54 (.91)[a]	2.38 (.96)[a]	18.6	.00	.05
	LC	1–4	2.16 (.61)	1.61 (.79)[a]	1.72 (.90)[a]	14.6	.00	.04
	CS	1–4	1.95 (.74)	1.56 (.79)[a]	1.56 (.79)[a]	9.9	.00	.02
Behavior	FR	1–5	2.37 (.56)	2.63 (.50)[a]	2.10 (.55)[a,b]	76.5	.00	.16
	NC	1–4	1.60 (.58)	1.60 (.50)	1.49 (.50)	3.9	.02	.01
	NEG	1–4	1.91 (.62)	2.07 (.63)[a]	1.85 (.70)[b]	8.7	.00	.02
	POS	1–4	2.12 (.66)	2.25 (.62)	1.98 (.70)[b]	12.4	.00	.03
	STI	1–4	2.36 (.69)	2.41 (.60)	2.14 (.70)[a,b]	13.8	.00	.03
	LC	1–4	1.96 (.61)	1.96 (.57)	1.84 (.65)	3.5	.03	.00
	CS	1–4	1.85 (.73)	1.85 (.62)	1.65 (.68)	8.6	.00	.02
Demographics	Age	18–72	28.85 (7.78)	26.54 (7.05)	32.81 (12.19)[a,b]	29.63	.00	.07
	Education	4–29	16.78 (3.16)	17.05 (3.14)	17.09 (3.23)	.33	.71	.00
	Gender[d]	–	58.5	65.4	73.9[c]	–	.04	–

Note. Means in the same row with different exponents differ at $p < .05$, using Student–Newman–Keuls post hoc tests. FR = frequency; NC = negative consequences; NEG = negative emotional context; POS = positive emotional context; STI = search for stimulation; LC = loss of control; CS = cognitive salience.
Chi-square analyses were performed to assess gender differences, χ^2 (2, $N = 770$) = 11.17, $p = .00$.
[a] Statistically significant in comparison to class 1.
[b] Statistically significant in comparison to class 2.
[c] Statistically significant in comparison to classes 1 and 2.
[d] The proportions of female members per class.

4. Discussion

The aim of the current study was to explore the prevalence and characteristics of potential addictive behaviors in the general population and to identify reliable subgroups of individuals displaying addictive behaviors. Relying on LCA, we identified three theoretically and clinically relevant subgroups of individuals. The first class groups problematic users (i.e., addiction-prone individuals). The second class groups at-risk users, who frequently engage in potentially addictive behaviors (especially overinvolvement in common behaviors such as eating, working, or buying) to regulate emotional states. The third class groups individuals who are not prone to addictive behaviors.

4.1. Prevalence and characteristics of addictive behaviors

The large majority of the sample had consumed alcohol within the last three months (83.36%), which is in line with numerous data showing that excessive alcohol consumption is an important health issue in Western countries (Harper & Matsumoto, 2005; Rehm et al., 2010). It is worth noting that in our sample, alcohol consumption is rarely associated with addiction symptoms and has thus to be considered as non-problematic for most of the participants (see Table 2). The prevalence of tobacco smoking was 39.07% in the current sample. Unlike alcohol consumption, smoking was frequently associated with an addictive pattern of use (the most pronounced symptoms were loss of control and negative mood regulation). The prevalence of cannabis use was 16.86%, and it appears that cannabis was mostly consumed for hedonic purposes (stimulation, pleasure) while experiencing positive affect states. Illegal drugs were consumed by only 5.94% of our sample (cocaine being consumed the most at 1.28% of the sample).

In our study, potential behavioral addictions were divided into two subtypes: activities in which only a part of the sample is involved (e.g., gambling, video gaming), and activities that are excessive manifestations of everyday behaviors (e.g., eating, shopping). The prevalence of gambling in the current sample was 29.84% (the most frequent types of gambling reported were lotteries and scratch cards). Gambling behaviors were generally driven by hedonic purposes (search for stimulation and pleasure) and were rarely related to loss of control or negative outcomes. It is worth noting that, for online activities, the use of social networks (the most reported at 32.58%) is frequently associated with the loss of control (for 52.3%). This finding is in line with recent proposals that social network involvement often results in excessive or addictive use (e.g., Griffiths et al., 2014; Wilson, Fornasier, & White, 2010). Also of note is that although online game use was reported by a small proportion of the participants, it was very often associated with loss of control (64.3%) and negative outcomes (57.1%), which confirms that this is a high-risk activity for an addictive pattern of use (Billieux, Deleuze, Griffiths, & Kuss, 2015; Kuss, Louws, & Wiers, 2012).

Regarding "excessive" manifestations of everyday behaviors, our results emphasized their high prevalence (see Table 2). They are generally performed for hedonic and mood regulation purposes and are less frequently associated with problematic involvement (e.g., loss of control, negative outcomes). Among these everyday behaviors, it appears that "binge" eating is the behavior that is most frequently triggered by negative emotional states, supporting the evidence that excessive eating is commonly used to cope with negative affect (e.g., Anestis, Selby, Fink, & Joiner, 2007; De Young, Zander, & Anderson, 2014). The case of excessive work warrants further discussion, as 44.1% of the sample reported negative outcomes and 46.9% reported being concerned with cognitive salience. Nevertheless, this result should be cautiously interpreted, as working schedules are mostly imposed by external factors and may be driven by factors that were not assessed in the current study (e.g., socio-economic status). Accordingly, working involvement cannot be easily compared with the other targeted behaviors in this study, in line with previous studies emphasizing the difficulty in distinguishing elevated work involvement from "workaholism" (e.g., Andreassen, Hetland, & Pallesen, 2013; Wojdylo, Baumann, Fischbach, & Engeser, 2014).

4.2. Latent class analysis

LCA allowed us to distinguish three profiles on the basis of the three-month prevalence of a wide range of potential addictive behaviors.

The first class (12.2% of the sample) represented addiction-prone individuals. As illustrated in Fig. 1, individuals who consume substances (alcohol, tobacco, cannabis, and other drugs) have a greater likelihood of belonging to this class. Compared with those in other classes, they have more frequent involvement in the investigated behaviors and are more often characterized by an addictive pattern of use associated with negative outcomes, loss of control, search for pleasure or stimulation, and cognitive salience. These results are in line with previous studies emphasizing that impulsivity (characterized by poor executive control and decision making, high sensation seeking, or a heightened sensitivity to conditioned cues; Bechara, 2005; Groman et al., 2009) constitutes a core construct of addictive behaviors.

We named the second class of participants (31.6% of the sample) the "mood regulators." Members of this class tend to regulate their mood through their involvement in the potentially excessive behaviors measured in the study. These members are not characterized by an addictive pattern per se. Indeed, our analyses demonstrated that although these members displayed excessive behaviors in negative and positive emotional contexts, these behaviors are not associated with key features of addiction such as loss of control, cognitive salience, or negative outcomes. However, we cannot exclude the possibility that these individuals may be susceptible to displaying problematic behaviors if their way of regulating emotions is maintained in the long run. For example, the *emotional cascade model* (Selby, Anestis, & Joiner, 2008) and the concept of *experiential avoidance* (Hayes, Wilson, Gifford, Follette, & Strosahl, 1996) suggest that addictive-like behaviors can develop in individuals who escape from uncomfortable feelings or experiences by consuming substances or engaging in distractive behaviors. As depicted in Fig. 1, the behaviors favored by these individuals are "excessive" manifestations of everyday behaviors, such as shopping, exercising, eating, or use of the mobile phone. These findings are consistent with the numerous data emphasizing that such types of behaviors are frequent in community samples. They are often displayed to enhance or maintain a positive mood or to avoid or reduce a negative mood (Billieux, Gay, Rochat, & Van der Linden, 2010; Cyders & Smith, 2008; Hayes et al., 1996; Selby et al., 2008; Thayer, Newman, & McClain, 1994).

The third class groups the majority of the sample (56.2%). They are considered to be non-prone to addictive disorders on the basis of their lower frequency of involvement and their lower probability (with respect to the other classes) of endorsing addiction symptoms. This class consisted of more female and younger participants than the other classes did. This latter finding can be considered in light of previous studies that emphasized that young age is associated with greater risks of displaying addictive behaviors (Chambers, Taylor, & Potenza, 2003; Whelan et al., 2012). A possible explanation is that both young age and being male are associated with high impulsivity and sensation seeking (e.g., Billieux et al., 2012; d'Acremont & Van der Linden, 2005), both of which are predictors of addictive behaviors (e.g., Harden & Tucker-Drob, 2011; Quinn & Harden, 2013; Steinberg, 2008).

4.3. Limitations, perspectives, and conclusions

The participants in the current study were a self-selected sample, which may influence the prevalence rates (Khazaal et al., 2014). Moreover, as the present analysis is based on a cross-sectional analysis that focused on the previous three months, we cannot take into account the variability of addictive behaviors and their evolution across time, neither the potential influence of the testing period (e.g., holiday, celebration period), which should be explored through longitudinal studies.

It is also worth noting that the effect size of the differences reported in Table 4 is of small amplitude, which could be due to the nature of the sample (community participants) and/or the fact that each addiction symptom was assessed with only one item. Therefore, the differences highlighted here between the classes should be confirmed in future studies by using more specific instruments (e.g., impulsivity questionnaire). Finally, behavioral measures (e.g., laboratory tasks that measure impulsivity) should be conducted to further determine the characteristics of each class.

Despite these limitations, this study is the first to use LCA in order to identify specific subgroups of individuals from the prevalence and characteristics of a wide range of addictive behaviors in a community sample. The strong proposal resulting from our study is that the "addictive behavior spectrum" groups heterogeneous behaviors. Some are non-problematic and are displayed for hedonic and mood regulation purposes, whereas others are more problematic and associated with loss of control, cognitive salience, and negative outcomes. This might lead to a renewal of the classic diagnosis-based approach to addictions and to a deep reconsideration of the "normal" versus "pathological" boundaries in the addiction field.

In conclusion, we would like to warn against the current trend that too easily assimilates a wide range of everyday behaviors (e.g., eating, shopping, mobile phone use, working, exercising) as behavioral addictions. For example, the current study suggests that excessive involvement in the targeted behaviors is not necessarily associated with the presence of core symptoms of addiction. Furthermore, this trend contributes to the pathologization of everyday behaviors (see Billieux et al., 2014; Mihordin, 2012). It also neglects the fact that the behaviors under the scope of investigation in the present paper are multi-determined and heterogeneous. Therefore, they should not necessarily be conceptualized as addictions.

Contributions

Joël Billieux, Lucien Rochat, Martial Van der Linden, Sophia Achab, Gabriel Thorens, Yasser Khazaal, and Daniele Zullino designed the study and elaborated the questionnaire used in the online survey. Joël Billieux, Jory Deleuze, and Lucia Romo acquired the data. Jory Deleuze and Stéphane Rothen did the statistical analyses. Jory Deleuze, Stéphane Rothen, and Joël Billieux interpreted the results. Jory Deleuze, Joël Billieux, Pierre Maurage, and Stéphane Rothen wrote the article. Martial Van der Linden, Sophia Achab, Gabriel Thorens, Yasser Khazaal, Daniele Zullino, Lucien Rochat, and Lucia Romo reviewed the manuscript. All authors approved the final version of the manuscript.

Declaration of interests

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References

Achab, S., Karila, L., & Khazaal, Y. (2014). Pathological gambling: update on decision making and neuro-functional studies in clinical samples. *Current Pharmaceutical Design*, *20*, 4000–4011. http://dx.doi.org/10.2174/13816128113199990625.

American Psychiatric Association (2013). *Diagnostic and statistical manual of mental disorders* (5th ed.). Arlington, VA: American Psychiatric Publishing.

Andreassen, C. S. (2014). Workaholism: An overview and current status of the research. *Journal of Behavioral Addictions*, *3*, 1–11. http://dx.doi.org/10.1556/JBA.2.2013.017.

Andreassen, C. S., Hetland, J., & Pallesen, S. (2013). Workaholism and work–family spillover in a cross-occupational sample. *European Journal of Work and Organizational Psychology*, *22*, 78–87. http://dx.doi.org/10.1080/1359432X.2011.626201.

Anestis, M. D., Selby, E. A., Fink, E. L., & Joiner, T. E. (2007). The multifaceted role of distress tolerance in dysregulated eating behaviors. *International Journal of Eating Disorders*, *40*, 718–726. http://dx.doi.org/10.1002/eat.20471.

Bechara, A. (2005). Decision making, impulse control and loss of willpower to resist drugs: A neurocognitive perspective. *Nature Neuroscience*, *8*, 1458–1463. http://dx.doi.org/10.1038/nn1584.

Berczik, K., Griffiths, M. D., Szabo, A., Kurimay, T., Kokonyei, G., Urbán, R., et al. (2014). Exercise addiction—The emergence of a new disorder. *Australasian Epidemiologist*, *21*(2), 36–40.

Billieux, J., Deleuze, J., Griffiths, M. D., & Kuss, D. J. (2015a). Internet addiction: The case of massively multiplayer online role playing games. In N. el-Guebaly, G. Carrà, & M. Galanter (Eds.), *The textbook of addiction treatment: International perspectives* (pp. 1515–1525). New York, NY: Springer.

Billieux, J., Gay, P., Rochat, L., & Van der Linden, M. (2010). The role of urgency and its underlying psychological mechanisms in problematic behaviours. *Behaviour Research and Therapy*, *48*, 1085–1096. http://dx.doi.org/10.1016/j.brat.2010.07.008.

Billieux, J., Maurage, P., Lopez-Fernandez, O., Kuss, D. J., & Griffiths, M. D. (2015b). Can disordered mobile phone use be considered a behavioral addiction? An update on current evidence and a comprehensive model for future research. *Current Addiction Reports*. http://dx.doi.org/10.1007/s40429-015-0054-y (Advance online publication).

Billieux, J., Philippot, P., Schmid, C., Maurage, P., De Mol, J., & Van der Linden, M. (2014). Is dysfunctional use of the mobile phone a behavioural addiction? Confronting symptom-based versus process-based approaches: Conceptualizing mobile phone dysfunctional use. *Clinical Psychology & Psychotherapy*. http://dx.doi.org/10.1002/cpp.1910 (Advance online publication).

Billieux, J., Rochat, L., Grazia, C., Carré, A., Offerlin-Meyer, I., Defeldre, A. C., et al. (2012). Validation of a short French version of the UPPS-P Impulsive Behavior Scale. *Comprehensive Psychiatry*, *53*, 609–615. http://dx.doi.org/10.1016/j.comppsych.2011.09.001.

Billieux, J., Van der Linden, M., & Rochat, L. (2008). The role of impulsivity in actual and problematic use of the mobile phone. *Applied Cognitive Psychology*, *22*, 1195–1210. http://dx.doi.org/10.1002/acp.1429.

Chambers, R. A., Taylor, J. R., & Potenza, M. N. (2003). Developmental neurocircuitry of motivation in adolescence: A critical period of addiction vulnerability. *American Journal of Psychiatry*, *160*, 1041–1052. http://dx.doi.org/10.1176/appi.ajp.160.6.1041.

Collins, L. M., & Lanza, S. T. (2013). *Latent class and latent transition analysis: With applications in the social, behavioral, and health sciences.* New York, NY: Wiley.

Cyders, M. A., & Smith, G. T. (2008). Emotion-based dispositions to rash action: Positive and negative urgency. *Psychological Bulletin*, *134*, 807–828. http://dx.doi.org/10.1037/a0013341.

d'Acremont, M., & Van der Linden, M. (2005). Adolescent impulsivity: Findings from a community sample. *Journal of Youth and Adolescence*, *34*, 427–435. http://dx.doi.org/10.1007/s10964-005-7260-1.

De Young, K. P., Zander, M., & Anderson, D. A. (2014). Beliefs about the emotional consequences of eating and binge eating frequency. *Eating Behaviors*, *15*, 31–36. http://dx.doi.org/10.1016/j.eatbeh.2013.10.012.

Development Core Team (2008). *R: A language and environment for statistical computing.* Vienna, Austria: R Foundation for Statistical Computing.

Grant, J. E., Brewer, J. A., & Potenza, M. N. (2006). The neurobiology of substance and behavioral addictions. *CNS Spectrums*, *11*(12), 924–930.

Grant, J. E., Potenza, M. N., Weinstein, A., & Gorelick, D. A. (2010). Introduction to behavioral addictions. *The American Journal of Drug and Alcohol Abuse*, *36*, 233–241. http://dx.doi.org/10.3109/00952990.2010.491884.

Griffiths, M. D., & Pontes, H. M. (2014). Internet addiction disorder and Internet gaming disorder are not the same. *Journal of Addiction Research & Therapy*, *5*(4), e124. http://dx.doi.org/10.4172/2155-6105.1000e124.

Griffiths, M. D., Kuss, D. J., & Demetrovics, Z. (2014). Chapter 6—Social networking addiction: An overview of preliminary findings. In K. Rosenberg, & L. Feder (Eds.), *Behavioral addictions: Criteria, evidence, and treatment* (pp. 119–141). San Diego, CA: Academic Press (Retrieved from http://www.sciencedirect.com/science/article/pii/B9780124077249000006).

Groman, S. M., James, A. S., & Jentsch, J. D. (2009). Poor response inhibition: At the nexus between substance abuse and attention deficit/hyperactivity disorder. *Neuroscience & Biobehavioral Reviews*, *33*, 690–698. http://dx.doi.org/10.1016/j.neubiorev.2008.08.008.

Harden, K. P., & Tucker-Drob, E. M. (2011). Individual differences in the development of sensation seeking and impulsivity during adolescence: Further evidence for a dual systems model. *Developmental Psychology*, *47*, 739–746. http://dx.doi.org/10.1037/a0023279.

Harper, C., & Matsumoto, I. (2005). Ethanol and brain damage. *Current Opinion in Pharmacology*, *5*, 73–78. http://dx.doi.org/10.1016/j.coph.2004.06.011.

Hayes, S. C., Wilson, K. G., Gifford, E. V., Follette, V. M., & Strosahl, K. (1996). Experiential avoidance and behavioral disorders: A functional dimensional approach to diagnosis and treatment. *Journal of Consulting and Clinical Psychology*, *64*, 1152–1168. http://dx.doi.org/10.1037/0022-006X.64.6.1152.

Khazaal, Y., van Singer, M., Chatton, A., Achab, S., Zullino, D., Rothen, S., et al. (2014). Does self-selection affect samples' representativeness in online surveys? An investigation in online video game research. *Journal of Medical Internet Research*, *16*(7), e164. http://dx.doi.org/10.2196/jmir.2759.

Ko, C. -H., Liu, G. -C., Yen, J. -Y., Chen, C. -Y., Yen, C. -F., & Chen, C. -S. (2013). Brain correlates of craving for online gaming under cue exposure in subjects with Internet gaming addiction and in remitted subjects. *Addiction Biology*, *18*, 559–569. http://dx.doi.org/10.1111/j.1369-1600.2011.00405.x.

Ko, C. -H., Yen, J. -Y., Chen, S. -H., Wang, P. -W., Chen, C. -S., & Yen, C. -F. (2014). Evaluation of the diagnostic criteria of Internet gaming disorder in the DSM-5 among young adults in Taiwan. *Journal of Psychiatric Research*, *53*, 103–110. http://dx.doi.org/10.1016/j.jpsychires.2014.02.008.

Kuss, D. J., Griffiths, M. D., Karila, L., & Billieux, J. (2014). Internet addiction: A systematic review of epidemiological research for the last decade. *Current Pharmaceutical Design*, *20*, 4026–4052. http://dx.doi.org/10.2174/13816128113199990617.

Kuss, D. J., Louws, J., & Wiers, R. W. (2012). Online gaming addiction? Motives predict addictive play behavior in massively multiplayer online role-playing games. *Cyberpsychology, Behavior and Social Networking*, *15*, 480–485. http://dx.doi.org/10.1089/cyber.2012.0034.

Landolfi, E. (2013). Exercise addiction. *Sports Medicine (Auckland, N.Z.)*, *43*, 111–119. http://dx.doi.org/10.1007/s40279-012-0013-x.

Linskiy, I. V., Minko, A. I., Artemchuk, A. P., Grinevich, E. G., Markova, M. V., Musienko, G. A., et al. (2012). Addictive behavior among young people in Ukraine: A pilot study. *Substance Use & Misuse*, *47*, 1151–1158. http://dx.doi.org/10.3109/10826084.2012.683926.

Linzer, D. A., & Lewis, J. B. (2011). poLCA: An R package for polytomous variable latent class analysis. *Journal of Statistical Software*, *42*(10), 1–29.

Mentzoni, R. A., Brunborg, G. S., Molde, H., Myrseth, H., Skouverøe, K. J. M., Hetland, J., et al. (2011). Problematic video game use: Estimated prevalence and associations with mental and physical health. *Cyberpsychology, Behavior and Social Networking*, *14*, 591–596. http://dx.doi.org/10.1089/cyber.2010.0260.

Mihordin, R. (2012). Behavioral addiction—Quo vadis? *The Journal of Nervous and Mental Disease*, *200*, 489–491. http://dx.doi.org/10.1097/NMD.0b013e318257c503.

Peleteiro, B., Castro, C., Morais, S., Ferro, A., & Lunet, N. (2015). Worldwide burden of gastric cancer attributable to tobacco smoking in 2012 and predictions for 2020. *Digestive Diseases and Sciences*. http://dx.doi.org/10.1007/s10620-015-3624-x.

Petry, N. M., & O'Brien, C. P. (2013). Internet gaming disorder and the DSM-5. *Addiction*, *108*, 1186–1187. http://dx.doi.org/10.1111/add.12162.

Petry, N. M., Rehbein, F., Gentile, D. A., Lemmens, J. S., Rumpf, H. -J., Mößle, T., et al. (2014). An international consensus for assessing internet gaming disorder using the new DSM-5 approach: Internet gaming disorder. *Addiction*, *109*, 1399–1406. http://dx.doi.org/10.1111/add.12457.

Quinn, P. D., & Harden, K. P. (2013). Differential changes in impulsivity and sensation seeking and the escalation of substance use from adolescence to early adulthood. *Development and Psychopathology*, *25*, 223–239. http://dx.doi.org/10.1017/S0954579412000284.

Rehm, J., Baliunas, D., Borges, G. L. G., Graham, K., Irving, H., Kehoe, T., et al. (2010). The relation between different dimensions of alcohol consumption and burden of disease: An overview. *Addiction*, *105*, 817–843. http://dx.doi.org/10.1111/j.1360-0443.2010.02899.x.

Rehm, J., Mathers, C., Popova, S., Thavorncharoensap, M., Teerawattananon, Y., & Patra, J. (2009). Global burden of disease and injury and economic cost attributable to alcohol use and alcohol-use disorders. *The Lancet*, *373*, 2223–2233. http://dx.doi.org/10.1016/S0140-6736(09)60746-7.

Selby, E. A., Anestis, M. D., & Joiner, T. E. (2008). Understanding the relationship between emotional and behavioral dysregulation: Emotional cascades. *Behaviour Research and Therapy*, *46*, 593–611. http://dx.doi.org/10.1016/j.brat.2008.02.002.

Sintov, N. D., Kendler, K. S., Young-Wolff, K. C., Walsh, D., Patterson, D. G., & Prescott, C. A. (2010). Empirically defined subtypes of alcohol dependence in an Irish family sample. *Drug and Alcohol Dependence*, *107*, 230–236. http://dx.doi.org/10.1016/j.drugalcdep.2009.11.003.

Spada, M. M., Caselli, G., Nikčević, A. V., & Wells, A. (2015). Metacognition in addictive behaviors. *Addictive Behaviors*, *44*, 9–15. http://dx.doi.org/10.1016/j.addbeh.2014.08.002.

Steinberg, L. (2008). A social neuroscience perspective on adolescent risk-taking. *Developmental Review*, *28*, 78–106. http://dx.doi.org/10.1016/j.dr.2007.08.002.

Thayer, R. E., Newman, J. R., & McClain, T. M. (1994). Self-regulation of mood: Strategies for changing a bad mood, raising energy, and reducing tension. *Journal of Personality and Social Psychology*, *67*, 910–925. http://dx.doi.org/10.1037/0022-3514.67.5.910.

UNODC (2012). World drug report 2012. Retrieved from http://www.unodc.org/documents/data-and-analysis/WDR2012/WDR_2012_web_small.pdf

Vanes, L. D., van Holst, R. J., Jansen, J. M., van den Brink, W., Oosterlaan, J., & Goudriaan, A. E. (2014). Contingency learning in alcohol dependence and pathological gambling: Learning and unlearning reward contingencies. *Alcoholism, Clinical and Experimental Research*, *38*, 1602–1610. http://dx.doi.org/10.1111/acer.12393.

Wareham, J. D., & Potenza, M. N. (2010). Pathological gambling and substance use disorders. *The American Journal of Drug and Alcohol Abuse*, *36*, 242–247. http://dx.doi.org/10.3109/00952991003721118.

Whelan, R., Conrod, P. J., Poline, J. -B., Lourdusamy, A., Banaschewski, T., Barker, G. J., et al. (2012). Adolescent impulsivity phenotypes characterized by distinct brain networks. *Nature Neuroscience*, *15*, 920–925. http://dx.doi.org/10.1038/nn.3092.

Wilson, K., Fornasier, S., & White, K. M. (2010). Psychological predictors of young adults' use of social networking sites. *Cyberpsychology, Behavior and Social Networking*, *13*, 173–177. http://dx.doi.org/10.1089/cyber.2009.0094.

Wojdylo, K., Baumann, N., Fischbach, L., & Engeser, S. (2014). Live to work or love to work: Work craving and work engagement. *PLoS ONE*, *9*(10), e106379. http://dx.doi.org/10.1371/journal.pone.0106379.

World Health Organization (2010). ATLAS on substance use (2010)—Resources for the prevention and treatment of substance use disorders. Retrieved from http://www.who.int/substance_abuse/publications/treatment/en/