Public Health 244 (2025) 105742

Contents lists available at ScienceDirect

Public Health

journal homepage: www.elsevier.com/locate/puhe

Original Research

Not all traders gamble, but some gamblers trade: a latent class analysis of trading and gambling behaviors among retail investors

Ainhoa Coloma-Carmona [a,b,*], José Luis Carballo [a,b], Fernando Miró-Llinares [c], Jesús C. Aguerri [c,d]

[a] Center for Applied Psychology, Miguel Hernández University of Elche, Elche, Spain
[b] Alicante Institute for Health and Biomedical Research (ISABIAL), Alicante, Spain
[c] CRÍMINA Research Center for the Study and Prevention of Crime, Miguel Hernández University of Elche, Elche, Spain
[d] University of Zaragoza, Zaragoza, Spain

ARTICLE INFO

Keywords:
Adults
Gambling
Investing
Trading
Cryptocurrency
Impulsivity
Cognitive biases
Population survey

ABSTRACT

Objectives: This study aimed to identify subgroups of retail investors based on their engagement in trading and gambling activities, and to examine differences in involvement, demographics, substance use, impulsivity, cognitive biases, problem gambling, and disordered trading.
Study design: Cross-sectional, population-based study using panel data. Quota sampling and post-stratification weights were applied using data from a prior population-based random digital dial telephone survey.
Methods: Data were collected from 1,429 Spanish adults (aged 18–64). Participants reported involvement in trading of 8 financial instruments (e.g., cryptocurrencies, stocks, ETFs) and 12 gambling (e.g., lotteries, sports betting) and gambling-like activities (e.g., loot boxes, skin betting). 28.6 % of respondents engaged in non-professional trading.
Results: Using weighted latent class analysis we identified three distinct subgroups of retail investors: *crypto-traders* (52.4 %), focused on cryptocurrency trading with minimal gambling; *stock-traders* (32 %), involved in stocks/ETFs and lotteries, and *gambling-traders* (15.6 %), heavily involved in high-risk trading and various gambling activities. Although *gambling-traders* were not the highest investors in terms of trading volume, this class exhibited the highest frequency of trading and gambling, impulsivity, gambling-related cognitive biases, rates of disordered trading, and illicit substance use. 24.9 % of *gambling-traders* scored for problem gambling (PGSI≥8), compared to 0.5 % of *crypto-traders* and 3.5 % of *stock-traders*. **Conclusions**: Not all retail investors seem to extend their gambling behaviors to financial markets; however, those with higher impulsive traits and gambling-related cognitive biases tend to combine trading with gambling. This combination is strongly associated with problem gambling and disordered trading.

1. Introduction

The trading of financial assets, such as cryptocurrencies, has gained popularity among the general public due to the availability of online platforms and widespread marketing campaigns, particularly in digital and sporting contexts.[1–4] In contrast to traditional investing, trading is an investment activity that seeks short-term profits and often involves frequent transactions based on fluctuating market trends. Trading strategies are typically classified by the duration of holding positions (i.e., the length of time the financial assets are held before they are sold). The four main styles are position trading, swing trading, day trading, and scalping. Position trading focuses on holding positions for weeks or even months, while swing trading involves keeping assets for several days to take advantage of price swings. Conversely, day trading limits all transactions to a single trading session and involves closing of positions before market closure, whereas scalping seeks to profit from rapid, small price movements within minutes or even seconds.[5] Trading activities, particularly day trading and scalping, are frequently regarded as forms of financial speculation, characterized by higher levels of uncertainty and increased risk of financial loss.[6,7] Despite market analysis and investing knowledge, trading outcomes can still be affected by sudden market fluctuations, which has led to trading being described as an

* Corresponding author. Department of Health Psychology, Miguel Hernández University, Avenida de la Universidad, s/n, Elche, 03202, Alicante, Spain.
E-mail address: ainhoa.coloma@umh.es (A. Coloma-Carmona).

https://doi.org/10.1016/j.puhe.2025.105742
Received 7 January 2025; Received in revised form 22 March 2025; Accepted 27 April 2025
Available online 14 May 2025

online gambling-like activity.[2,8–10] Because of these features, trading has been compared to activities such as sport betting or poker, where although gambler skills may influence outcomes, there is still an element of chance.[9,11,12]

The similarities between these activities are further supported by empirical evidence, which reveals a considerable overlap between gambling and trading behaviors. Previous studies show that over half of regular gamblers engage in trading activities, with these behaviors being more common among younger males with higher levels of education and income.[2,11,13–15] Trading behavior is also strongly linked to cognitive distortions, impulsivity, and risky decision-making, all established predictors of gambling disorder.[2,11,12,16–19] Furthermore, problem gambling, in particular, seems to be the strongest predictor of intense and severe trading behaviors.[14]

Several studies have suggested that trading may serve as a substitute for gambling, since some retail investors view the buying and selling of financial assets as an entertainment activity.[20–23] Indeed, prior findings indicate that between 4 and 10 % of this population exhibit problematic gambling behaviors within the financial markets.[16,24] The substitution hypothesis is also supported by studies indicating that trading volume among retail investors declines during weeks with large lottery jackpots[20,25] and increases during periods such as the COVID-19 pandemic, when gambling opportunities were limited due to the closure of gambling venues and the suspension of gambling-related activities, such as sporting events.[2,21,26]

In line with trends observed in other countries,[2] widely advertised platforms such as eToro or Plus500 have facilitated general access to trading in Spain. Recent population-based data indicate that 13.3 % of the Spanish general population engages in trading, yet only around 1 % do so professionally, highlighting the predominantly amateur nature of these activities.[27] Strikingly, although less than 2 % of individuals report a high level of knowledge about financial assets such as cryptocurrencies,[28] almost 40 % of the general population traded in more than one asset.[27]

However, despite the growing popularity of trading, the available worldwide evidence is largely limited to studies focusing on cryptocurrency or high-risk stock traders.[6,14] Consequently, investigations into the patterns and risk profiles of retail investors remain limited, even though trading platforms allow users to access a wide range of financial products, including high-risk securities. Latent class analysis (LCA), a statistical method that identifies subgroups based on shared characteristics, offers a promising approach to examining the heterogeneity of trading and gambling behaviors.[29] While LCA has been widely applied to gambling studies, its application to the combined analysis of trading and gambling behaviors is still underexplored.

This study aims to address these gaps by using LCA to classify retail investors based on trading and gambling behaviors. It also examines how these profiles differ in terms of demographic characteristics, trading and gambling involvement, substance use, impulsivity, and gambling-related cognitive biases.

2. Methods

2.1. Design and participants

A cross-sectional online survey was conducted between 24 March and 22 April 2022 among a sample of Spanish residents aged 18–64 years. Participants were recruited from an online panel maintained by an independent Spanish research agency. Prior to recruitment, a pre-test of the final survey was conducted on a sample of $n = 100$ panel members to ensure feasibility and quality of the survey. To reduce complexity, the survey was designed to adapt to participant responses and included questions on demographic characteristics, gambling and trading behaviors, and gambling-related risk factors. The average completion time was approximately 25 min. Quotas were set for age, sex, region, and habitat size in order to ensure representativeness.

Of the 8,549 survey invitations sent out, 3,749 individuals initiated the survey after reading the aims and objectives of the study and giving informed consent. A total of 2,320 responses were excluded due to incompleteness, rapid completion, quota limits, inconsistencies, or automated response patterns detected using the dichotomous scale format (*yes/no*) of the Oviedo Infrequency Scale.[30,31] This scale includes items such as 'The distance between Madrid and New York is greater than the distance between Madrid and Barcelona'. Participants who provided three or more incorrect answers were considered to have provided random responses.[32,33] This resulted in 1,429 valid cases and a sampling error of 3.2 % (Z = 1.96, confidence level = 95.5 %). Participation was voluntary, although panel members receive incentives (redeemable points) from the panel provider. The study procedures were approved by the Committee of Research and Ethics at the first author's university (Reference: DPP.ACC.01.21).

2.2. Measures

2.2.1. General demographics

Participants provided demographic information, including age, sex, marital status, education, employment status, and monthly income.

2.2.2. Trading behaviors

Participants reported past-year engagement (*yes/no*) in trading activities across eight asset types (e.g., Forex, cryptocurrencies, stock markets, ETFs) and provided data on trading frequency, trade size (in euros), daily engagement, and market monitoring based on items proposed by Delfabbro et al.[17] to measure cryptocurrency engagement. Measures also included the preferred holding periods for the traded financial assets (e.g., seconds, days) and the use of brokers or trading apps. Disordered trading (score $\geq$5 criteria) was assessed using the Trading Disorder Scale (TDS),[10] developed based on the 13 criteria proposed by Guglielmo et al.[34] to identify maladaptive trading behaviors.

2.2.3. Gambling behaviors

Participants indicated past-year engagement (*yes/no*) in eight traditional gambling activities (e.g., lotteries, sports betting, bingo, casino) and four in-game activities with gambling components, such as skin betting or buying loot boxes.[35] For each activity, participants reported the frequency and highest amount spent in a single day of gambling, as well as the mode of participation in traditional gambling (land-based and/or online). The preferred form of gambling was determined by the most frequently used mode across all traditional gambling activities. The Spanish version of the Problem Gambling Severity Index (PGSI)[36,37] was used to assess gambling severity, classifying participants as follows: non-problem (PGSI = 0), low risk (PGSI = 1–2), moderate risk (PGSI = 3–7), or problem gambling (PGSI$\geq$8). Participants who had not engaged in gambling activities during the assessed period were assigned a PGSI score of 0.[38]

2.2.4. Gambling-related risk factors

Gambling-related cognitive distortions were measured using the scale developed by Labrador et al.,[39] while impulsivity was assessed with the Spanish UPPS-P scale.[40,41] Past-year substance use (alcohol, tobacco, cannabis, cocaine, and hallucinogens) was screened using ad hoc items based on the EDADES Survey.[42]

See supplementary material for a complete description of all measures, including response formats and psychometric properties.

2.3. Data analysis

To ensure representativeness of the study population, post-stratification weights were applied to all cases using data from prior random digit dial telephone survey (N = 1,011) we conducted, assessing the prevalence of gambling-like activities in the Spanish population aged 18-64 years.[27] LCA with sampling weights was conducted in Mplus v8.8.[43] The optimal number of latent classes was determined using three criteria: (1) the Bayesian Information Criterion (BIC; lower values indicate better fit), chosen for its robustness and because it accounts for complex sampling features;[44,45] (2) interpretability in line with the theoretical framework and previous research; and (3) class size distribution, excluding models with classes representing less than 5 % of the sample. Conditional probabilities were interpreted as low (<0.40), moderate (0.40-0.69), and high (≥0.70).[29]

Class comparisons between were conducted in SPSS v.27 using complex survey commands with results interpreted at a 95 % confidence level. The Rao-Scott-adjusted χ^2 test[46] was used to evaluate differences in non-continuous variables, followed by a Bonferroni-corrected post-hoc z-test on the adjusted residuals for all significant χ^2 results. For continuous variables, differences were assessed using general linear models for complex samples, with post-hoc pairwise comparisons also adjusted using Bonferroni corrections to minimize Type I error. Outliers (values > 1.5 times the interquartile range) were examined and found not to affect the results. Accordingly, all cases were included in the reported analyses.

3. Results

3.1. Sample characteristics

The unweighted survey sample (N = 1,429) was sex-balanced (51.8 % male, *n*=740), with a mean age of 37.43 years (SD = 12.36). Most participants were employed (64.5 %, *n*=921), and had completed high school (43.3 %, *n*=619) or university studies (51.5 %, *n*=736). Both unweighted and weighted sample characteristics are detailed in Table 1.

A total of 408 participants (28.6 %) reported engaging in financial asset trading over the past year. The weighted prevalence of trading activities was 11.5 % (95 % Confidence Interval [95 % CI]: 9.9–13.5 %). In order to comply with the study's objectives, weighted descriptive and inferential analyses excluded professional traders (1.2 %, *n*=5) and focused on retail investors (98.8 %, *n*=403).

The sample of retail investors was predominantly male (72.2 % [65.4–78.1 %]), with high educational levels (60.9 % [53–68.2 %] had a university degree), and had a mean age of 41.8 (SE = 1.1) years. The most frequently traded assets were stocks (54.3 % [46.8–61.6 %]), cryptocurrencies (47.9 % [40.4–55.6 %]), and exchange-traded funds (43.5 % [35.8–51.5 %]). Trading of other high-risk assets, including Forex (16.7 % [11.3–23.9 %]), commodities (9.6 % [6.1–14.9 %]), futures (4.5 % [2.6–7.6 %]), options (2.7 % [1.4–5.1 %]), or CFDs (1.5 % [0.7–3.3 %]), was less prevalent.

3.2. Latent classes of gambling and trading behaviors among retail investors

Fit indices of the weighted latent class models are presented in Table 2. The BIC values improved with increasing model complexity from one to three classes. As the smallest class in the 4-class solution contained less than 5 %, therefore, the 3-class solution was deemed optimal, balancing BIC values and interpretability. Fig. 1 illustrates the probabilities of past-year engagement in trading and gambling behaviors for each class.

The most prevalent class (52.4 %, *n*=211), designated as *crypto-traders*, comprised investors who were primarily engaged in cryptocurrency trading and reporting minimal involvement in gambling or gambling-like activities, except for a moderate probability of lottery play (41.3 %). The second largest class (32 %, *n*=119), labelled *stock-traders*, showed a high probability of trading stocks and ETFs which, like stocks, are bought and sold on a stock exchange, and lottery playing. The smallest class (15.6 %, *n*=63), termed *gambling-traders,* included investors with moderate to high probabilities of engaging in nearly all trading activities assessed. The conditional probabilities were high for cryptocurrency trading, and moderate for Forex, the stock market, commodities, and ETFs (in descending order of probability). This group also exhibited moderate probabilities of engaging in various traditional gambling activities (e.g., lotteries, sports betting, bingo, casino), and was the only class reporting gambling-like activities such as eSports or skin betting and buying loot boxes, although with low probabilities.

Table 1
Survey respondents' characteristics (N = 1,429).

Characteristics	Total sample (N = 1,429)		Retail investors (n = 403)	
	Unweighted, % (n) or Mean (SD)	Weighted, % (95 % CI) or Mean (SE)	Unweighted, % (n) or Mean (SD)	Weighted, % (95 % CI) or Mean (SE)
Age (years)	37.4 (12.4)	43.6 (0.5)	38.44 (12.9)	41.8 (1.1)
Sex				
Female	48.2 (689)	50 (46–53.9)	34.7 (140)	27.8 (21.9–34.6)
Male	51.8 (740)	50 (46.1–54)	65.3 (263)	72.2 (65.4–78.1)
Marital status				
Single	52.4 (749)	40.2 (36.5–44)	50.6 (204)	47.5 (40–55.1)
Married	36.9 (527)	47.6 (43.6–51.6)	40.2 (162)	42.3 (35–49.9)
Divorced	4.5 (64)	5.7 (4.2–7.7)	4.2 (17)	5.6 (2.8–10.8)
Widowed	1 (14)	1.8 (0.8–4.2)	0.7 (3)	0.5 (0.1–1.7)
Other	5.2 (75)	4.7 (3.3–6.5)	4.2 (17)	4.2 (1.9–9.2)
Education level				
None	0.4 (6)	0.3 (0.1–1)	0.2 (1)	0 (0–0.2)
Primary	4.8 (68)	7.6 (5.4–10.6)	3 (12)	4.6 (2.2–9.4)
High School	43.3 (619)	44.2 (40.2–48.2)	36 (145)	34.5 (27.4–42.3)
University studies	51.5 (736)	47.9 (43.9–51.9)	60.8 (245)	60.9 (53–68.2)
Employment status				
Student	14.5 (207)	7.7 (6.4–9.1)	9.4 (38)	6.4 (4.1–9.8)
Employed	64.5 (921)	62.1 (58.1–66)	76.4 (308)	75.6 (68–82)
Unemployed/domestic work	17.2 (246)	23.2 (19.8–27)	10.9 (44)	11.5 (7.6–17)
Retired	3.8 (55)	7 (5–9.7)	3.2. (13)	6.5 (2.7–15.1)
Income				
<1,000€	18.8 (268)	18.3 (15.3–21.7)	13.6 (55)	10.9 (7.3–16.1)
1,000–1,999€	38.8 (555)	37.2 (33.5–41.1)	43.2 (174)	46 (38.5–53.7)
≥2,000€	14.8 (212)	15 (12.5–18)	23.8 (96)	26.4 (20.1–33.8)
Don't know/Prefer not to disclose	27.6 (394)	29.5 (25.9–33.4)	19.4 (78)	16.6 (12.3–22.1)

Abbreviations: *n* unweighted count, *SD* standard deviation, *CI* confidence interval, *SE* standard error.

Table 2
Fit indices of the weighted latent class solutions.

Model	Log-likelihood	AIC	BIC	SABIC	Entropy	Smallest class count (n)	Smallest class size (%)
1-class	−2216.864	4473.729	4553.708	4490.246	NA	403	100 %
2-classes	−2059.124	4200.248	4364.205	4234.107	0.941	71	17.6 %
3-classes	**−1972.619**	**4069.238**	**4317.172**	**4120.440**	**0.802**	**63**	**15.6 %**
4-classes	−1916.321	3998.642	4330.554	4067.186	0.828	5	1.2 %

Abbreviations: *AIC* Akaike's information criterion, *BIC* Bayesian information criterion, *SABIC* sample size adjusted BIC, *NA* not applicable.
Note: Smallest class in the 4-class solution was <5 %, and therefore no further classes were added. Optimal class solution is indicated by bold text.

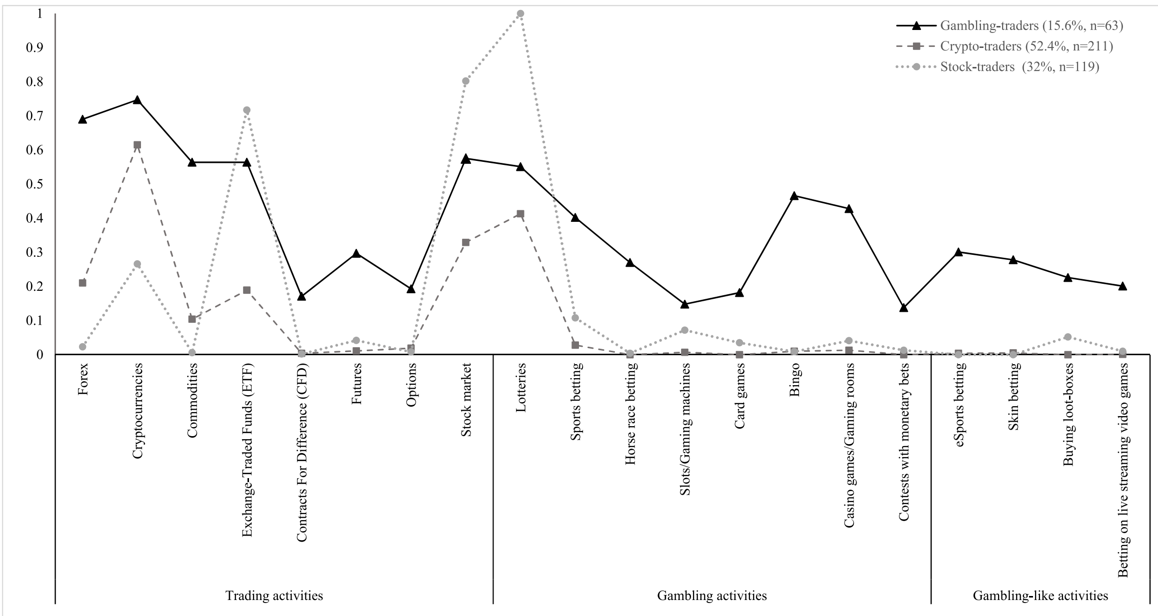

Fig. 1. Weighted latent class analysis. Estimated indicator probabilities and latent class proportions for the 3-class model.

Table 3
Demographic characteristics (weighted estimates) of each latent class (N = 403).

Variables	Gambling-traders (n = 63)	Crypto-traders (n = 211)	Stock-traders (n = 129)	Statistic (p)
Age (years)	34.3(3.5)[a]	38.2(1.3)[a]	47.1(1.6)[b]	13.077 (<0.001)**
Sex				
Female	38.3 (14.8–68.9)	34.8 (26.3–44.2)	**18.2 (11.6–27.4)**	3.185 (0.043)*
Male	61.7 (31.1–85.2)	65.2 (55.8–73.7)	**81.8 (72.6–88.4)**	
Marital status				
Single	39.6 (19.8–63.6)	56.5 (46.8–65.7)	38.4 (26.6–51.7)	2.644 (0.018)*
Married	37.5 (18.4–61.5)	35 (26.6–44.5)	52.3 (38.5–63.9)	
Divorced	**1.2 (0.3–4.2)**	5.1 (1.7–14.1)	6.9 (2.7–16.2)	
Widowed	–	0.5 (0.1–3)	0.5 (0.1–3.2)	
Other	21.7 (3.6–67.1)	2.9 (1.1–7.6)	3 (1.1–7.9)	
Education level				
None	0.3 (0–2.5)	–	–	0.791 (0.550)
Primary	4 (0.6–23.3)	5.8 (2.1–14.9)	3.4 (1.1–10.1)	
High School	39.5 (19.2–64.1)	28.4 (21–37.3)	40.6 (28.1–54.4)	
University studies	56.2 (31.6–78.1)	65.7 (56.2–74.2)	56.1 (42.7–68.6)	
Employment status				
Student	2.4 (0.7–7.9)	8.9 (5.3–14.5)	4.1 (1.5–10.3)	3.865 (0.254)
Employed	87.4 (64.8–96.3)	74.7 (65.1–82.4)	74.9 (60.7–85.2)	
Unemployed/domestic work	8.7 (1.6–35.6)	13 (7.4–21.8)	10.2 (5.3–19)	
Retired	1.5 (0.2–10.2)	2.4 (0.9–12.9)	5.9 (3.5–28.7)	
Income				
<1,000€	13.3 (4.7–32)	13.7 (8.3–21.9)	7.4 (3.3–15.8)	5.127 (0.024)*
1,000–1,999€	60.4 (36.8–79.9)	40.9 (31.7–50.8)	49.6 (37–62.4)	
≥2,000€	16.2 (6.6–34.5)	21.6 (15–30.2)	33.5 (22.2–46.9)	
Don't know/Prefer not to disclose	10.2 (3.7–25.2)	**23.7 (16.7–32.5)**	**9.5 (5.1–16.7)**	

Data are weighted means (standard errors) in continuous outcomes, and weighted percentages (95 % confidence intervals) in non-continuous outcomes. Weighted percentages are rounded and may not add up to 100 %.
Note: Different superscripts letters in the same row indicate significant differences in pairwise comparisons. Bold type indicates significant differences according to z-tests on the adjusted residuals (all based on Bonferroni-adjusted p-values).
*Significant at $p < 0.05$, **Significant at $p < 0.01$, - No cases in this category.

3.3. Differences in demographic characteristics between latent classes

The demographic data for each latent class is presented in Table 3. In comparison to those classified as *gambling-* and *crypto-traders*, who exhibited a similar male-to-female ratio and mean ages, *stock-traders* were predominantly male (p=.043), and older ($p < .001$). The monthly income of the *gambling-traders* class was the lowest (p=.024) and the proportion of divorced individuals was the smallest (p=.018). A significantly higher proportion of *crypto-traders* did not provide income data, with 23.7 % (95 % CI: 16.7–32.5 %) of individuals in this class responding, 'don't know/prefer not to answer'. No statistically significant differences were observed in educational level or employment status across classes ($p > .05$).

3.4. Differences in trading involvement between latent classes

The use of trading apps and the number of hours spent analyzing markets did not differ significantly across classes ($p > .05$). The *stock-traders* class reported the highest mean trade size (mean = 7,639€, SE = 1,183.9) compared to *gambling-traders* (mean = 2,018.2€, SE = 588) and *crypto-traders* classes (mean = 1,065.4€, SE = 262, $p < .001$). However, investors in the *gambling-traders* class generally reported a more intense and severe pattern of trading behavior than individuals in the other two classes.

Compared to *crypto-traders* (mean = 1.5, SE = 0.8) and *stock-traders* (mean = 1.9, SE = 0.1), *gambling-traders* traded a broader range of financial instruments (mean = 4, SE = 0.4, $p < .001$) and more

Table 4
Trading and gambling behaviors (weighted estimates) across latent classes (N = 403).

Variables	Gambling-traders (n = 63)	Crypto-traders (n = 211)	Stock-traders (n = 129)	Statistic (p)
Trading involvement				
No. of financial assets traded	4 (0.4)[a]	1.5 (0.8)[b]	1.9 (0.1)[c]	13.715 (<0.001)**
Past-year frequency of trading[†]				
Less than once a month	**16.3 (6.9–33.9)**	57 (47.3–66.2)	63.7 (50.5–75.1)	4.078 (0.002)**
Monthly	49.1 (24.7–73.8)	29.4 (21.3–39)	31.7 (20.9–45)	
Weekly	31.8 (14.7–55.7)	11 (6.3–18.4)	4.3 (1.5–12)	
Daily	2.8 (0.6–12.8)	2.7 (1–6.6)	**0.2 (0–1.7)**	
Mean trade size values (in euros)[†]	2,018.2 (588)[a]	1,065.4 (262)[a]	7,673.9 (1,183.9)[b]	20.653 (<0.001)**
Shortest preferred time frame for trading[†]				
Seconds (Scalping)	20.3 (7.9–43.2)	35.3 (25.4–46.7)	25 (13.9–40.9)	5.503(<0.001)**
Hours (Day trading)	**57.6 (32.4–79.4)**	13.1 (8.4–19.9)	10.4 (4.9–20.9)	
Days (Swing trading)	19 (7.8–39.3)	11.3 (6.5–18.9)	27.8 (15.4–45)	
Weeks-months (Position trading)	**3 (1–8.5)**	40.2 (29.7–51.7)	36.8 (25.1–50.2)	
Daily market monitoring				
Never or not daily	**13.8 (5.7–29.7)**	61.6 (51.5–70.7)	45 (33.1–57.4)	8.132 (<0.001)**
1–3 times per day	49.1 (24.8–73.8)	35.3 (26.3–45.4)	50.3 (37.6–63)	
Every hour	26.9 (11.6–50.8)	2.8 (1.1–7.3)	4.4 (1.3–14.3)	
Every few minutes	**10.2 (2.3–35.8)**	0.3 (0.1–1.2)	0.3 (0.1–1.3)	
Hours per day researching/studying markets	2.9 (0.6)	1.5 (0.3)	1.5 (0.3)	1.749 (0.079)
Use of trading apps	65 (41.6–82.9)	46.2 (36.8–55.9)	48.9 (36.2–61.8)	0.828 (0.431)
Trading disorder				
Met ≥5 criteria	**40.5 (19.9–65)**	3.6 (1.6–8.2)	3.6 (1.5–8.6)	20.364 (<0.001)**
Total severity score	4.4 (0.7)[a]	0.7 (0.2)[b]	0.9 (0.2)[b]	10.005 (<0.001)**
Gambling involvement[††]				
Participated in gambling and in-game activities	**96.1 (78.8–99.4)**	**41.6 (32.7–51)**	100 (100–100)	59.398 (<0.001)**
No. of gambling and in-game activities	3.6 (0.4)[a]	0.5 (0.1)[b]	1.3 (0.1)[c]	66.109 (<0.001)**
Preferred gambling mode				
Land-based	**16.2 (5.2–40.6)**	61.2 (47.4–73.4)	63.8 (51.1–74.8)	6.130 (0.002)**
Online	**83.8 (59.4–94.8)**	38.8 (26.6–52.6)	36.2 (25.2–48.9)	
Past-year frequency of traditional gambling				
Less than once a month	21.6 (7.7–47.6)	42.4 (30.4–55.5)	49 (36.3–61.8)	2.124 (0.068)
Monthly	47.3 (22.5–73.6)	35.3 (23.6–49.1)	31.6 (21.8–43.4)	
Weekly	24.1 (11.1–44.7)	21.8 (11.6–37)	19.1 (11–31.3)	
Daily	**7 (1.9–22.1)**	0.5 (0.1–2.2)	**0.2 (0–1.5)**	
Past-year frequency of gambling-like activities (in-game)				
Less than once a month	14.3 (4.3–38.1)	62.6 (13.7–94.6)	39.9 (8.9–81.8)	0.680 (0.603)
Monthly	34.7 (16.4–59)	–	21.5 (2.8–72.4)	
Weekly	50.8 (27.8–73.4)	37.4 (5.4–86.3)	33.5 (5.1–82.5)	
Daily	0.3 (0–2.3)	–	5 (0.6–32.7)	
Maximum amount bet in a single day (in euros)	214.3 (108.9)[a]	16.9 (2.4)[a,b]	32.2 (3.7)[a,c]	10.249 (0.001)**
Problem gambling				
Non-problem gambling (PGSI = 0)	**39.7 (16.1–69.4)**	**90 (83.5–94.1)**	77.6 (67.1–85.4)	8.898 (<0.001)**
Low-risk gambling (PGSI = 1–2)	18.9 (8–38.2)	7 (3.6–13)	17 (10.4–26.5)	
Moderate-risk gambling (PGSI = 3–7)	16.5 (5.6–39.4)	2.6 (0.9–6.8)	2 (0.9–4.4)	
Problem gambling (PGSI ≥8)	24.9 (11.7–45.5)	**0.5 (0.1–1.8)**	3.5 (0.9–12.2)	
Total severity score	4.3 (1.3)[a]	0.3 (0.1)[b]	0.7 (0.3)[b]	5.370 (0.010)*

Data are weighted means (standard errors) in continuous outcomes, and weighted percentages (95 % confidence intervals) in non-continuous outcomes. Weighted percentages are rounded and may not add up to 100 %.
Note: Different superscripts letters in the same row indicate significant differences in pairwise comparisons. Bold type indicates significant differences according to z-tests on the adjusted residuals (all based on Bonferroni-adjusted p-values).
*Significant at $p < 0.05$, **Significant at $p < 0.01$, - No cases in this category.
[†]Trading frequency is based on the financial asset most actively traded. Mean trade size refers to the average amount of money invested per trade. Preferred time frame refers to the shortest holding period between the purchase and sale of a financial asset.
[††]Gambling involvement data (i.e., number of gambling and gambling-like activities, amount bet and past-year frequency) refer exclusively to participants who reported engaging in gambling or gambling-like activities; consequently, the sample size for these variables could be smaller than the total sample size for each class. Frequency of gambling was determined by the gambling activity in which the participant has engaged the most. The preferred gambling mode indicates the most used format for gambling within traditional products. Participants who had not engaged in past-year gambling or gambling-like activities were assigned a PGSI score of 0.

frequently than the other groups (p=.002). The majority of *crypto-* (57 % [95 % CI: 47.3–66.2 %]) and *stock-traders* (63.7 % [95 % CI: 50.5–75.1 %]) reported trading less than monthly, while *gambling-traders* predominantly traded on a monthly (49.1 % [95 % CI: 24.7–73.8 %]) or weekly basis (31.8 % [95 % CI: 14.7–55.7 %]). The proportion of individuals trading on a daily basis was minimal across all groups (<3 %).

In terms of the preferred transaction duration (i.e., the length of time the financial assets are held before they are sold), cross-class comparisons revealed that a similar number of investors in each class hold positions on ultra-short time frames. The proportion of investors holding purchased assets for a period of seconds (commonly referred as scalping) ranged from 20.3 % to 35 % across all three classes (see Table 4 for complete results with 95 % confidence intervals). However, 57.6 % (95 % CI: 32.4–79.4 %) of individuals classified as *gambling-traders* reported holding assets for hours, consistent with day trading, whereas this trading modality dropped to values between 10.4 and 13.1 % in the other classes. Moreover, only 3 % (95 % CI: 1–8.5 %) of those classified as *gambling-traders* employed long-term strategies, such as holding positions for weeks or months (position trading). In contrast, this time frame was the most prevalent among *crypto-traders* (40.2 % [95 % CI: 29.7–51.7 %]) and *stock-traders* (36.8 % [95 % CI: 25.1–50.2 %]).

Gambling-traders also monitored markets more frequently, with 10.2 % (95 % CI: 2.3–35.8 %) checking updates every few minutes, compared to only 0.3 % of the investors in the other classes (p < .001). Additionally, 61.6 % (95 % CI: 51.5–70.7 %) of *crypto-traders* and 45 % (95 % CI: 33.1–57.4 %) of *stock-traders* reported never or not daily monitoring of markets, while the proportion in the *gambling-traders* class was significantly lower (13.8 % [95 % CI: 5.7–29.7 %]).

Moreover, 40.5 % (95 % CI: 19.9–65 %) of individuals in the *gambling-traders* class met the criteria for disordered trading (i.e., Trading Disorder Scale score ≥5), compared to 3.6 % in the other two classes (p < .001). This group also exhibited the most severe trading behaviors, with an average of 4.4 (SE = 0.7) of the criteria met (p < .001). Complete data on cross-class comparisons of variables related to trading behaviors are presented in Table 4.

3.5. Differences in gambling involvement and gambling-related risk factors between latent classes

While *gambling-* and *stock-traders* classes showed similar past-year gambling participation rates (nearly 100 %), their preferred gambling modalities differed significantly (p = .002). While 83.8 % (95 % CI: 59.4–94.8 %) of *gambling-traders* primarily mostly participated in online gambling, only 36.2 % (95 % CI: 25.2–48.9 %) of *stock-traders* reported this modality as their preferred gambling mode. Moreover, *gambling-traders* engaged in more gambling activities (mean = 3.6, SE = 0.4) and with a greater frequency, including a 7 % prevalence of daily gambling. This class also reported the highest levels of problem gambling severity (mean PGSI scores = 4.3, SE = 1.3, p < .001), with fewer rates of non-problem gambling (39.7 % [95 % CI: 16.1–69.4 %]) compared to *crypto-traders* (90 % [95 % CI: 83.5–94.1 %]; see Table 4). This latter class exhibited the lowest prevalence of engagement in gambling and gambling-like activities (41.6 % [95 % CI: 32.7–51 %], p < .001), and also exhibited a significantly lower prevalence of online gambling (38.8 % [26.6–52.6 %]) in comparison to *gambling-traders*.

A similar pattern of differences between latent classes was observed in the context of impulsivity scores and gambling-related cognitive biases (Table 5). *Gambling-traders* exhibited higher scores on all cognitive distortions assessed (p < .01), except for the erroneous beliefs regarding the self-correcting nature of chance, which scored similarly across three latent classes (p=.398). This group also reported higher levels of impulsivity compared to *crypto-* and *stock-traders* (p < .01), as indicated by the total UPPS-P score and scores in the following dimensions: negative urgency, lack of perseverance, and positive urgency. Additionally, lack of premeditation was also significantly higher in *gambling-traders* when compared to *stock-traders* (p=.008).

Rates of past-year alcohol, tobacco, and cannabis use were found to be similar across all three latent classes of retail investors (p > .05). However, the highest rates of cocaine and hallucinogen use were reported by those in *gambling-* and *crypto-traders* classes (p < .01). The prevalence of cocaine and hallucinogen use was 7 % (95 % CI: 2.9–15.7) and 3 % (95 % CI: 1.1–7.8), respectively, among *crypto-traders,* while 7 % of *gambling-traders* reported using both substances. In contrast, the proportion of *stock-traders* endorsing the use of these substances was almost zero (Table 5 presents complete data with weighted prevalences

Table 5
Gambling-related risk factors (weighted estimates) across latent classes (N = 403).

Variables	Gambling-traders (n = 63)	Crypto-traders (n = 211)	Stock-traders (n = 129)	Statistic (p)
Gambling-related cognitive distortions				
Total score	19 (0.6)[a]	15.4 (0.4)[b]	15.1 (0.6)[b]	8.166 (<0.001)**
Illusion of control	3.8 (0.2)[a]	2.9 (0.1)[b]	2.9 (0.1)[b]	5.656 (<0.001)**
Illusory correlation	3.9 (2.6)[a]	3.0 (0.1)[b]	3 (0.1)[b]	3.215 (0.004)**
Luck as responsible for outcomes	4.8 (0.2)[a]	4.1 (0.1)[b]	3.9 (0.2)[b]	4.145 (0.003)**
Self-correcting chance	2.3 (0.2)	2.2 (0.1)	2.1 (0.1)	0.660 (0.398)
Biased evaluation of outcomes	2.1 (0.1)[a]	1.5 (0.1)[b]	1.6 (0.1)[b]	4.589 (0.005)**
Outcome prediction	2.1 (0.1)[a]	1.7 (0.7)[b]	1.6 (0.1)[b]	3.191 (0.009)**
Impulsivity (UPPS-P)				
Total score	47.61 (1.4)[a]	41.5 (0.7)[b]	40.4 (0.9)[b]	8.221 (<0.001)**
Negative urgency	11 (0.5)[a]	9.2 (0.3)[b]	9.3 (0.4)[b]	3.170 (0.018)*
Lack of premeditation	7.4 (0.3)[a]	6.8 (0.2)[a,b]	6.4 (0.2)[b]	3.711 (0.008)**
Lack of perseverance	8 (0.4)[a]	7 (0.2)[b]	6.7 (0.2)[b]	3.803 (0.005)**
Sensation seeking	10.6 (0.5)	9.5 (0.3)	9.1 (0.3)	2.160 (0.051)
Positive urgency	10.6 (0.4)[a]	9 (0.2)[b]	8.9 (0.3)[b]	4.807 (0.001)**
Past-year substance use				
Alcohol	86.6 (70.3–94.6)	89.4 (83.4–93.4)	93.6 (86.3–97.1)	1.049 (0.345)
Tobacco	38.8 (19.1–62.9)	22.3 (14.9–32)	17.7 (11–27.3)	1.691 (0.185)
Cannabis	18.6 (7.1–40.7)	11.3 (6.6–18.8)	7.5 (3.2–16.4)	1.059 (0.344)
Cocaine	7.1 (1.9–22.8)	**7 (2.9–15.7)**	**0.2 (0–1.3)**	8.228 (<0.001)**
Hallucinogens	7.6 (2.2–23.1)	3 (1.1–7.8)	**0.2 (0–1.3)**	5.923 (0.005)**

Data are weighted means (standard errors) in continuous outcomes, and weighted percentages (95 % confidence intervals) in non-continuous outcomes. Weighted percentages are rounded and may not add up to 100 %.
Note: Different superscripts letters in the same row indicate significant differences in pairwise comparisons. Bold type indicates significant differences according to z-tests on the adjusted residuals (all based on Bonferroni-adjusted p-values).
*Significant at $p < 0.05$, **Significant at $p < 0.01$.

and 95 % confidence intervals).

4. Discussion

This study employed latent class analysis to examine trading and gambling behaviors among retail investors, identifying three distinct profiles: *crypto-traders*, *stock-traders*, and *gambling-traders*.

The majority of the sample was classified as *crypto-traders* (52.4 %), engaging primarily in cryptocurrency trading with minimal involvement in gambling, except for participation in lotteries. The *stock-traders* class (32 %) comprised amateur investors who primarily traded stocks and ETFs, with a high probability of participating in lotteries. The group of investors classified as *gambling-traders* (15.6 %) exhibited a diverse range of trading behaviors, engaging in high-risk assets such as Forex, commodities, and stocks, while also participating in a wide variety of gambling activities, including lottery, sports betting, bingo, and casino games. Notably, this was the only group that also reported participating in in-game activities with gambling components (e.g., loot boxes, skin betting), albeit with low probabilities. These findings align with previous research that identified cryptocurrencies and stocks as the most commonly traded assets among private investors.[47]

The *gambling-traders* group exhibited the most severe trading and gambling behaviors. While *stock-traders* reported the highest mean trade sizes, *gambling-traders* traded more frequently, preferred shorter holding periods, and monitored markets more intensively. Notably, despite their higher trading frequency, *gambling-traders* reported lower mean trade sizes, mirroring a behavior observed among frequent gamblers, who often place more frequent bets with smaller amounts of money.[48,49] Analogous trading patterns have also been observed amongst retail investors who fulfil the criteria for disordered trading, characterized by compulsive engagement and impaired control over trading activities, despite psychosocial and financial negative consequences. Consistent with this, almost 41 % of *gambling-traders* in our study met the criteria for disordered trading,[10,34] compared to fewer than 4 % in the other two classes.

Moreover, in line with previous studies, younger males were more prevalent in classes with higher probabilities of cryptocurrency trading and shorter holding periods.[14,18,47,50] Day trading was common across all three classes, but *gambling-traders* were the most likely to engage in this practice, with 97 % of individuals in this group reporting holding positions for less than one day. This short-term trading modality has been linked to problem gambling,[50,51] and recent research by Leslie et al.[18] concluded that many day traders are heavily involved traditional gamblers who combine day trading with their gambling activities. Our findings contribute to this body of literature by showing that *gambling-traders,* the group with the highest proportion of day traders, also reported the most intense and severe gambling behaviors.

The hypothesis that investors in this class are predominantly heavy gamblers who engage in an array of trading activities is further supported by other key findings. Although both *gambling-* and *crypto-traders* primarily engaged in cryptocurrency trading, their trading and gambling patterns differed, as did their rates of problem gambling. Previous research indicates that cryptocurrency traders are more likely to experience problem gambling than traders of other financial instruments.[2,52] However, our results suggest that there is no consistent correlation between cryptocurrency trading and problem gambling. The proportion of problem gamblers (PGSI scores $\geq$8) was significantly higher among *gambling-traders* (24.9 %) than *crypto-traders* (0.5 %), suggesting that the risk is greater when cryptocurrency trading is combined with other gambling activities. This aligns with previous findings where individuals who engaged in both cryptocurrency trading and sports betting were at a higher risk of problem gambling than those who engaged in only one of these activities.[17]

Interestingly, our study also demonstrates that higher rates of problem gambling cannot be exclusively attributed to the concurrent participation in both trading and gambling activities. While the proportion of gamblers was similar between *stock-* and *gambling-traders* (100 % and 96.5 %, respectively), *stock-traders* engaged in fewer gambling activities and with less frequency, exhibiting lower rates of problem gambling (3.5 %). Furthermore, *stock-traders* were predominantly land-based gamblers (63.8 %), similar to *crypto-traders* (61.2 %), while 83.8 % of *gambling-traders* preferred online gambling. These results align with previous studies suggesting that participation in online gambling may be an indicator of greater gambling involvement in general.[53] Our findings further support prior research suggesting that, akin to traditional gambling studies,[54,55] the number of gambling activities is associated with moderate-risk and problem gambling among day traders.[18] It also aligns with research suggesting that trading stocks had a lower addictive effect compared to cryptocurrencies, which *gambling-traders* primarily used.[47]

Additionally, *gambling-traders* reported lower income and higher gambling biases, and the highest levels of impulsivity and risky behaviors, such as illegal substance use. These findings are consistent with studies identifying elevated levels of these variables among high-risk and pathological traders.[2,10,18,56] Characteristics such as impulsivity and cognitive distortions are also well-known features of gambling disorder[19,55,57] and could potentially explain the higher prevalence of problem gambling in this group. Moreover, *gambling-traders* were the only group likely to engage in strategic gambling (e.g., sports betting, poker), which has been associated with younger age groups, and higher levels of impulsivity and cognitive biases.[57,58] Finally, it is noteworthy that both *crypto-* and *stock-traders* showed similar levels of cognitive distortions and impulsivity, despite *stock-traders* participating in more trading and gambling activities. In fact, *stock-traders* displayed the lowest average values in these gambling-related risk factors and exhibited more controlled gambling behaviors, which could also be partially explained by their older age.[54,59,60] This leads to the question of whether retail investors trading more traditional financial instruments, such as stocks, might employ more rational strategies and make lower-risk decisions, while those with risk-seeking tendencies and irrational beliefs might be more attracted to 'gamblified' financial products, such as cryptocurrencies, with higher levels of risk and volatility.[47,61] Future research on the rationality and decision-making of speculative investors, using instruments such as the Iowa Gambling Task, may be useful in addressing this subject.

This study has several limitations that warrant consideration. The cross-sectional design of the study precludes causal inferences about the relationship between problem gambling and trading behaviors. Moreover, given the volatility of financial markets and the fluctuations in the popularity of specific financial assets, longitudinal research is needed to explore whether the profiles identified in this study are influenced by market conditions or the timing of data collection. Self-reported data may also be influenced by recall and social desirability biases. Additionally, participants were recruited from an online panel, which may differ from non-panel members in terms of higher Internet use, education levels and socioeconomic status.[62] Nevertheless, respondents were weighted to match the Spanish population and national proportions of trading and gambling behaviors, based on the findings of a previous population-based random telephone survey.[27] Finally, the smaller sample size of the *gambling-traders* group resulted in wider confidence intervals and large standard errors, highlighting the need for replication with larger samples to increase the precision of estimates.

To our knowledge, this is the first study to identify distinct profiles of retail investors engaging in trading and gambling behaviors, using a representative sample. Despite the structural parallels between trading and gambling, not all investors seem to approach trading in a manner resembling gambling.[17] Investors who exhibited such behavior primarily combined cryptocurrency trading with multiple gambling activities, and showed differences in cognitive factors, personality traits, and demographic characteristics compared to other investors. Further longitudinal studies are necessary to confirm these findings, but our results provide robust evidence to help characterize investors who gamble in financial markets and to identify those at heightened risk of problem gambling.

Author statements

Ethical approval

Committee of Research and Ethics of Miguel Hernández University (Reference: DPP.ACC.01.21).

Funding

This project has been funded by the Social Observatory of the "La Caixa" Foundation [Ref. No. LCF/PR/FS21/60000002]. All authors of the manuscript are part of the GamerVictim research network funded by the PROMETEO Program 2023 [CIPROM/2022/33].

Competing interests

None.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.puhe.2025.105742.

References

1. Andrade M, Newall PWS. Cryptocurrencies as gamblified financial assets and cryptocasinos: novel risks for a public health approach to gambling. *Risks*. 2023;11(3):49. https://doi.org/10.3390/risks11030049.
2. Oksanen A, Mantere E, Vuorinen I, Savolainen I. Gambling and online trading: emerging risks of real-time stock and cryptocurrency trading platforms. *Public Health*. 2022;205:72–78. https://doi.org/10.1016/j.puhe.2022.01.027.
3. Torrance J, Heath C, Andrade M, Newall P. Gambling, cryptocurrency, and financial trading app marketing in English Premier League football: a frequency analysis of in-game logos. *J Behav Addict*. 2023;12(4):972–982. https://doi.org/10.1556/2006.2023.00066.
4. Newall PWS, Xiao LY. Gambling marketing bans in professional sports neglect the risks posed by financial trading apps and cryptocurrencies. *Gaming Law Rev*. 2021;25(9):376–378. https://doi.org/10.1089/glr2.2021.0027.
5. Sattarov O, Muminov A, Lee CW, et al. Recommending cryptocurrency trading points with deep reinforcement learning approach. *Appl Sci*. 2020;10(4):1506. https://doi.org/10.3390/app10041506.
6. Arthur JN, Williams RJ, Delfabbro PH. The conceptual and empirical relationship between gambling, investing, and speculation. *J Behav Addict*. 2016;5(4):580–591. https://doi.org/10.1556/2006.5.2016.084.
7. Mosbey A, Delfabbro P, King D. The harmful consequences of cryptocurrency speculation and associated risk factors. *Int J Ment Health Addiction*. 2024. https://doi.org/10.1007/s11469-024-01405-x. Published online October 17.
8. Delfabbro P, King D. The evolution of young gambling studies: digital convergence of gaming, gambling and cryptocurrency technologies. *Int Gambl Stud*. 2023;23(3):491–504. https://doi.org/10.1080/14459795.2023.2171469.
9. Roza TH, Tavares H, Kessler FHP, Passos IC. Problematic trading: gambling-like behavior in day trading and cryptocurrency investing. *Trends Psychiatr Psychother*. 2024;46, e20230623. https://doi.org/10.47626/2237-6089-2023-0623.
10. Coloma-Carmona A, Carballo JL, Miró-Llinares FC, Aguerri J, Griffiths MD. Development and validation of the Trading Disorder Scale for assessing problematic trading behaviors. *J Behav Addict.*. 2025 https://doi.org/10.1556/2006.2025.00019. Published online March 24.
11. Mills DJ, Nower L. Preliminary findings on cryptocurrency trading among regular gamblers: a new risk for problem gambling? *Addict Behav*. 2019;92:136–140. https://doi.org/10.1016/j.addbeh.2019.01.005.
12. Coloma-Carmona A, Carballo JL, Sancho-Domingo C, Rodríguez-Espinosa S, Miró-Llinares FC, Aguerri J. Engagement in new gambling practices and its association with gambling disorder, impulsivity, and cognitive distortions: findings from a nationally representative sample of Spanish gamblers. *J Gambl Stud*. 2024. https://doi.org/10.1007/s10899-024-10361-z. Published online October 7.
13. Heinen R. *Personality Traits and Crypto Market Participation*. Radboud Universiteit; 2022.
14. Johnson B, Co S, Sun T, et al. Cryptocurrency trading and its associations with gambling and mental health: a scoping review. *Addict Behav*. 2023;136, 107504. https://doi.org/10.1016/j.addbeh.2022.107504.
15. Plieger T, Grünhage T, Duke É, Reuter M. Predicting stock market performance: the influence of gender and personality on financial decision making. *J Indiv Differ*. 2021;42(2):64–73. https://doi.org/10.1027/1614-0001/a000330.
16. Cox R, Kamolsareeratana A, Kouwenberg R. Compulsive gambling in the financial markets: evidence from two investor surveys. *J Bank Finance*. 2020;111, 105709. https://doi.org/10.1016/j.jbankfin.2019.105709.
17. Delfabbro P, King D, Williams J, Georgiou N. Cryptocurrency trading, gambling and problem gambling. *Addict Behav*. 2021;122, 107021. https://doi.org/10.1016/j.addbeh.2021.107021.
18. Leslie RD, Shaw CA, McGrath DS. Correlates of gambling behaviours among day traders: evidence from a national study. *J Gambl Stud*. 2025;41(1):51–66. https://doi.org/10.1007/s10899-024-10314-6.
19. Otis E, Yakovenko I, Sherry S, et al. Applicability of the four-factor personality vulnerability model for substance misuse in understanding gambling behaviour and gambling problems. *Pers Indiv Differ*. 2021;169, 110400. https://doi.org/10.1016/j.paid.2020.110400.
20. Gao X, Lin TC. Do individual investors treat trading as a fun and exciting gambling activity? Evidence from repeated natural experiments. *Rev Financ Stud*. 2015;28(7):2128–2166. https://doi.org/10.1093/rfs/hhu075.
21. Guzmán A, Pinto-Gutiérrez C, Trujillo MA. Trading cryptocurrencies as a pandemic pastime: COVID-19 lockdowns and bitcoin volume. *Mathematics*. 2021;9(15):1771. https://doi.org/10.3390/math9151771.
22. Mosenhauer M, Newall PWS, Walasek L. The stock market as a casino: associations between stock market trading frequency and problem gambling. *J Behav Addict*. 2021;10(3):683–689. https://doi.org/10.1556/2006.2021.00058.
23. Prachayanant P, Kraiwanit T, Chutipat V. Cryptocurrency gamification: having fun or making money. *J Govern Regul*. 2023;12(2):184–193. https://doi.org/10.22495/jgrv12i2art17.
24. Kamolsareeratana A, Kouwenberg R. Compulsive gambling in the stock market: evidence from an emerging market. *Economies*. 2023;11(1):28. https://doi.org/10.3390/economies11010028.
25. Dorn AJ, Dorn D, Sengmueller P. Trading as gambling. *Manag Sci*. 2015;61(10):2376–2393. https://doi.org/10.1287/mnsc.2014.1979.
26. Chiah M, Zhong A. Trading from home: the impact of COVID-19 on trading volume around the world. *Finance Res Lett*. 2020;37, 101784. https://doi.org/10.1016/j.frl.2020.101784.
27. Coloma-Carmona A, Carballo JL, Miró-Llinares FC, Aguerri J. *Place Your Investments or Place Your Bets? Relationship between Gambling Addiction and Trading.* The Social Observatory - La Caixa Foundation; April 2024. Published online https://elobservatoriosocial.fundacionlacaixa.org/en/-/invertimos-o-apostamos-relacion-entre-la-adiccion-al-juego-y-las-inversiones.
28. Comisión Nacional del Mercado de Valores. *Estudio Sobre Las Criptomonedas y La Efectividad de Las Medidas Impulsadas Por La CNMV*. Comisión Nacional del Mercado de Valores; 2022. https://www.cnmv.es/portal/verDoc.axd?t=%7B714e1e4c-b334-4252-b1f5-677cf438bcb5%7D. Accessed March 20, 2025.
29. Lanza ST, Flaherty BP, Collins LM. Latent class and latent transition analysis. In: Schinka JA, Velicer WF, eds. *Handbook of Psychology: Research Methods in Psychology*. vol. 2. John Wiley & Sons, Inc.; 2003:663–685. https://doi.org/10.1002/0471264385.wei0226.
30. Fonseca-Pedrero E, Paíno-Piñeiro M, Lemos-Giráldez S, Villazón-García U, Muñiz J. Validation of the schizotypal personality questionnaire-brief form in adolescents. *Schizophr Res*. 2009;111(1-3):53–60. https://doi.org/10.1016/j.schres.2009.03.006.
31. Fonseca-Pedrero E, Menéndez LF, Paino M, Lemos-Giráldez S, Muñiz J. Development of a computerized adaptive test for schizotypy assessment. *PLoS One*. 2013;8(9), e73201. https://doi.org/10.1371/journal.pone.0073201.
32. Chapman L.J., Chapman J.P. Infrequency scale. Published online. https://scholar.google.com/scholar_lookup?title=Infrequency%20scale&author=L.%20J.%20Chapman&author=J.%20P.%20Chapman&publication_year=1983, 1983. [Accessed 21 March 2025].
33. Fonseca-Pedrero E, Gooding DC, Ortuño-Sierra J, Paino M. Assessing self-reported clinical high risk symptoms in community-derived adolescents: a psychometric evaluation of the Prodromal Questionnaire-Brief. *Compr Psychiatry*. 2016;66:201–208. https://doi.org/10.1016/j.comppsych.2016.01.013.
34. Guglielmo R, Ioime L, Janiri L. Is pathological trading an overlooked form of addiction? *Addict Health*. 2016;8(3):207–209.
35. Zendle D. Beyond loot boxes: a variety of gambling-like practices in video games are linked to both problem gambling and disordered gaming. *PeerJ*. 2020;8, e9466. https://doi.org/10.7717/peerj.9466.
36. Ferris J, Wynne H. *The Canadian Problem Gambling Index: Final Report*. Canadian Centre on Substance Abuse. Canadian Consortium for Gambling Research; 2001.
37. Lopez-Gonzalez H, Estévez A, Griffiths MD. Spanish validation of the Problem Gambling Severity Index: a confirmatory factor analysis with sports bettors. *J Behav Addict*. 2018;7(3):814–820. https://doi.org/10.1556/2006.7.2018.84.
38. Browne M, Delfabbro P, Thorne HB, et al. Unambiguous evidence that over half of gambling problems in Australia are caused by electronic gambling machines: results from a large-scale composite population study. *J Behav Addict*. 2023;12(1):182–193. https://doi.org/10.1556/2006.2022.00083.
39. Labrador M, Labrador FJ, Crespo M, Echeburúa E, Becoña E. Cognitive distortions in gamblers and non-gamblers of a representative Spanish sample. *J Gambl Stud*. 2020;36(1):207–222. https://doi.org/10.1007/s10899-019-09870-z.
40. Billieux J, Rochat L, Ceschi G, et al. Validation of a short French version of the UPPS-P impulsive behavior scale. *Compr Psychiatry*. 2012;53(5):609–615. https://doi.org/10.1016/j.comppsych.2011.09.001.
41. Cándido A, Orduña E, Perales JC, Verdejo-García A, Billieux J. Validation of a short Spanish version of the UPPS-P impulsive behaviour scale. *Trastor Adict*. 2012;14(3):73–78. https://doi.org/10.1016/S1575-0973(12)70048-X.
42. Spanish Observatory on Drugs and Addictions. Report 2023. Alcohol, Tobacco and Illegal Drugs in Spain. Ministerio de Sanidad. Delegación del Gobierno para el Plan

Nacional sobre Drogas, 270 https://pnsd.sanidad.gob.es/profesionales/sistemasInformacion/sistemaInformacion/pdf/2022_Informe_EDADES.pdf; 2023.
43. Muthén LK, Muthén BO. *Mplus User's Guide*. eighth ed. Muthén & Muthén; 2017.
44. Nylund KL, Asparouhov T, Muthén BO. Deciding on the number of classes in latent class analysis and growth mixture modeling: a Monte Carlo simulation study. *Struct Equ Model: A Multidiscip J*. 2007;14(4):535–569. https://doi.org/10.1080/10705510701575396.
45. Tein JY, Coxe S, Cham H. Statistical power to detect the correct number of classes in latent profile analysis. *Struct Equ Model*. 2013;20(4):640–657. https://doi.org/10.1080/10705511.2013.824781.
46. Rao JNK, Scott AJ. On simple adjustments to Chi-Square tests with sample survey data. *Ann Stat*. 1987;15(1):385–397.
47. Kim H. An empirical analysis of navigation behaviors across stock and cryptocurrency trading platforms: implications for targeting and segmentation strategies. *Electron Commer Res*. 2024;24(3):2113–2141. https://doi.org/10.1007/s10660-022-09612-1.
48. Gainsbury S, Sadeque S, Mizerski D, Blaszczynski A. Wagering in Australia: a retrospective behavioural analysis of betting patterns based on player account data. *Journal of Gambling Business and Economics*. 2012;6(2):50–68.
49. Petry NM, ed. *Behavioral Addictions: DSM-5 and beyond*. Oxford University Press; 2016.
50. Arthur JN, Delfabbro P. Day traders in South Australia: similarities and differences with traditional gamblers. *J Gambl Stud*. 2017;33(3):855–866. https://doi.org/10.1007/s10899-016-9659-x.
51. Arthur J, Delfabbro P, Williams R. Is there A relationship between participation in gambling activities and participation in high-risk stock trading? *Journal of Gambling Business and Economics*. 2015;9(3):34–53.
52. Kim HJ, Hong JS, Hwang HC, Kim SM, Han DH. Comparison of psychological status and investment style between bitcoin investors and share investors. *Front Psychol*. 2020;11, 502295. https://doi.org/10.3389/fpsyg.2020.502295.
53. Hing N, Russell AM, Browne M. Risk factors for gambling problems on online electronic gaming machines, race betting and sports betting. *Front Psychol*. 2017;8:779. https://doi.org/10.3389/fpsyg.2017.00779.
54. Dowling NA, Merkouris SS, Greenwood CJ, Oldenhof E, Toumbourou JW, Youssef GJ. Early risk and protective factors for problem gambling: a systematic review and meta-analysis of longitudinal studies. *Clin Psychol Rev*. 2017;51:109–124. https://doi.org/10.1016/j.cpr.2016.10.008.
55. Moreira D, Azeredo A, Dias P. Risk factors for gambling disorder: a systematic review. *J Gambl Stud*. 2023;39(2):483–511. https://doi.org/10.1007/s10899-023-10195-1.
56. Sonkurt HO, Altınöz AE. Cryptocurrency investment: a safe venture or a new type of gambling? *Journal of Gambling Issues*. 2021:199–216. https://doi.org/10.4309/jgi.2021.47.8. Published online July 21.
57. Mallorquí-Bagué N, Vintró-Alcaraz C, Verdejo-García A, et al. Impulsivity and cognitive distortions in different clinical phenotypes of gambling disorder: profiles and longitudinal prediction of treatment outcomes. *Eur Psychiatry*. 2019;61:9–16. https://doi.org/10.1016/j.eurpsy.2019.06.006.
58. Navas JF, Billieux Joël, Perandrés-Gómez Ana, et al. Impulsivity traits and gambling cognitions associated with gambling preferences and clinical status. *Int Gambl Stud*. 2017;17(1):102–124. https://doi.org/10.1080/14459795.2016.1275739.
59. Hodgins DC, Holub A. Components of impulsivity in gambling disorder. *Int J Ment Health Addict*. 2015;13(6):699–711. https://doi.org/10.1007/s11469-015-9572-z.
60. Krotter A, Secades-Villa R, Iza-Fernández C, González-Roz A. Risk factors of at-risk/problem gambling among young adult Spanish students. *J of Prevention*. November 21, 2024. https://doi.org/10.1007/s10935-024-00814-x. Published online.
61. Newall PWS, Weiss-Cohen L. The gamblification of investing: how a new generation of investors is being born to lose. *Int J Environ Res Public Health*. 2022;19(9):5391. https://doi.org/10.3390/ijerph19095391.
62. Hays RD, Liu H, Kapteyn A. Use of Internet panels to conduct surveys. *Behav Res Methods*. 2015;47(3):685–690. https://doi.org/10.3758/s13428-015-0617-9.