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Using latent class analysis to identify Finnish gambler types and potential risk

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ABSTRACT

The trend of increasing liberalization in gambling markets has been matched by a need for both effective approaches to promote responsible gambling practices and for improved prevention strategies. Given that the majority of players do not experience problematic gambling, it is in the public interest that knowledge is generated which helps identify activities or clusters of activities which are associated with at-risk behaviors. This study uses a representative sample of the Finnish population aged 15–74, to identify distinct types of gamblers based on their behavioral patterns and predictors of class membership via Latent Class Analysis. Cross-sectional random sample data were collected in 2019 ($n = 3148$). In addition to confirming existing knowledge for gamblers characterized by high engagement and high risk, it offered insights into three further classes: the largest (ME-HR, 45%), was characterized by moderate engagement, but participated in activities associated with higher levels of risk. Additionally, low-risk classes were differentiated by both gambling preferences and demographic characteristics. Given that the largest class was associated with significant potential for the development of problematic behaviors, this work makes several recommendations for preventative actions, including targeted awareness campaigns and psychoeducation addressing erroneous beliefs about gambling.

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Introduction

Recent decades have been marked by a general trend of increasingly liberalized approaches to the regulation of gambling, most notably in Europe and the United States. While there is no single cause to which this can be attributed, it is in line with the increased access to, and diversity of gambling activities afforded by the development

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of internet and digital technologies. The increased accessibility and greater range of gambling activities available to individuals in online environments have been associated with both a general increase in participation and in the prevalence of problematic gambling behaviors (Gainsbury et al., 2015; Kim et al., 2022b; Sulkunen et al., 2021). Consequently, regulators have required that the provision of responsible gambling tools is a condition of receiving a license to operate (Forsström & Cisneros Örnberg, 2019), while operators are often required to contribute to research, to public education campaigns, and the treatment of those experiencing problematic consumption behaviors.

Responsible gambling tools and public campaigns are not one-size-fits-all solutions, however, with recent research highlighting that their efficacy is dependent upon several contextual factors including, but not limited to, individual personality, socio-economic factors, and types of gambling games played (Australian Capital Territory. Gambling and Racing Commission, 2019). Similarly, for those who do experience problematic gambling behaviors, treatment seeking level is low (Håkansson & Ford, 2019) and success in treatment varies and is often related to comorbid conditions and burdening financial situation (Karlsson & Håkansson, 2018; Maniaci et al., 2017; Merkouris et al., 2016; Palomäki et al., 2022, 2023). While those who develop gambling problems are in the minority, it remains the case that the overwhelming majority of gambling-related research is dedicated to investigating this population, both in clinical and non-clinical contexts. Given that the majority of players do not experience harms, it is in the public interest that knowledge is generated which helps identify activities or clusters of activities which are associated with at risk behaviors, including expenditure, duration of gambling, and number of games gambled (Jonsson et al., 2022; Kim et al., 2022b), and the motivational and attitudinal factors which characterize such groups. Identification of these clusters of activities can be used to assist in the development of efficient preventive strategies and to address at-risk behaviors. This research applies Latent Class Analysis to a nationally representative sample of Finnish gamblers to identify distinct types of gamblers based on their self-reported behavioral patterns. Additionally, it utilizes these classes to identify characteristics that can predict membership of each individual class of gambler. It is expected to increase awareness and produce knowledge which can be employed in both the prevention and treatment of problematic gambling behaviors, as well as informing both policy development and public information campaigns.

Background

Different motivations for gambling co-exist alongside, and influence, attitudes to gambling and increase risk for gambling frequency and pose risk preferences for particular activities (A. H. Salonen et al., 2017). It is reasonable to conclude that particular activities gratify specific motivational drivers, indeed research has shown that different populations of gamblers share certain characteristics (Hagfors et al., 2022; Vuorinen et al., 2022). There is an abundant body of work which examines the gambling preferences of certain groups, whether according to socio-demographic characteristics such as gender, features of personality, or specific activities such as horse racing or sports betting (Palomäki et al., 2021).

However, most of such research has, to date, considered the issue in reference to such specific populations, from adolescent gamblers (De Luigi et al., 2018) to those seeking treatment for pathological gambling behaviors (Moragas et al., 2015). Indeed, there is a notable absence of research which attempts to define classes of gamblers at the national level, ones which incorporate many potential forms of gambling and all types of consumption behavior.

Female gender has commonly been found to be associated with a preference for chance-based activities, such as slots machines and lotteries, while male gender is often associated with a preference for skill-based activities such as sports betting and poker (Baggio et al., 2018; Hing & Breen, 2001; Welte et al., 2002; M. Young & Stevens, 2009). However, the influence of gender has been found to be overestimated, with some researchers highlighting the need to concentrate on more detailed player profiles (LaPlante et al., 2006). This need is supported when considering the interaction of age and gender, and of other cultural factors.

Prior research has highlighted the differing ways in which the structural characteristics of particular activities both gratify specific motivational drivers and facilitate potential problematic behavior (Auer & Griffiths, 2022; Cemiloglu et al., 2023; Lopez-Gonzalez et al., 2019). The advent of online markets, however, has given rise to more problem gambling associated with increased access to high-risk, high-reward betting options (Lopez-Gonzalez et al., 2018). Given that problematic gambling behaviors are associated with increased participation across a range of activities (Mazar et al., 2020), understanding how these activities group together may allow common underlying factors to be identified.

Latent Class Analysis (LCA) is a technique which examines multivariate, categorical data in order to extract underlying, or latent, groups based on conditional probabilities (Weller et al., 2020). The use of LCA to identify sub-types of gamblers has been growing in recent years with the focus of research moving from the classification of problem gambling typologies (Kong et al., 2014; McBride et al., 2010; Vachon & Bagby, 2009) and gambling behaviors (De Luigi et al., 2018; Dufour et al., 2015; Kang et al., 2018), to the etiology of problem gambling (Black & Allen, 2022; Nower et al., 2022; Sleczka et al., 2022). Other common approaches address the relationship between gambling and correlates such as mental health or substance use (Khazaal et al., 2017; Lloyd et al., 2010; Sanscartier et al., 2018). Commonly, results indicate the presence of three or four classes, with a class of non-problem or non-regular gamblers making up the majority. Notable exceptions are works which extract classes based on gambling activities, often producing seven or eight discrete classes in total (De Luigi et al., 2018; Faregh & Leth-Steensen, 2011; Wall et al., 2021). Of these, those studies which used representative datasets revealed that the majority of respondents were likely to belong to a class characterized by low levels of participation, with lotteries being the most common activity. Probability of class membership declined with the inclusion of sports betting and skill games, and as the range of activities increased (De Luigi et al., 2018; Faregh & Leth-Steensen, 2011). Taken together, these results highlight that the majority of those who gamble do so without experiencing problematic behaviors and participation is limited, often to casual activities such as lotteries. A small number of people, however, participate in a large range of gambling activities and suffer negative consequences.

The majority of research that employs LCA does so in reference to a specific population or group of interest, most commonly featured groups are existing gamblers, existing problem gamblers, or emerging gamblers. Somewhat surprisingly, there is little research which examines nationally representative datasets, with such example limited to the UK (Lloyd et al., 2010; McBride et al., 2010), Canada (Faregh & Leth-Steensen, 2011), and Finland (Halme, 2011), notably, these studies all make use of data collected in 2007 or before.

This study makes use of a nationally representative dataset addressing gambling, problem gambling, and attitudes and opinions toward gambling in Finland, a market currently experiencing notable structural change. Until the end of 2016, three state-controlled gambling operators had exclusive rights to organize gambling in Finland: Finland's Slot Machine Association (RAY), Veikkaus Oy and Fintoto Oy. The Finnish gambling system was reformed in January 2017, with the three gambling operators merging to form Veikkaus Ltd. The purpose of the merger was to eliminate competition between the three former gambling operators and to prevent and reduce gambling harms more effectively (Macey et al., 2023).

Under the current monopoly system, no gambling licenses are available in Finland. According to the Finnish Lotteries Act, Veikkaus, a state-owned private limited liability company, currently has the exclusive right to provide gambling services in mainland Finland. Gambling services falling under the exclusive right of Veikkaus cover both land-based and online gambling operations. The Åland Islands is an autonomous region of Finland that has its own regional government regulating gambling; as with Veikkaus, which has its exclusive right to organize gambling in mainland Finland, Penningautomatförening ('PAF') similarly operates gambling in the Åland Islands.

According to the current government program, Finland will begin to liberalize access to gambling by introducing a licensing system which covers digital casino games and digital sports betting no later than the beginning of 2026; other game types will remain under Veikkaus' exclusive rights with specific details regarding the licensing system are yet to be determined (Järvinen-Tassopoulos et al., 2023).

Although Veikkaus is the sole provider of gambling services in mainland Finland, whether online or offline, in practice Finnish citizens are able to make use of foreign providers' services. Between 2015 and 2019, gambling on non-monopoly services increased by 20% (A. Salonen et al., 2020) while recent research has estimated that the amount of money spent on Veikkaus' digital offerings is approximately equal to that spent outside the monopoly system (Heiskanen et al., 2024). As such, while technically a less liberalized market than many others, Finnish gamblers have access to other providers and are increasingly making use of this opportunity.

Finally, LCA has also been employed to extract classes among users of responsible gambling tools (Forsström et al., 2016), gamblers who access consumer credit (Swanton & Gainsbury, 2020), incarcerated criminals who gamble in England and Scotland (May-Chahal et al., 2017), and those who have contact with providers of gambling services (Jonsson et al., 2021). Together, these works show that LCA is a useful tool for identifying heterogeneous gambling behaviors across a range of contexts and populations. Therefore, this research aims to contribute to the existing body of work utilizing LCA, by focusing on a large and representative dataset of Finnish gamblers. Our work is explorative and not guided by formal hypotheses, but the results have the potential to not only increase awareness of latent gambler sub-types in the population but also to inform policy decision-making and public harm prevention campaigns.

Data and Methods

Sample and participants

We used the Finnish Gambling 2019 population survey, a population-representative sample of 3994 individuals living in mainland Finland aged between 15 and 74. Data was collected by Statistics Finland using computer-assisted personal communication in Finnish and Swedish between September and December 2019. Data collection was based on systematic random sampling from the Population Register Center's sampling frame, which initially targeted 7800 individuals; the response rate was thus 51.2% (full sampling details in A. Salonen et al., 2020). We excluded respondents who reported not having participated in any form of gambling during the last 12 months ($n = 846$). Thus, our final analyzed sample included 3148 individuals (42.8% female, $M_{\text{age, females/males}} = 48.5/50.4$).

The research protocol for the Finnish Gambling 2019 population survey was approved by the Ethics Committee of the Finnish Institute for Health and Welfare (Statement THL/744/6.02.01/2019). Potential participants received written information about the study and were informed about their rights and the principles of voluntary participation.

Data availability

This study uses publicly available empirical data accessed from the Finnish Social Science Data Archive (https://www.fsd.uta.fi/en/).

Measures

At-risk gambling behaviors were measured using the Problem Gambling Severity Index (PGSI; Ferris & Wynne, 2001: Cronbach's alpha = .85) items are evaluated from 0 = 'never' to 3 = 'almost always' and the scores are summed. The response distribution for the sum scores was zero-inflated. The scores were categorized as 0 = 'No problems' ($n = 2785$), 0.01–2.99 = 'Low level of problems' ($n = 257$), 3–7.99 = 'Moderate level of problems' ($n = 82$) and 8+ = 'High level of problems' ($n = 24$). Given the low number of individuals in the problem-level categories, the 'Moderate' and 'High' categories were collapsed, resulting in three categories: 1) No gambling problems, 2) Low level of problems, and 3) High level of problems.

We used the 8-item Attitudes Towards Gambling Scale (ATGS, Wardle & Griffiths, 2011; Cronbach's alpha = .69), which asks participants to rate their responses to statements such as 'People should have the right to gamble whenever they want', with responses anchored from 1 = 'Strongly agree' to 5 = 'Strongly disagree'. Therefore, higher scores reflecting more positive attitudes toward gambling, the 8-item scale asks includes four reverse coded items.

Participants were asked to recall their previous 12 months and estimate money (€) spent on gambling either weekly, monthly, or during the whole year (participants could choose which timeframe to use for responding). We transformed all responses into 'money spent weekly' (see Table 1): if participants had reported their monthly or yearly spending, amounts were divided by 4 or 52, respectively.

Demographic covariates were age (numeric), gender (dichotomous), education (ordinal with 7 levels from 1 = 'Have not finished any school', to 7 = 'Master's degree or

Table 1. Average weekly spend (€).

Range	0 - 4.99	5 - 9.99	10 - 49.99	50 - 99.99	100 - 499.99	500 - 999.99	1000+
n	2072	434	450	32	18	1	3

Table 2. Distribution of responses to dichotomous indicator variables (participation in gambling activities) used in LCA, in descending order of 'yes' responses.

Gambling type	Yes (= 1)	No (= 0)
Lottery	2662	484
Scratch cards	1858	1287
Slot machines	1184	1962
Sports betting	518	2629
Cruise gambling	407	2740
Online gambling on PAF, foreign sites, and online poker on Veikkaus	241	2906
Horse betting	194	2953
Casino gambling	157	2989
Private betting pools	149	2997

higher'), and income (net average monthly; numerical, log-transformed for analyses). See Table 2 for descriptive statistics.

Participants were asked about their previous 12 months' gambling participation (yes/no) on several gambling activities: 1) Lotteries (including weekly and daily lotteries, and quick raffles), 2) Scratch cards (both online and offline), 3) Casino games (including gambling and table games with a croupier), 4) Online gambling specifically on PAF[1] and foreign sites, 5) Horse betting, 6) Sports betting, 7) Slot machines (both online and offline), 8) Private betting pools, and 9) Cruise gambling. Full details of reported frequencies of participation for all activities are presented in the appendices. There were additional categories of land-based gambling outside of continental Finland and online poker, which had very few 'yes' responses (34 and 39, respectively). Thus, the former category was omitted, and the latter combined with Online gambling (category 4). The categories were coded as 0 = has not participated in the said activities during past 12 months, 1 = has participated in the said activities at least once (see Table 2 for a breakdown of responses). These dichotomous gambling participation variables were used in Latent Class Analysis (LCA) to discover latent classes of gambler subtypes based on preferred forms of gambling.

The participants' main reason for gambling during the past 12 months was collected using a dichotomous yes/no answer on the following items: i) Excitement, entertainment, fun, ii) To win money, iii) To develop skills, iv) To compete or challenge yourself, v) To socialize, vi) To support worthy causes, vii) To escape, relax, or relieve stress, viii) Because it made me feel good or skillful, ix) Other reason (Williams et al., 2017).

Data analysis

Data analysis was conducted in two separate stages: in the first stage, class models were extracted from participants' reported gambling activities using Latent Class Analysis. In the second stage, these models were used as dependent variables in multinomial regression in order to identify predictors of class membership. Independent variables used in multinomial regression were as follows: age, education, income, gender, weekly spend on gambling (€), PGSI category, and ATGS score.

The proportions of missing values for age, education, income, gender, and the full scales of PGSI and ATGS were 7.21%, 8.2%, 12.8%, 7.21%, 4%, and 0%, respectively. These missing values were imputed using Predictive Mean Matching (PMM) multiple imputation on the mice R package (Buuren & Groothuis-Oudshoorn, 2011) for a multinomial regression analysis. The imputed multinomial regression model was fitted five times based on separate PMM-imputed datasets, and the pooled estimates of these models are reported.

Latent class analysis

We used the poLCA library (Linzer & Lewis, 2011) for fitting latent class models, which applies the expectation-maximization and Newton-Raphson algorithms. To determine the appropriate number of latent classes, we fit multiple models for 2–7 latent classes, using 3000 maximum iterations for each fit. Tolerance was set at 10^{-5}, meaning that when the one-iteration change in the estimated model log-likelihood was less than 10^{-5}, maximum log-likelihood was considered found. Given the maximum likelihood estimation method, missing values in the manifest variables were retained in model estimation. Each model was estimated 10 times, which helps to find the global, rather than just the local, maximum of the log-likelihood function. The most appropriate model was determined based on examining log-likelihood-, Bayesian Information Criterion (BIC), and Akaike Information Criterion (AIC) values (Nylund et al., 2007), as well as interpretability considering existing research and theory. We also examined bivariate residuals (BVRs) between the indicator variables, and entropy r^2 values. Higher BVR-values indicate higher within-class item correlations (and thus local dependence), and higher entropy r^2 values indicate better classification accuracy based on individuals' responses compared with only knowing the overall proportions of individuals within each class.

Next, we assigned each participant a class membership based on the highest posterior class probability (modal assignment). Class membership was used as the dependent variable in a multinomial regression model with all other variables as predictors (missing values imputed using PMM), and as an independent variable for visualizations in exploratory analyses (see Figures 2–3). These analyses may yield biased estimates, because not all individuals will be assigned their 'true' class due to uncertainty in modal class assignment. Thus, we also fit a covariate adjusted LCA model and a multinomial regression model simultaneously, the results of which largely mirrored the previous analysis (see Appendix Table A1 and Figures A1 - A4), indicating that the analysis is robust.

Table 3. Model fit statistics for LCAs with 2–7 classes.

# of classes	LL	BIC	AIC	Interpretability	Entropy r^2	BVR range
1	−10964	22000	21946	Loglinear independence model	–	4.1 – 401.6
2	−10399	20952	20837	Poor	0.62	5.3 – 85.5
3	−10301	20837	20661	Decent	0.49	5.6 – 72.7
4	−10236	**20786**	20550	**Good**	0.59	4.3 – 52.2
5	−10210	20815	20518	Poor	0.60	3.1 – 40.0
6	−10178	20832	20474	Poor	0.54	2.7 – 29.2
7	**−10162**	20880	**20462**	Very poor	**0.63**	**2.4 – 27.6**

LL = Best log-likelihood; BIC = Bayes Information Criterion; AIC = Akaike Information Criterion; Entropy r^2 = (entropy of class proportions – mean entropy of individual-wise posterior class membership probability)/entropy of class proportions, i.e., (error prior – error posterior)/error prior. BVR = Bivariate Residuals. Note: Bold values highlight best results per evaluation criteria, with BIC value being considered the most influential.

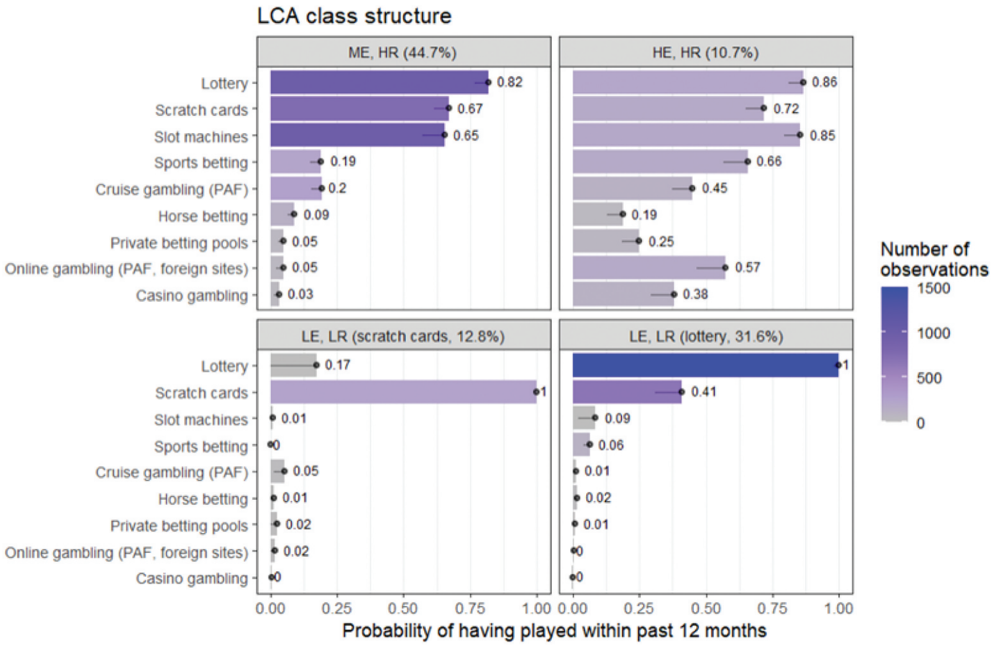

Figure 1. Structure of the four-class LCA. Numbers shown are estimated probabilities of having participated in specific gambling activities within the past 12 months. Error-bars are 95% confidence intervals, visualized only downwards since they are symmetrical. ME-HR = moderate engagement, high Risk; HE-HR = high engagement, high Risk; LE-LR = low engagement, low Risk; LE-LR = low engagement, low risk (with population share % in brackets). The bars are colored according to the number of observations for each reported gambling activity within each class (blue = higher, gray = lower; assignment by modal posterior probability). The observations can exceed the number of participants, because respondents could select more than one gambling activity.

Results

Latent class analysis

We determined that a 4-class solution was the best fit for the data: it had the lowest BIC-value, good interpretation, and a relatively high entropy r^2-value. Models with

Table 4. Predicted class-wise descriptive statistics across all predictor variables.

Predicted class (population share %)	PGSI score	ATGS score	Age	Median education	Median income (net, monthly)	Median weekly spent (euros)	Males %
ME-HR (44.7%)	0.345	2.95	46.1	Voc. school	2000	3.75	63.1%
HE-HR (10.7%)	1.57	3.03	34.3	Voc. school	2050	10	87.9%
LE-LR (scratch cards; 12.8%)	0.109	2.70	40.9	Voc. school	1700	0.38	26.5%
LE-LR (lottery; 31.6%)	0.075	2.83	56.0	Voc. college	2000	2	45.2%

PGSI = Problem Gambling Severity Index. ATGS = Attitudes Towards Gambling Scale. Predicted class is based on LCA modal posterior probability. ME-HR = Moderate Engagement, High Risk; HE-HR = high Engagement, High Risk; LE-LR = Low Engagement, Low Risk; LE-LR = Low Engagement, Low Risk (with population share % in brackets). Voc. = Vocational.

Table 5. Multinomial regression analyses predicting the four LCA classes.

Multinomial regression analysis (PMM multiple imputation, pooled estimates)						
	ME-HR (pop. 44.7%)		LE-LR (scratch cards, pop. 12.8%)		LE-LR (lottery, pop. 31.6%)	
Reference category: HE-HR (pop. 10.7%)	*OR*	*95% CI*	*OR*	*95% CI*	*OR*	*95% CI*
Gender (ref: Males)						
Females	3.91***	2.36–6.48	14.7***	8.2–26.5	6.46***	3.86–10.8
Log(Income +1)	0.78**	0.67–0.92	0.59***	0.50–0.70	0.77***	0.65–0.91
Age	1.07***	1.05–1.08	1.06***	1.04–1.08	1.12**	1.11–1.14
Education	0.95	0.85–1.07	1.02	0.88–1.19	1.09	0.96–1.23
PGSI category (ref: No problems)						
Low problem level	0.34***	0.22–0.51	0.13***	0.05–0.31	0.19***	0.11–0.31
High problem level	0.18***	0.10–0.32	0.14*	0.02–0.73	0.03***	0.01–0.10
Spent weekly (euros)	0.99***	0.98–0.99	0.92	0.76–1.10	0.94***	0.93–0.95
ATGS	0.76*	0.58–0.99	0.47***	0.33–0.67	0.65**	0.49–0.86

*** $p < .001$, ** $p < .01$, * $p < .05$. PMM = Predictive Mean Matching. ATGS = Attitudes Towards Gambling Scale. PGSI = Problem Gambling Severity Index. Pop. = % of individuals in class. CI = Confidence Interval. ME-HR = Moderate Engagement, High Risk; HE-HR = high Engagement, High Risk; LE-LR = Low Engagement, Low Risk; LE-LR = Low Engagement, Low Risk (with population share % in brackets).

5–7 classes had higher log-likelihood and lower AIC-values, but poor interpretability. Across the models, BVR-values were somewhat high (see Table 3), which suggested non-trivial violations of the local independence assumption of LCA. As a robustness check, we combined the indicator categories 'horse betting' and 'sports betting' and omitted the categories 'casino gambling' and 'private betting pools' (which had the most unbalanced response distributions, see Table 2) and reran the LCA. This resulted in acceptable BVR-values between 0.18 and 5.9 for the 4-class model without significantly affecting the pattern of the results. Thus, we determined that BVR-values between 4.3 and 52.2 were acceptable (this represented, on average, a 90% reduction in BVR-values compared with the loglinear independence model). A visualization of the final class model is provided in appendix A3. Finally, Table 4 shows predicted class membership valuesof all predictor variables for each of the four finalised classes.

Upon inspection, the classes clearly appeared to reflect both gambling *engagement* and the level of *risk* involved, and thus we named them as 1: "Moderate Engagement, High Risk (ME-HR, 45%); 2: "High Engagement, High Risk (HE-HR, 10.7%); 3: 'Low

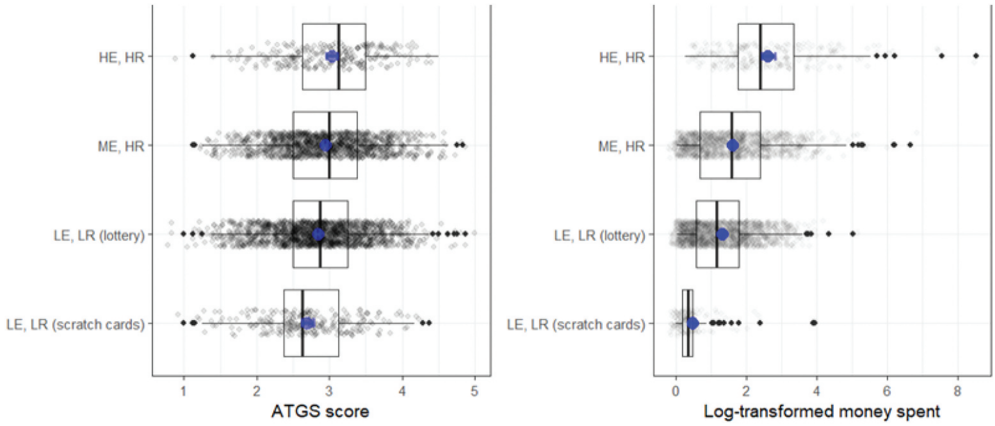

Figure 2. Attitudes towards gambling scale (ATGS) scores (left) and log-transformed money spent weekly (in euros; right) as a function of predicted LCA class. Blue dots on boxplots represent class-wise mean values with 95% confidence intervals, grayed dots represent individual observations (random jitter is added to improve readability). ME-HR = moderate engagement, high Risk; HE-HR = high engagement, high Risk; LE-LR = low engagement, low Risk; LE-LR = low engagement, low risk.

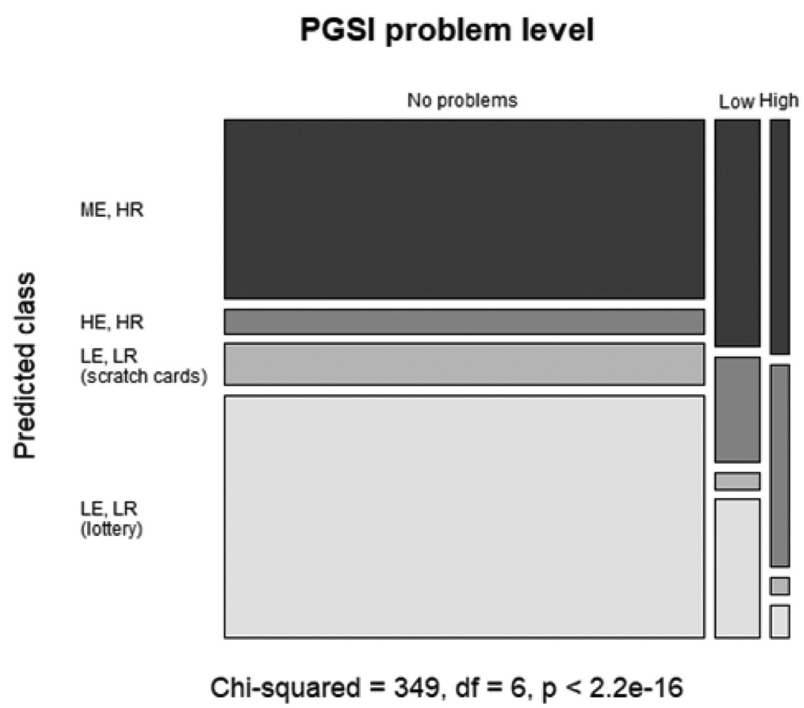

Figure 3. Mosaic-plot depicting the proportions of individuals across LCA predicted classes and Problem Gambling Severity Index (PGSI) score-based problem levels, with chi-squared statistics. ME-HR = moderate engagement, high Risk; HE-HR = high engagement, high Risk; LE-LR = low engagement, low Risk; LE-LR = low engagement, low risk.

Table 6. Number of participants (within-class percentages in brackets) across predicted classes and reported reasons for gambling.

Reason for gambling	ME-HR	HE-HR	LE-LR (scratch cards)	LE-LR (lottery)
Excitement, entertainment, fun	427 (35.3)	119 (50)	89 (36.1)	310 (22.7)
To win money	576 (47.6)	74 (31.1)	55 (22.3)	894 (65.6)
To develop skills	3 (0.02)	1 (0.4)	0	0
To compete or challenge yourself	2 (0.01)	1 (0.4)	0	4 (0.3)
To socialize	43 (3.5)	8 (3.3)	16 (6.5)	21 (1.5)
To support worthy causes	29 (2.3)	2 (0.8)	10 (4.1)	35 (2.5)
To escape, relax or relieve stress	18 (1.4)	6 (2.5)	2 (0.8)	7 (0.5)
Because it made me feel good or skillful	0	2 (0.8)	0	0
Other reason	111 (9.1)	25 (10.5)	74 (30.1)	92 (6.7)

ME-HR = Moderate Engagement, High Risk; HE-HR = high Engagement, High Risk; LE-LR = Low Engagement, Low Risk; LE-LR = Low Engagement, Low Risk.

Engagement, Low Risk (Scratch Cards), 12.8%'; 4: 'Low Engagement, Low Risk (Lottery), 31.6%'. Figure 1 depicts the LCA class structure.

Descriptives

Multinomial regression analyses

Table 5 presents a multinomial regression analysis predicting LCA class membership with missing values multiply imputed using predictive mean matching (PMM). As a robustness check, we also fit a covariate-adjusted LCA model and a multinomial regression model simultaneously (see Appendix), the results of which closely resembled the main analysis. Participants were significantly *less* likely assigned to the 'High Engagement, High Risk' class, compared with any of the other three classes, if they were females (ORs = 3.91–14.7, *ps* at least < .001), had lower income (ORs = 0.59–0.78, *ps* at least < .01), were older (ORs = 1.06–1.12, *ps* at least < .01), had a more negative attitude toward gambling (ORs = 0.47–0.76, *ps* at least < .05), had no gambling problems (ORs = 0.03–0.34, *ps* at least < .05), or spent less money on gambling (ORs = 0.92–0.99, *ps* < .001).

Additional analyses

Table 6 presents the distribution of individuals across predicted classes and self-reported reasons for gambling. The main reasons for gambling were 'To win money' in the 'ME-HR' and 'LE-LR' classes, and 'Excitement, entertainment, or fun' in the 'HE-HR' and 'LE-LR' classes.

Figures 2 and 3 depict the predicted classes as independent variables, without control variables. As can be seen in Figure 2, the 'High Engagement, High Risk' class had the most positive attitudes to gambling (measured using the ATGS) as well as reported spending the most money on a weekly basis on gambling. The 'Low Engagement, Low Risk (scratch card)' class had the least positive attitudes to gambling and lowest weekly spending on gambling.

Figure 3 depicts the distribution of PGSI categories across the predicted classes. The 'High Engagement, High Risk' class is over-represented in the Low- and High-risk PGSI groups, compared with the 'No problems' group. The 'Medium Engagement, High Risk' class, on the other hand, is well represented across all PGSI categories.

Discussion

This work used Latent Class Analysis to examine a nationally representative dataset of Finnish gamblers to identify distinct gambling types and potential predictors for membership of each type. Results indicate four distinct gambling sub-types which were delineated according to a combination of gambling engagement (activities) and risk profiles; these sub-types were named High Engagement, High Risk (HE-HR); Moderate Engagement, High Risk (ME-HR); Low Engagement, Low Risk Lottery (LE-LR Lottery); and Low Engagement, Low Risk Scratch Card (LE-LR Scratch cards). Membership of sub-types was found to be predicted by gender, age, income, PGSI score, and ATGS score.

The identification of the HE-HR class does not itself contribute new knowledge to the field, instead it confirms existing research which has described a population of gamblers where higher levels of problematic gambling behavior are associated with younger males, higher levels of spending, participation in a broad range of activities, and more positive attitudes to gambling (Wardle & Griffiths, 2011; M. M. Young et al., 2022). Furthermore, it validates research from a range of different contexts using representative, Finnish samples (Hagfors et al., 2022; A. Salonen et al., 2020). Taken together, these facts suggest the likelihood that such findings can be considered generalizable outside of the Finnish context.

While the findings associated with the HE-HR class are not novel, the other classes identified through latent class analysis do offer a greater understanding of gambling practices. Most significant is the identification of class which although lower in engagement is still characterized by high levels of at-risk behavior, class ME-HR. This class has significantly higher PGSI scores and more positive attitudes to gambling than classes LE-LR (scratch cards) and LE-LR (lottery) despite having a higher average age and same median income, respectively. Furthermore, despite exhibiting PGSI scores approaching those observed in HE-HR, members of class ME-HR are likely to participate in significantly fewer gambling activities. Given that class ME-HR was found to constitute approximately 45% of the Finnish population, it is likely to be beneficial if greater attention would be focused on this group in order to prevent increased risk of developing problematic or disordered gambling behaviors.

Finally, the identification of two distinct, low-risk classes offers a more nuanced understanding of contemporary practices as they are distinguished both by preferred gambling activities and demographic characteristics. Both classes exhibit similarly low PGSI scores, that of class LE-LR (scratch cards) is slightly higher, despite holding more negative attitudes to gambling and being significantly lower in average age than class LE-LR (lottery). Furthermore, members of class LE-LR (scratch cards) have lower average income and spend notably smaller amounts of money on gambling per week than LE-LR (lottery), they are also significantly more likely to be female, 73.5% compared to 54.8%. Considering that findings on the HE-HR group appear to be cross-cultural, further investigation is required in order to establish whether findings related to the remaining groups are replicated in other contexts and populations.

Prior works using gambling activities as the basis for LCA often extract seven or eight classes (De Luigi et al., 2018; Wall et al., 2021); however, in this work, results revealed the presence of four distinct classes. The results in this work are more similar to studies using problem gambling categorization or etiology (Black & Allen, 2022; Kong et al., 2014) as the basis for LCA. This is supported by subsequent analysis which showed that the most diverse set of gambling activities was for the group most likely to be categorized as a problem gambler using PGSI. Similarly, those who participated in the least number of activities (typically scratch cards or lotteries) were most likely to be categorized as non-problem gamblers. This is possibly explained by the fact that in Finland gambling services are provided by a monopoly, and there is little opportunity to visit casinos or other such establishments. While other alternatives are possible, for example online gambling, it may be that Finns are less trusting of outside providers (Marionneau & Hellman, 2020). However, the results of this work are markedly different from a prior Finnish study which found six classes where the primary distinction was with respect to playing online poker or other online gambling games (Halme, 2011). A potential explanation for this difference is a change in trends; the prior study used data collected in 2007 when internet poker was more popular; furthermore, the continued expansion of online gambling in general has increased ease of access to multiple gambling activities even via the same service provider.

Latent class analysis using problem gambling measures often yields models with three or four classes, of these the overwhelming majority are likely to belong to a class variously described as 'non-problem gamblers', 'casual gamblers', or similar. A smaller percentage, around 10%, are categorized as 'preoccupied', 'risky', etc., and 1% or 2% as 'problem' or 'pathological' gamblers (Kong et al., 2014; Sanscartier et al., 2018). Even studies with a high number of classes fit the pattern wherein the majority are non-problem/casual, a small percentage, 1–2%, is highly engaged or problematic gamblers, with the remainder of the sample split between different types of activities. Typically, the highest rates of problem gambling are associated with participation in a broad range of activities, with lower rates of problem gambling associated with a preference for either skill games or games of chance, with the lowest likelihood of problem gambling being associated with infrequent or casual play and predominantly lottery play (De Luigi et al., 2018; Faregh & Leth-Steensen, 2011). The results of this work are somewhat different in that they suggest two distinct classes of high-risk gamblers, distinguished between those who were involved in a broad range of activities and those who predominantly participate in chance-based activities (lotteries, scratch cards, slot machines). Furthermore, this work identified two distinct classes of low-risk gamblers distinguished by a preference for either lottery or scratch cards.

Finally, these results are somewhat different from prior research in that the single largest class is that we termed 'medium engagement, high risk' rather than one categorized as low-risk. In fact, the likelihood of someone belonging to this class was marginally larger (44.7%) than belonging to either of the low-risk classes combined (44.2%).

Many different stakeholders work to prevent or minimize gambling-related harms, including those developing responsible gambling initiatives or programs, public health professionals developing awareness campaigns, and those developing training materials for prevention and early detection. A potentially useful strategy would be to target identified groups with the recently developed Lower Risk Gambling Guidelines (LRGG), incorporating the guidelines into their products and promotional activities as an additional component of a wider public health approach reducing gambling-related harm.

The Canadian Lower Risk Gambling Guidelines (LRGG) are developed based on rigorous scientific work (M. M. Young et al., 2022) with the specific recommendations that are 'To reduce risks of experiencing harms from gambling, follow all three of these guidelines': Gamble no more than 1% of household income before tax for month, Avoid regularly gambling at more than two types of games, and Gamble no more than 4 days a month. The first two principles are particularly relevant to the group ME-HR: first, they are likely to spend similar amounts to the HE-HR group but are likely to report a lower average income; second, they are likely to engage in a range of gambling activities.

While information regarding the number of times individuals gambled per month was not collected in this survey, it is conceivable that given the amount spent on gambling and the range of activities participated, embers of the ME-HR group are likely to exceed that threshold. Furthermore, the positive attitudes to gambling and the motivations for gambling suggest that they may benefit from targeted psychoeducational information about gambling-related harms and the realistic chances of winning money.

As is the case in most Western countries, lotteries are the most typical form of gambling in Finland. Lotteries have been found to be less problematic than online gambling, EGMs (including slots) and poker, due the lower speed of play, less visual and auditory effects, less illusionary control features, and longer payout intervals (Kim et al., 2022b). Given the restrictions of the data collection method, in our analysis, 'lotteries' includes both offline and online versions, including quick draw games which share structural characteristics with online slot machines, as such it is likely that the lotteries category also includes activities more associated with problematic consumption than traditional lotteries. While the ME-HR group includes a significant degree of likely slot machine play, other potentially risky activities (online gambling and poker) are not notably present. This is a major point of difference between the HE-HR and ME-HR groups, meaning that preventing the uptake of online gambling and enhance the used of mandatory responsible gambling (RG) tools (Auer et al., 2020) and promote gamblers to self-assess their gambling (e.g. using LRGG – risk assessment tool) may be one way to reduce the likelihood of individuals within ME-HR developing gambling problems. Examining classes potentially associated with the development of gambling disorder revealed that physical channels were far more common than online channels, thereby raising issues related to the delivery of RG tools, particularly those suited to physical rather than online channels.

Examining the distribution of PGSI categories by gambling sub-type reveals that there are very few non-problem gamblers in HE-HR (as a percentage of class), and very few high-risk gamblers in LE-LR (lottery). However, the fact that the proportions for non-problem, low-risk, and high-risk gamblers are very similar for ME-HR suggests that this class is one which is likely to benefit from increased attention. The similarity in proportions of PGSI score can be potentially explained if we consider this class to be the one with the most churn; it includes both those who are recovering from problematic behaviors (moving down the continuum) and those whose play is becoming more problematic (moving up the continuum).

This potential churn is also reflected in the reported motivations for gambling, with class ME-HR exhibiting the most diverse range of motivations of all four classes. The most endorsed motivation is to win money; however, the activities in which members of this class participate are almost entirely chance-based. For such individuals, an effective approach is to provide an accurate information about probability, independence of turns in probability (e.g. features of chance-base game EGMs) and gambling-related erroneous thoughts, for example, the 'gamblers fallacy', which is the tenacious belief that win will come soon even though outcome of bets is based on pure randomness (Ladouceur, 2004).

Outside of preferred activities, the primary distinguishing factor between LE-LR (scratch cards) and LE-LR (lottery) is reflected in the reported motivations for gambling, with scratch cards primarily being associated with excitement and lotteries with the hope of winning money. Interestingly, despite the low average PGSI score, class LE-LR (scratch cards) also appears to have an equal distribution of members across all three categories (non-problem, low-risk, and high-risk). Furthermore, the most endorsed motivation for gambling is excitement, as is the case for the HE-HR class; such indicators suggest that this group bears closer attention and may be more likely to transition from low engagement, low-risk gambling to more engaged and higher-risk behaviors.

Finally, the relationship between attitudes to gambling and group membership appears to be uncomplicated; as attitudes toward gambling increase in positivity, individuals are more likely to move from low-risk to high-risk classes. While the range of ATGS scores is similar for each class, there is a steady increase in overall values as engagement increases. Therefore, enhancing public awareness about gambling-related harm promotes mandatory responsible gambling tools, which are shown to be effective in reducing gambling-related harm and are viewed positively by gamblers (Engebø et al., 2019) and keep following up the ATGS scores overtime using longitudinal approach (Hellumbråten Kristensen et al., 2022).

Limitations

LCA extracts unobserved clusters or groupings from a set of observed variables, producing probabilities of class membership. As such, the classes cannot be considered categorical and fixed representations of reality, instead there is likely to be some degree of variation in the results, for example in the percentage of population represented by each class. This is a known characteristic of the method and is reflected in the fact that the suggested models need to be assessed by balancing sometimes contradictory fit indices with domain knowledge and usability considerations (Nylund et al., 2007; Nylund-Gibson & Choi, 2018). This work has presented the rationale used in selecting a four-class model and has provided output related to an alternative method (covariate adjusted LCA) as supplementary material for reference. In addition, the large sample size used in this study enhances the likelihood of the proposed class structure being robust.

The second potential limitation is that this work constitutes a secondary analysis of publicly available data collected by the Statistics Finland in collaboration with the Finnish Institute for Health and Welfare as part of an ongoing series of surveys 'Finnish Gambling 2019' addressing gambling, problem gambling, and attitudes and opinions toward gambling. The survey was, therefore, not designed with this study in mind and does not contain all the data necessary to add further depth to the discussion of the findings. For example, the survey which was targeted to the general population rather than a clinical sample uses the PGSI, but did not explicitly collect data regarding gambling-related harms potentially experienced by participants other than those items that are contained within the PGSI. Neither does it collect information regarding previous gambling activity, or on experiences of gambling outside of the 12-month period prior to data collection.

A further limitation is that LCA requires data in the form of dichotomous variables, meaning that no distinction is made between individuals whose frequency of participation in a given activity differs, for example daily or monthly. However, there is a growing body of research in which LCA has been applied to gambling activities in order to identify common groupings and their characteristics; this work seeks to add this domain by applying the technique to a nationally representative sample.

Furthermore, the data used in this study did not always differentiate between online and offline channels for all activities and, by extension, there was no differentiation between types of sports betting. However, computational limitations exist in relation to LCA and in practice the number of class predictors should be kept to a low number. As such, this work chose to group gambling activities together which shared structural characteristics and mechanisms rather than grouping according to the channel by which the activities were accessed. It is hoped that future surveys will more explicitly separate activities according to both characteristics and mode of access to allow researchers more freedom to group activities according to a range of potential perspectives or rationales.

Conclusion

This study identified four classes of gamblers using self-reported behavioral data as well as attitudes to and motivations for gambling. In addition to confirming existing knowledge relating to those gamblers characterized by high levels of engagement and potential risk, it offered valuable insights into three further sub-types. It identified of a group constituting approximately 45% of the Finnish population which would benefit from increased attention to prevent the development of potentially problematic gambling. Additionally, a greater understanding of low-risk gamblers was provided, with two distinct groups differentiated by both gambling preferences and demographic characteristics. Given that findings on the HE-HR group appear to be cross-cultural, it is recommended that further studies investigate whether findings related to the remaining groups are also replicated in other populations.

Note

1. Online gambling through PAF and other foreign sites was considered separately as Veikkaus' online projects were captured in other categories.

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Data availability statement

This study uses publicly available empirical data ($n = 3,148$) accessed from the Finnish Social Science Data Archive (https://www.fsd.uta.fi/en/).

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APPENDICES

Covariate-adjusted LCA

The LCA class assignment in the main text may be biased, because not all individuals will be assigned their ‘true’ class due to inherent uncertainty in modal assignment. We therefore fit a covariate adjusted LCA model and a multinomial regression model simultaneously (using the glca package in R; Kim et al., 2022b), which reduces class assignment bias.

For the covariate-adjusted LCA, we used median-imputation for missing covariate values, since complementing the analysis with multiple PMM imputation was not possible with any existing algorithms we were aware of. As can be seen in the figure, the pattern of results in terms of estimated probabilities between the two methods (the results presented in the main text, and below) is largely similar, with some differences within the LE-LR -class. The population shares are similar within HE-HR and LE-LR (scratch cards) but differ somewhat between ME-HR (44.7% vs. 30.3%) and LE-LR (lottery) (31.6% vs. 42.6%).

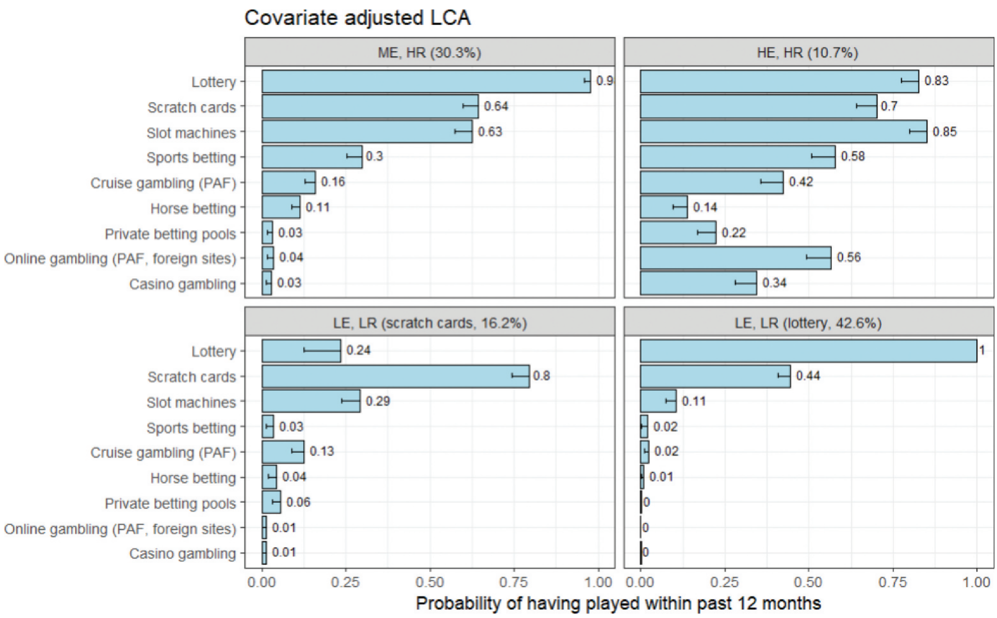

Figure A1. Structure of the four-class covariate-adjusted LCA. Numbers shown are estimated probabilities of having participated in specific gambling activities within the past 12 months. Error-bars are 95% confidence intervals, visualized only downwards since they are symmetrical. ME-HR = moderate engagement, high Risk; HE-HR = high engagement, high Risk; LE-LR = low engagement, low Risk; LE-LR = low engagement, low risk (with population share % in brackets).

Table A1. Multinomial regression analyses predicting the four (covariate-adjusted) LCA classes.

	Multinomial regression analysis Covariate-adjusted LCA (median imputation)					
	ME-HR (pop. 30.3%)		LE-LR (scratch cards pop. 16.2%)		LE-LR (lottery, pop. 42.6%)	
Reference category: HE-HR (pop. 10.7%)	*OR*	*95% CI*	*OR*	*95% CI*	*OR*	*95% CI*
Gender (Ref: Males)						
Females	6.5***	2.79–15.3	14.2***	5.92–34.4	13.5***	8.2–26.5
Log(Income+1)	1.04	0.76–1.41	0.60***	0.49–0.73	0.80	0.61–1.05
Age	1.14***	1.11–1.85	1.15***	1.11–1.19	1.23***	1.19–1.27
Education	0.81*	0.67–0.98	0.84	0.69–1.02	0.91	0.75–1.10
PGSI category (Ref: No problems)						
Low problem level	0.28***	0.13–0.59	0.07***	0.02–0.23	0.08***	0.03–0.19
High problem level	0.18***	0.07–0.51	0.16*	0.03–0.72	0.01*	5.5e05-0.46
Spent weekly (euros)	0.92***	0.89–0.94	0.53***	0.47–0.60	0.80***	0.76–0.83
ATGS	0.99	0.63–1.56	0.49**	0.30–0.79	0.53**	0.33–0.84

***p < .001, **p < .01, *p < .05. ATGS = Attitudes Towards Gambling Scale. PGSI = Problem Gambling Severity Index. Pop. = % of individuals in class. CI = Confidence Interval. ME-HR = Moderate Engagement, High Risk; HE-HR = High Engagement, High Risk; LE-LR = Low Engagement, Low Risk; LE-LR = Low Engagement, Low Risk (with population share % in brackets).

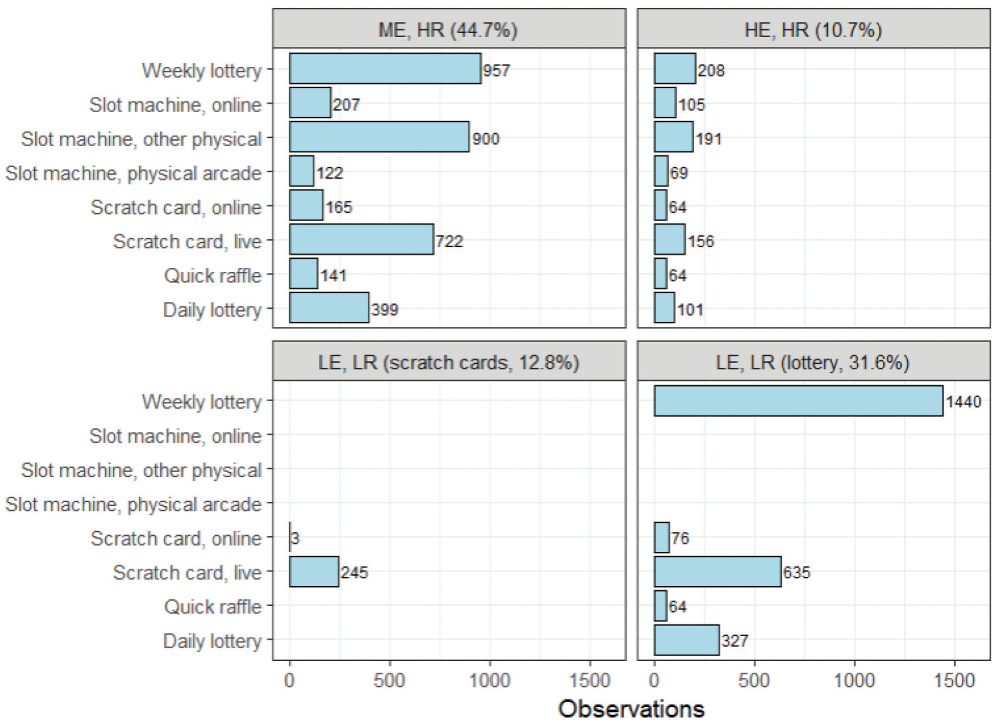

Figure A2. Number of observations for the "uncollapsed" reported gambling activities of lotteries, slot machines and scratch cards within each class (assignment by modal posterior probability). The observations can exceed the number of participants, because respondents could select more than one gambling activity. ME-HR = moderate engagement, high Risk; HE-HR = high engagement, high Risk; LE-LR = low engagement, low Risk; LE-LR = low engagement, low risk (with population share % in brackets). The bars are colored according to the number of observations for each.

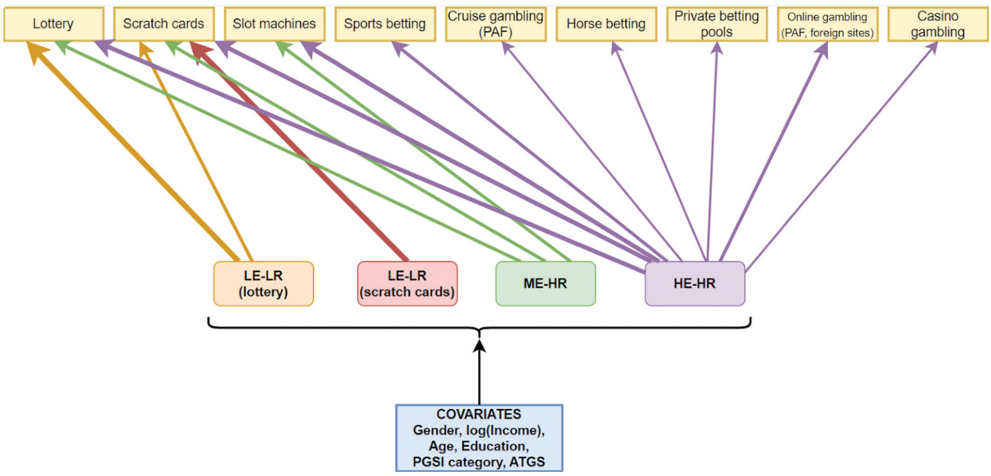

Figure A3. Diagram of the LCA model. The dichotomous indicator variables are shown at the top in yellow boxes; the LCA classes are shown in the middle; and covariates are shown at the bottom. Thickness of the colored arrows represents the estimated probabilities (see Figure 1), with probabilities < .20 suppressed. LE-LR = low engagement - low Risk; ME-HR = medium engagement - high Risk; HE-HR = high engagement - high Risk; ATGS = attitudes towards gambling scale. PGSI = problem gambling severity Index.

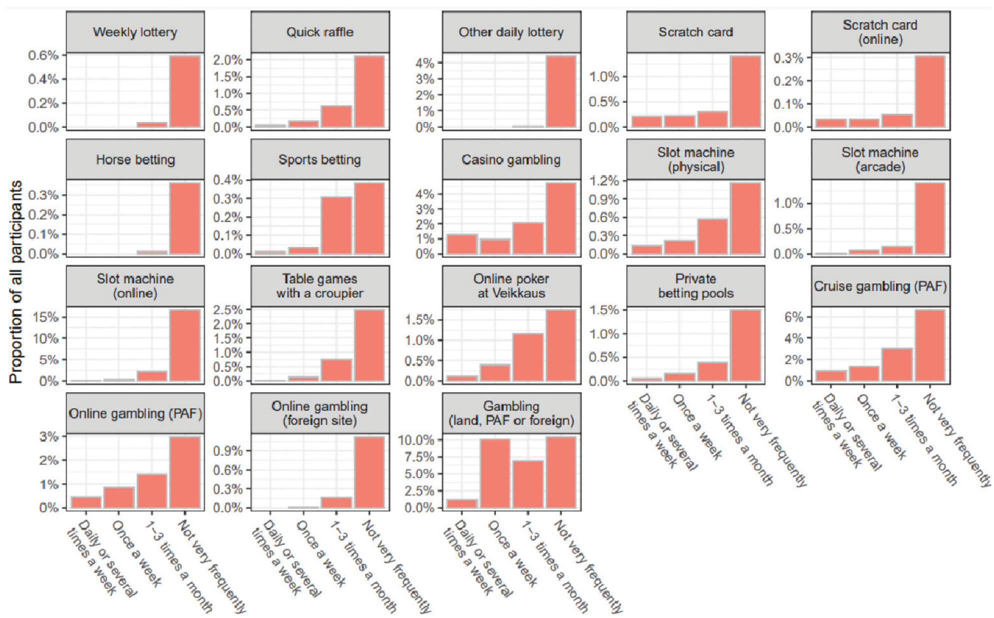

Figure A4. Panel histogram depicting frequency of gambling activity across all gambling types (i.e. dichotomous indicator variables used in the LCA). Note that this panel histogram does not combine any of the categories, unlike the main analysis. PAF = gambling authority of the åland Islands.

Depicting frequency of gambling (Likert scale; Daily or several times a week, Once a week, 1–3 times a month, or Not very frequently) across all measured gambling types. (Note that this panel histogram does not combine any of the categories, as was done in the LCA.)