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Development and validation of the Trading Disorder Scale for assessing problematic trading behaviors

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ABSTRACT

Background and Aims: There is growing evidence regarding the overlap between trading behaviors and gambling. However, problematic trading behaviors are often assessed using gambling-related instruments, which may not fully capture the nuances of trading. The present study developed and evaluated the psychometric properties of the Trading Disorder Scale (TDS), grounded in in the research criteria proposed by Guglielmo et al. (2016), based on DSM-5 criteria for gambling disorder and internet gaming disorder. *Methods:* A cross-sectional survey was administered to 403 Spanish amateur traders. The TDS was tested for reliability, validity, and factorial structure. Latent class analysis (LCA) was used to identify patterns of disordered trading. *Results:* EFA and CFA supported a one-factor solution for the TDS, which showed strong internal consistency ($\omega_{u\text{-cat}} = 0.938$, KR-20 = 0.877). The scale showed good concurrent validity with PGSI ($r = 0.559$) and good convergent validity with trading-related variables. LCA identified three classes: non-disordered trading (72.2%), at-risk trading (17.6%), and disordered trading (10.2%). Individuals in the disordered trading group scored higher on TDS, traded more frequently, monitored markets more intensively, and exhibited higher rates of problem gambling (PGSI≥5), impulsivity, and substance use. Guglielmo's cut-off point (≥5 criteria) effectively differentiated individuals with disordered trading behaviors from those at-risk and those without disordered trading. *Conclusions:* The TDS is a reliable and valid instrument for assessing disordered trading among amateur investors. Further research is needed to explore the scale's predictive validity.

KEYWORDS

behavioral addiction, gambling, trading addiction, cryptocurrency, stock market trading, psychometric evaluation

INTRODUCTION

The expansion of online trading platforms has significantly increased access to a wide range of financial activities, from traditional stock investments to highly speculative investments such as cryptocurrencies (Campino & Yang, 2024; Kamolsareeratana & Kouwenberg, 2023; Oksanen, Mantere, Vuorinen, & Savolainen, 2022; Senarathne, 2019). This marked increase in platform availability, coupled with extensive advertising campaigns, has resulted in a sharp rise in the number of individuals engaging in non-professional trading activities

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(Andrade & Newall, 2023; Chong, Ong, & Tan, 2021; Griffiths, 2018; Johnson, Co, et al., 2023; Lee, Lewis, & Mills, 2023; Oksanen, Mantere, et al., 2022; Torrance, Heath, Andrade, & Newall, 2023).

While trading offers opportunities for financial gain, it has also raised concerns due to its speculative nature, short-term profit-seeking, and rapid transactions, sometimes completed within the same day, which bear striking similarities to gambling behaviors (Arthur, Williams, & Delfabbro, 2016; Delfabbro, King, & Williams, 2021; Mosenhauer, Newall, & Walasek, 2021). The financial market as a space for risky gambling behavior is not a novel concept. The South Oaks Gambling Screen (SOGS; Lesieur & Blume, 1987), one of the most widely used tools for assessing problem gambling, includes an item specifically addressing gambling on the stock and commodities market. However, an increasing body of evidence now links trading, particularly in high-risk assets, to gambling disorder (Johnson, Co, et al., 2023; Lee et al., 2023).

Both trading and gambling share key structural characteristics, including high levels of risk, uncertainty, and the potential for significant financial losses (Arthur et al., 2016; Delfabbro, King, & Williams, 2021; Delfabbro, King, Williams, & Georgiou, 2021; Oksanen, Mantere, et al., 2022). Previous studies have suggested that some investors view trading as form of entertainment, either as a substitute for or an extension of traditional gambling (Guzmán, Pinto-Gutiérrez, & Trujillo, 2021; Huang et al., 2022; Mosenhauer et al., 2021; Prachayanant, Kraiwanit, & Chutipat, 2023; Weidner, 2022). This overlap has led to concerns about excessive involvement in trading, which has been found to be strongly correlated with disordered gambling, both in terms of behavioral similarities and the profiles of individuals engaging in these activities (Coloma-Carmona et al., 2024; Grall-Bronnec et al., 2017; Johnson, Co, et al., 2023; Oksanen, Hagfors, Vuorinen, & Savolainen, 2022; Steinmetz, 2023; Sudzina, Dobes, & Pavlicek, 2023). However, problematic trading behavior has largely been analyzed through the lens of its relationship with gambling disorder, using gambling-related tools or criteria that were not fully adapted or validated for the trading context (Arthur & Delfabbro, 2017; Cox, Kamolsareeratana, & Kouwenberg, 2020; Delfabbro, King, & Williams, 2021; Grall-Bronnec et al., 2017; Granero et al., 2012; Shin, Choi, Ha, Choi, & Kim, 2015).

To address this gap, Guglielmo, Ioime, and Janiri (2016) proposed 13 research criteria for disordered trading, primarily based on the DSM-5 criteria for gambling disorder (APA, 2013). These criteria capture maladaptive and recurrent trading behaviors that negatively impact personal, familiar, and professional life, including symptoms such as loss of control, chasing losses, tolerance, and withdrawal. Additionally, Guglielmo et al. included symptoms such as sleep disturbances and suicidal ideation, observed in both amateur and professional investors (Guglielmo et al., 2016; Johnson, Sun, Stjepanović, Vu, & Chan, 2023; Koh & Han, 2023). While these symptoms are not part of the standard DSM-5 gambling diagnosis, they align with the components model of addiction (Griffiths, 2005), which outlines six core components of addictive behavior: salience, mood modification, tolerance, withdrawal symptoms, conflict, and relapse (Table 1).

Although Guglielmo's criteria have been cited in multiple studies on disordered trading (Johnson, Co, et al., 2023; Roza, Tavares, Kessler, & Passos, 2024; Sonkurt & Altınöz, 2021; Turan, Kokaçya, Yılmaz, & Arı, 2024; Vismara, Caricasole, Varinelli, & Fineberg, 2022; Yığman, Bora Nazlı, & Yılmaz, 2023; Şentürk, Coşar, & Arikan, 2023), they have not yet been formalized into a validated assessment tool. Furthermore, the proposed diagnostic threshold (i.e., meeting five or more criteria) has not been empirically tested for its accuracy in identifying truly problematic trading behaviors.

In contrast, more recent tools such as the Stock Addiction Index (Youn, Choi, Kim, & Choi, 2016) and the Problematic Cryptocurrency Trading Scale (Mentes, Yolbas, & Bulut, 2021) have adapted existing measures such as the Problem Gambling Severity Index (PGSI; Ferris & Wynne, 2001), to assess problematic trading behaviors. However, these instruments were designed for specific financial assets, such as cryptocurrencies (Mentes et al., 2021), or specific investor groups, such as stock traders (Youn et al., 2016), without accounting for whether the sample comprised professional or amateur investors. Amateur investors have experienced the most significant growth in recent years and are more likely to use mobile trading apps, which increase accessibility and can lead to excessive involvement in trading activities (Davies & Ferris, 2022; Newall & Weiss-Cohen, 2022; Weiss-Cohen et al., 2024). Furthermore, those with limited experience in trading often suffer the most adverse consequences and financial losses as a result of their involvement in trading activities (Khan, 2022). Therefore, there remains a need for instruments applicable across various financial assets and investor profiles, particularly in the context of retail investors. Moreover, neither of the existing scales provide a clear cut-off point for identifying problematic trading behaviors.

Consequently, the present study developed and validated a scale based on Guglielmo's criteria for disordered trading among a sample of amateur investors involved in trading of different financial assets (e.g., cryptocurrencies, Forex, exchange-traded funds). The study examined the scale's factor structure, internal consistency, and validity (concurrent and convergent), as well as its ability to distinguish different levels of trading severity using a latent class analysis approach.

METHODS

Participants and procedure

The sample comprised 403 amateur investors, the majority of whom were male (65.3%, $n = 263$) and highly educated, with 60.8% ($n = 245$) having completed university-level studies. The average age of participants was 38.44 years

Table 1. Components evaluated according to the criteria proposed by Guglielmo (2016) for disordered trading

	DSM-5 criteria for gambling disorder[a] and internet gaming disorder[b]	Addiction components model (Griffiths, 2005)
1. Have you often found your mind occupied with investment and/or trading activities (e.g., reliving past investment experiences, analyzing, or planning the next investment, reading literature or online forums related to the financial world, making investments/trading the main activity of your daily life)?	Preoccupation[a.b]	Salience (cognitive)
2. Have you felt the need to invest and/or trade increasingly larger amounts of money to achieve the desired excitement?	Tolerance[a]	Tolerance
3. Have you felt the need to spend more and more time making investments/trading and/or looking for new financial instruments to invest in?	Tolerance[b]	Tolerance
4. Have you been nervous or irritable when you tried to reduce or stop investing and/or trading?	Withdrawal[a.b]	Withdrawal
5. Has your sleep pattern been disrupted by investment and/or trading activities (e.g., staying up at night to be online at the opening of foreign financial markets)?	–	Salience (behavioral)
6. Have you made repeated efforts to control, reduce, or stop investing and/or trading, always without succeeding?	Loss of control[a.b]	Relapse
7. Except for investments and/or trading, have you lost interest in social and/or recreational activities that you previously enjoyed because of investments/trading?	Decrease in other activities[b]	Conflict (with other activities)
8. Have you often invested and/or traded when you felt distressed (e.g., helplessness, guilt, anxiety, depression)?	Trading when feeling distressed[a.b]	Mood modification
9. After losing money in investments and/or trading, have you immediately or another day invested again to try to recover the losses?	Chasing losses[a]	Relapse
10. Have you lied to conceal your level of involvement with investments and/or trading (e.g., lying about financial losses, only talking about investments where you made money)?	Lie/Deception[a.b]	Conflict (interpersonal)
11. Have you jeopardized or lost an important relationship, your job, or opportunities in your studies or career because of investments and/or trading activities?	Jeopardized or lost significant matters[a.b]	Conflict (with other activities)
12. Do you rely on others to give you money to relieve your desperate financial situation caused by investments and/or trading?	Relying on others financially[a]	Conflict (interpersonal)
13. Due to investments and/or trading, have you had thoughts about taking your own life, with or without planning, or have you attempted to take your own life?	–	Conflict (intra-psychic)

Note: Superscript letters indicate which DSM-5 criteria for [a]Gambling Disorder and [b]Internet Gaming Disorder correspond to each item. The relationship between items and Griffiths' components model of behavioral addictions (2005) is also displayed in the table.

(SD = 12.9). The most frequently reported trading activities included cryptocurrency trading (47.9%, $n = 193$), stock market investments (44.7%, $n = 180$), and trading in exchange-traded funds (ETFs; 22.8%, $n = 92$). Engagement in higher-risk trading activities such as commodities (16.6%, $n = 67$), Forex (9.7%, $n = 39$), futures (8.7%, $n = 35$), contracts for difference (CFDs; 5.2%, $n = 21$), and options (5%, $n = 20$) was less frequent. Supplementary Table S1 provides more detailed information on the sample characteristics based on the study variables.

The sample was derived from a larger set of 1,429 Spanish individuals who completed an online cross-sectional survey conducted between March 24 and April 22, 2022. This broader sample was recruited through an online panel managed by an independent research agency. The sample's representativeness was ensured by setting quotas based on age, gender, geographic region, and population size of the participants' living area. To confirm feasibility and refine the survey, a pretest was conducted with 100 individuals, confirming that the average survey completion time was 25 minutes.

A total of 8,549 invitations were sent to adults aged 18–64 years residing in Spain. Of these, 3,749 individuals initiated the survey after reviewing the study's aims and providing informed consent. To ensure data validity and reliability, several quality control procedures were applied. Out of the 3,749 initial respondents, 2,320 were excluded due to incomplete responses, unusually short completion times, exceeding predefined quotas, data inconsistencies, or evidence of automated response patterns. Additionally, respondents scoring higher than 3 on the Oviedo Infrequency Scale (Fonseca-Pedrero, Paíno-Piñeiro, Lemos-Giráldez, Villazón-García, & Muñiz, 2009) were excluded to avoid random or inattentive responses. Following these exclusions, 1,429 valid responses remained, yielding a maximum margin of error of 3.2% with a confidence level of 95.5% ($Z = 1.96$). Of these, 409 participants reported engaging in financial trading within the past 12 months. Six professional traders were excluded from the analysis because the study focused solely on amateur investors, resulting in a final sample of 403 amateur traders. This sample size was sufficient for factor analysis and estimating IRT parameters (Edelen & Reeve, 2007; Guadagnoli & Velicer, 1988; Muñiz & Fonseca-Pedrero, 2019).

Measures

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

Trading Disorder Scale (TDS). The Trading Disorder Scale was developed based on the 13 criteria proposed by Guglielmo et al. (2016) for assessing disordered trading behaviors. Following the International Test Commission guidelines (Muñiz, Elosua, & Hambleton, 2013), the criteria were translated into Spanish, after which a back-translation into English was performed. No significant discrepancies were identified between the original and back-translated versions, confirming the accuracy of the translation. Each criterion was presented as a checklist, with participants providing ‘yes/no’ responses to indicate whether they had experienced each symptom over the past 12 months (see Appendix A and B). Participants endorsing five or more criteria were classified as exhibiting disordered trading behaviors (Guglielmo et al., 2016).

Other trading-related variables. Participants reported their engagement in financial trading over the past year for various assets: Forex, cryptocurrencies, commodities, exchange-traded funds (ETFs), contracts for difference (CFDs), futures, options, and stock market investments. Based on items proposed by Delfabbro King, Williams, et al. (2021), they indicated trading frequency on a six-point Likert scale (ranging from “less than monthly” to “daily”). The highest reported frequency was used to categorize participants as less than monthly, monthly, weekly, or daily traders.

Additional data collected included hours spent researching or analyzing markets daily, frequency of checking market data during trading days, and mean trade size in euros (i.e., the average amount of money invested per trade across all traded assets). The preferred time frame for trades (i.e., the length of time – measured in seconds, hours, days, or weeks/months-, that an investor retains ownership of a specific financial asset, also known as holding position) was also collected. Participants were categorized based on the financial asset they held for the shortest period. Moreover, they were asked to indicate whether they engaged in trading as professional or as retail investors.

Gambling-related variables and psychological correlates. Participants were also asked to provide information regarding their participation in gambling activities during the preceding 12 months. These activities included buying lottery tickets/scratch-cards, sports betting, horse race betting, slot machine gambling, card game gambling (e.g., poker), playing bingo, playing casino games, and contests involving monetary bets (Spanish Observatory on Drugs and Addictions, 2023). The Problem Gambling Severity Index (PGSI; Ferris & Wynne, 2001) was administered to evaluate the severity of gambling problems, using the nine-item Spanish version (Lopez-González, Estévez, & Griffiths, 2018). This version has demonstrated robust reliability ($\alpha_{ordinal}$ = 0.97) and convergent validity with DSM-IV scores ($r = 0.77$). A cut-off score of ≥5 was applied to identify individuals with problem gambling (Williams & Volberg, 2014) and those with a PGSI score of 0-4 were classed as non-problem gamblers. Impulsivity was assessed using the Spanish version of the UPPS-P scale (Billieux et al., 2012; Cándido, Orduña, Perales, Verdejo-García, & Billieux, 2012), which evaluates five dimensions of impulsivity across 20 items. A total score for general impulsivity was also computed, with higher scores indicating greater levels of impulsivity. Substance use in the past year, including alcohol, tobacco, cannabis, cocaine, and hallucinogens, was assessed through binary items (yes/no).

Statistical analysis

Statistical analysis was conducted using SPSS v.27, R packages *misty* and *DescTools* and Mplus v.8.8 (Muthén & Muthén, 2017).

Descriptive analysis. Descriptive statistics (frequencies, percentages, means, and standard deviations) were calculated to analyze participants’ demographics and the endorsement rates of items on the TDS.

Structure validity. To assess the factor structure of the TDS, the dataset ($N = 403$) was randomly split into two groups. Exploratory factor analysis (EFA) was conducted on the first group ($n = 191$) using the Weighted Least Square Mean and Variance Adjusted (WLSMV) estimator with Geomin oblique rotation, assuming correlation among factors. Given that χ^2 statistic is sensitive to sample size, multiple criteria were used to determine the number of factors to retain, including eigenvalues greater than one, Root Mean Square Error of Approximation (RMSEA) with its 90% Confidence Interval (CI), Comparative Fit Index (CFI), and Tucker–Lewis index (TLI). Standardized Root Mean Square Residuals (SRMR) performance has been found to be inconsistent with binary data, therefore it is not reported. Instead, RMSEA, CFI, and TLI were prioritized for model evaluation (Yu, 2002). The best factor solution was selected based on pattern of standardized factor loadings (λ), interpretability of the factor solution, and overall fit indices. Strong primary factor loadings were defined as $\lambda \geq 0.40$, with cross-loadings above 0.30 being problematic (Brown, 2015).

Inferential model comparisons were also performed using the chi-square difference test ($\Delta\chi^2$). A p-value below 0.05 indicated a significant difference between models, suggesting that the more complex model provides a significantly better fit. Confirmatory factor analysis (CFA) on the second group’s data ($n = 212$) evaluated the hypothesized model, using the following thresholds for good model fit: RMSEA <0.05, CFI >0.95, and TLI >0.95 (Hu & Bentler, 1999).

Reliability, concurrent validity, and convergent validity. Reliability of the TDS was assessed using both Classical Test Theory and Item Response Theory (IRT) frameworks. Internal consistency was assessed with Kuder Richardson Formula 20 (KR-20) and McDonalds' categorical omega ($\omega_{u\text{-cat}}$) coefficients, with values > 0.70 indicating acceptable reliability (Nunnally & Bernstein, 1994). Corrected item-total correlations were computed to evaluate item quality, adjusting for item overlap. Based on Ebel and Frisbie (1991), item discrimination was categorized as excellent (≥0.40), good (0.30–0.39), acceptable (0.20–0.29), or poor (<0.20). From the IRT perspective, item discrimination (*a*) and difficulty (*b*) were estimated. Discrimination values (ranging 0–3) reflected how well items differentiated between individuals with different levels of disordered trading behavior. Following Kim and Baker (2018), discrimination levels were classified as very low (<0.34), low (0.35–0.64), moderate (0.65–1.34), high (1.35–1.69), and very high (≥1.70). Difficulty parameters, typically ranging from −3 to 3, indicate the level of the trait required for a 50% chance of endorsing the item. Higher difficulty values indicate that a greater severity of disordered trading is necessary to endorse the item.

Concurrent and convergent validity of the TDS were assessed with Pearson's *r* for continuous variables and Spearman's ρ correlations for ordinal variables. Correlations were calculated between the TDS, the PGSI, and various trading-related variables, including past-year frequency of trading, number of assets traded, hours spent daily studying markets, frequency of daily market monitoring, preferred time frame for trading, and mean trade size values (i.e., average amount of money invested per trade). Correlation strengths were interpreted as small ($r/\rho < 0.30$), moderate ($r/\rho = 0.30$–0.49), or large ($r/\rho \geq 0.50$), according to Cohen's (1988) guidelines.

Latent class analysis. Latent class analysis (LCA) was conducted to determine whether the scale effectively captured distinct patterns of disordered trading behaviors among amateur investors. Optimal number of latent classes was determined based on (i) log-likelihood values, with higher values indicating a better model fit; (ii) the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), and Sample-size Adjusted BIC (SABIC), where lower values suggest a better model fit and parsimony; and (iii) the *p*-values of the Vuong-Lo-Mendell-Rubin LRT, and Adjusted Lo-Mendell-Rubin LRT that compare model with k classes and k-1 classes, where a *p*-value below 0.05 indicates that solution with the one fewer class should be rejected. Although the bootstrapped LRT (BLRT) *p*-values were reported, they were not considered because previous studies have demonstrated that BLRT may favor models with more classes (Sinha, Calfee, & Delucchi, 2021). Entropy values were used to assess class separation, with values closer to 1.0 indicating clearer distinctions. Conditional probabilities were categorized as low (<0.40), moderate (0.40–0.69), or high (≥0.70) (Lanza, Flaherty, & Collins, 2003).

Sociodemographic, trading-related, gambling-related, and psychological variables across latent classes were analyzed using chi-square tests (χ^2) with Bonferroni-corrected pairwise comparisons for non-continuous variables, and Kruskal-Wallis (H) tests with post hoc Mann-Whitney U tests for continuous variables because variables did not meet the assumption of normality. Effect sizes were computed for each test, with φ and Cramér's V being used for categorical variables (with values of ≥0.10, ≥0.30, and ≥0.50 representing small, moderate, and large effect sizes respectively; or ≥0.06, ≥0.17, ≥0.29, when degrees of freedom were ≥3), and eta squared (η^2) for continuous variables (small ≥0.01, moderate ≥0.06, large ≥0.14) (Cohen, 1988).

In the absence of a gold-standard measure for disordered trading, the latent classes were also compared to the prevalence of disordered trading, as defined by the ≥5 cut-off point proposed by Guglielmo (2016). To further assess the appropriateness of this cut-off, all assessed variables were analyzed based on whether individuals were categorized as experiencing disordered trading (TDS scores ≥5) or not (TDS<5). Chi-square tests with effect sizes (φ or Cramér's V) were used for categorical variables, and Mann-Whitney U tests were applied for continuous variables, with Rosenthal's *r* as the effect size (small ≥0.10, moderate ≥0.30, large ≥0.50).

Sensitivity analysis. The main analyses were conducted using the raw data. To assess the robustness of the findings, sensitivity analyses were performed using winsorized values for those continuous variables with identified outliers (*z*-scores ± 3.29). In this process, extreme outliers were replaced with the closest non-outlier value. Outliers were identified in the following variables: TDS total scores ($n = 5$), number of financial assets traded ($n = 3$), mean trade size ($n = 8$), hours per day studying markets ($n = 9$), PGSI total scores ($n = 5$), and UPPS-P lack of premeditation dimension ($n = 1$), with the overall percentage of outliers being less than 2.5%. As the findings remained consistent across both analyses, the results presented are based on the original, non-winsorized data. Supplementary Table S1 provides data distribution overview for all assessed variables.

Ethics

The study was conducted in line with the principles of the Declaration of Helsinki and approved by the Committee of Research and Ethics at the first author's university (Reference: DPP.ACC.01.21). Participation in the study was entirely voluntary, although panel members were compensated with redeemable points by the panel provider for completing the survey. All participants were informed about the study and provided their informed consent to participate.

RESULTS

Exploratory and confirmatory factor analysis

Several EFA models with different number of factors were tested to determine the best representation of the data

(Table S2). While all models showed acceptable fit, the three-factor solution exhibited the best fit indices (χ^2 = 95.100, df = 65, CFI = 0.982, TLI = 0.978, RMSEA = 0.049). However, the chi-square difference test ($\Delta\chi^2$) between the two- and three-factor models was non-significant ($p > 0.05$), favoring the simpler two-factor model for its parsimony. Despite this, the correlation between the two factors was high ($r = 0.618$), suggesting a lack of distinctiveness between them (Table S3). Additionally, all items had strong standardized factor loadings on both factors (Factor 1: λ range = 0.577–0.898; Factor 2: λ range = 0.437–0.955), and cross-loadings above 0.30, which complicated the interpretation of the two-factor model. Therefore, the one-factor model was considered as the most parsimonious solution, with all items loading strongly onto a single factor (λ range = 0.706–0.955).

The results from the CFA supported the one-factor structure identified through the EFA. All items loaded strongly onto a single latent factor, with factor loadings ranging from λ = 0.701 (Item 1: Mind occupied with investment and/or trading activities) to λ = 0.972 (Item 12: Rely on others to provide money to relieve a desperate financial situation caused by investing/trading). The model also showed satisfactory fit indices (χ^2 = 93.920, df = 65, CFI = 0.985, TLI = 0.982, RMSEA = 0.045), confirming that the scale adequately assesses a single dimension of disordered trading behavior (Table S3).

Reliability, concurrent validity, and convergent validity

Table 2 shows results of reliability statistics for the TDS, using both CTT and IRT approaches. The scale demonstrated very good to excellent internal consistency ($\omega_{u\text{-cat}}$ = 0.938, and KR-20 = 0.877). According to values obtained using CTT, item discrimination was excellent, with corrected item-test correlations ranging from 0.476 (Item 1: Mind occupied with investment and/or trading activities) to 0.650 (Item 5: Sleep pattern disrupted by investment and/or trading activities). Item discrimination indices (a) obtained using IRT were also high or very high for almost all items of the scale (range of a values: 1.415–4.133), except for Item 1 (Mind occupied with investment and/or trading activities), Item 10 (Lie to conceal the extent of involvement in investing/trading), and Item 8 (Use of investing/trading to escape/relieve a negative emotion), which showed moderate discrimination power (a-values of 0.982, 0.990, and 1.118, respectively).

The difficulty parameters (b) for all items on the scale were positive, ranging from 1.187 (Item 1) to 2.021 (Item 8). According to the b-values, a greater level of disordered trading severity was needed to endorse items assessing mood modification (trading when feeling distressed) and conflicts (lied/deceived, jeopardized, or lost significant matters, experienced suicidal ideation, and relied on others financially), which had the highest b-values. On the contrary, cognitive

Table 2. Descriptive and reliability statistics for the Trading Disorder Scale (N = 403)

Items of the *Trading Disorder Scale*	Endorsement, % (n)[a]	CTT† Item discrimination[b]	IRT† Item discrimination a (SE)	IRT† Item difficulty b (SE)	KR-20 if deleted	$\omega_{u\text{-cat}}$ if deleted
Item 1. Mind occupied with investment and/or trading activities	23.1 (93)	0.476	0.982 (0.191)	1.187 (0.185)	0.876	0.865
Item 2. Need to invest/trade with increasing amounts of money	7.4 (30)	0.530	1.993 (0.570)	1.571 (0.175)	0.869	0.928
Item 3. Need to invest/trade with increasing amounts of time	10.4 (42)	0.523	1.439 (0.309)	1.415 (0.177)	0.869	0.927
Item 4. Restlessness when cutting down (withdrawal)	15.4 (62)	0.586	1.486 (0.332)	1.269 (0.164)	0.866	0.924
Item 5. Disrupted sleep pattern	10.9 (44)	0.650	2.541 (0.744)	1.413 (0.149)	0.862	0.928
Item 6. Unsuccessful efforts to control or stop trading/investing	10.7 (43)	0.627	2.025 (0.517)	1.498 (0.167)	0.864	0.927
Item 7. Loss of interest in previous hobbies	9.2 (37)	0.580	2.206 (0.576)	1.507 (0.160)	0.866	0.933
Item 8. Trading/investing to cope negative emotions	8.7 (35)	0.608	1.118 (0.293)	2.021 (0.318)	0.865	0.931
Item 9. Chasing losses	12.7 (51)	0.587	1.415 (0.317)	1.452 (0.183)	0.866	0.932
Item 10. Lie about trading/investing	9.2 (37)	0.544	0.990 (0.261)	1.995 (0.340)	0.868	0.935
Item 11. Jeopardized or lost a significant relationship/job/career	4.7 (19)	0.516	2.284 (0.829)	1.940 (0.232)	0.871	0.925
Item 12. Rely on others for money	6.7 (27)	0.586	4.133 (1.885)	1.630 (0.156)	0.867	0.909
Item 13. Suicidal behavior (ideation, plans or acts)	5.5 (22)	0.531	2.090 (0.638)	1.804 (0.204)	0.870	0.923

†Item discrimination and difficulty was assessed using Classical Test Theory (CTT) and Item Response Theory (IRT).
[a]Percentage of the sample (403 amateur investors that reported trading financial assets at least once in the previous 12-month period) endorsing the item. [b]Corrected item-total correlation.
Reliability of the total scale: Categorical McDonalds' omega coefficient ($\omega_{u\text{-cat}}$) = 0.938 (95% CI: 0.929–0.947), Kuder Richardson Formula 20 (KR-20) = 0.877 (95% CI: 0.872–0.882).

salience (i.e., mind occupied with trading activities) was the least difficult criterion compared to the other criteria, as well as the most frequently endorsed (23.1%, $n = 93$).

The results from Pearson's r and Spearman's ρ-correlations between TDS and measures related to both trading behaviors and disordered gambling provided evidence for concurrent validity and convergent validity. TDS score demonstrated a strong positive correlation with the PGSI score ($r = 0.559$, $p < 0.001$). Additionally, TDS score showed significant correlations with several trading-related variables, including past-year frequency of trading ($\rho = 0.356$, $p < 0.001$), number of assets traded ($r = 0.439$, $p < 0.001$), hours spent daily studying/researching markets ($r = 0.233$, $p < 0.001$), and frequency of daily market monitoring ($\rho = 0.462$, $p < 0.001$).

In contrast, the TDS score did not show significant correlations with financial aspects of trading, such as the shortest preferred time frame (i.e., the shortest holding period use for the financial assets traded, $\rho = -0.010$, $p = 0.862$) or the average amount of money invested per trade ($r = 0.026$, $p = 0.603$).

Latent class analysis

Table S4 provides model fit statistics for the one- to four-class solutions. Model fit improved substantially from the one to three-class models, with significant reductions in AIC, BIC and SABIC values, and significant LRT p-values ($p < 0$ .05), while maintaining good class separation (entropy $= 0.864$). The four-class model offered only marginal improvement, as indicated by non-significant Vuong-Lo-Mendell-Rubin and Adjusted Lo-Mendell-Rubin LRT p-values ($p > 0.05$), suggesting that the three-class solution was the most optimal. Figure 1 shows the estimated indicator probabilities and class proportions for this model.

Class 1, termed *non-disordered trading*, comprised the majority of the sample (72.2%, $n = 291$) and showed minimal endorsement of any disordered trading indicators, with probabilities near zero for nearly all items on the scale. In contrast, individuals in Class 2, labeled *disordered trading* (10.2%, $n = 41$), exhibited the highest severity of disordered trading, with moderate to high endorsement probabilities across all items. Preoccupation with trading, disrupted sleep patterns, and using trading to cope with negative emotions were the symptoms with the highest endorsement probabilities. Additionally, members of this class also commonly endorsed feeling restlessness when attempting to cut down or stop trading, chasing losses, and difficulty controlling their trading activities. Lastly, individuals in Class 3, termed *at-risk trading* (17.6%, $n = 71$), displayed symptoms such as preoccupation, withdrawal, and chasing losses, though with lower endorsement probabilities compared to those in the *disordered trading* class. However, items related to financial, social, or interpersonal problems were infrequently endorsed in this class.

Differences between latent classes and TDS categories

Cross-class comparisons of the three identified latent classes showed significant differences across trading-related variables and supported the appropriateness of Guglielmo's proposed cut-off for disordered trading (2016). Specifically, 97.6% (40 out 41) of individuals in the *disordered trading* class met

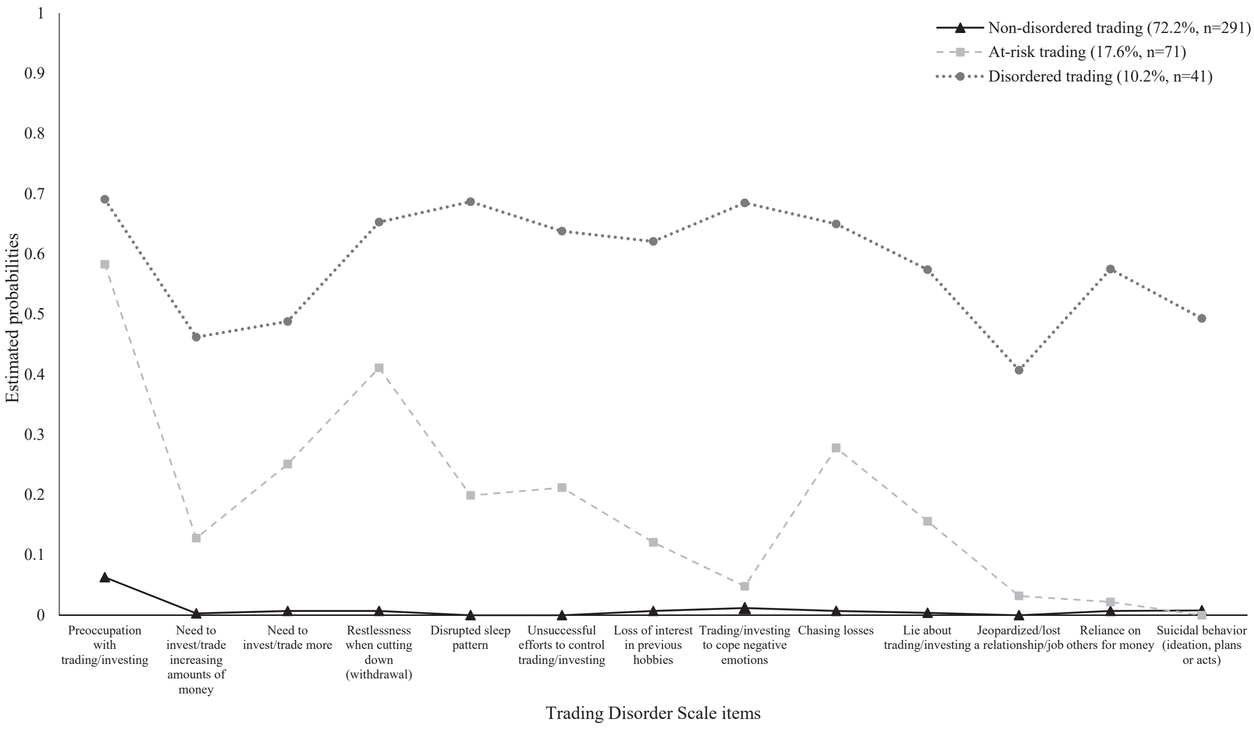

Fig. 1. Latent class analyses of the Trading Disorder Scale items. Plot show the estimated indicator probabilities and class proportions for the 3-class model

the five or more criteria cut-off, compared to 8.5% (6 out 71) in the *at-risk trading* class and 0% in the *non-disordered trading* class, with a very large effect size (Cramér's V = 0.92, $p < 0.001$). Individuals in the *disordered trading* class also had the highest total TDS scores (mean = 7.7, SD = 2.1), traded more frequently, held positions for shorter periods of time, monitored markets more intensively, and spent more time studying markets compared to the *at-risk trading* and *non-disordered trading* groups ($p < 0.001$), with moderate to large effect sizes (Table 4). Interestingly, participants belonging to the *disordered trading* class had a significantly lower amount of money invested per trade (mean = €3,854.5, SD = 10,929.3) compared to those in the *at-risk trading* class (mean = €4,537.7, SD = 10,688), although the effect size was small ($\eta^2 < 0.01$, $p < 0.001$).

In addition, comparisons across latent classes demonstrated significant differences in gambling-related variables and psychological correlates (Table 4). Participants in the *disordered trading* class exhibited significantly higher gambling severity (PGSI mean = 9.2, SD = 6.3) compared to those in the *at-risk* (mean = 1.9, SD = 3.4) and *non-disordered trading* classes (mean = 0.9, SD = 2.8; $p < 0.001$), with a large effect size ($\eta^2 = 0.35$). Moreover, 58.5% of individuals in this class met the threshold for problem gambling (PGSI ≥5), compared to 9.9% in the *at-risk* and 3.4% in the *non-disordered trading* classes (Cramér's V = 0.54, $p < 0.001$). Impulsivity scores (total and per dimension) were found to be significantly higher in the *disordered trading* class compared to the other groups ($p < 0.001$, $\eta^2 =$ 0.03–0.09), although with small effect sizes. Similarly, a significantly higher prevalence of tobacco, cannabis, cocaine, and hallucinogen use was found in this group ($p < 0.01$), with moderate effect sizes (Cramér's V = 0.17–0.21).

No significant demographic differences were found among the classes, except for educational level, where a higher proportion of individuals in the *disordered trading* class had not completed basic educational studies (Cramér's V = 0.18, $p = 0.044$) (Table 3). The observed pattern of differences during cross-class comparisons were maintained when participants were classified based on the proposed TDS cut-off score (Tables 3 and 4).

Sensitivity analysis

In order to ensure the robustness of the findings, sensitivity analyses were conducted by winsorizing outliers in continuous variables. These analyses yielded results that were consistent with the original dataset, with no substantial changes in statistical significance, observed differences, or the strength of correlations between TDS scores, PGSI scores, and trading-related variables (see Supplementary Tables S5 and S6 for the results using winsorized data).

DISCUSSION

Problematic trading behaviors have mostly been assessed using tools designed for gambling disorder. For this reason, the present study developed and validated a scale for disordered trading behaviors based on the proposed criteria by Guglielmo et al. (2016). The exploratory and confirmatory factor analysis supported a unidimensional structure for the scale, consistent with the DSM-5's conceptualization of a continuum of disorder severity in addictive behaviors (Király et al., 2017; Petry et al., 2014; Sleczka, Braun, Piontek, Bühringer, & Kraus, 2015). The scale also demonstrated very good to excellent internal consistency ($\omega_{u\text{-cat}} = 0.938$, and KR-20 = 0.877), with most items showing high or very high discrimination indices.

The results obtained using the IRT framework showed that items related to using trading to cope with negative emotions, and those reflecting intra-psychic (i.e., suicidal ideation due to trading), interpersonal (i.e., lying about trading), and conflicts with others (i.e., jeopardizing or losing significant matters), had the highest difficulty values. This indicates that endorsing these items requires a higher level of trading disorder severity, which was further corroborated by the results from the LCA.

The LCA identified three distinct classes of trading behaviors: *non-disordered trading*, *at-risk trading*, and *disordered trading*. The majority of participants were classified as engaging in *non-disordered trading* (72.2%), displaying minimal or no endorsement of disordered trading symptoms. Participants in the *at-risk trading* (17.6%) and *disordered trading* (10.2%) groups exhibited shared symptoms, including preoccupation with trading, withdrawal, and chasing losses behaviors. However, individuals in the *disordered trading* class were more likely to endorse these and other symptoms, showing more severe trading patterns.

Notably, items such as trading as an emotional coping mechanism, loss of control, disrupted sleep patterns, conflicts (e.g., lying, risking significant matters, relying on others financially), and suicidal ideation were almost exclusively endorsed by participants in the *disordered trading* class. These findings are consistent with existing research in gambling and internet-related disorders, such as internet gaming disorder, where more severe cases are characterized by loss of control, negative consequences, and interpersonal conflicts (James, O'Malley, & Tunney, 2016; Király et al., 2017; Mide, Arvidson, & Gordh, 2023; Sleczka et al., 2015). On the other hand, individuals classed as *at-risk trading* aligned with the profile of "preoccupied chasers" frequently observed in studies examining patterns of symptoms among gamblers and internet gamers (Banerjee, Chen, Clark, & Noël, 2023; Chamberlain, Stochl, Redden, Odlaug, & Grant, 2017; McBride, Adamson, & Shevlin, 2010). "Preoccupied chasers" experience significant involvement in their activity, particularly with preoccupation and loss-chasing behaviors, yet have not progressed to the severe consequences typically associated with pathological levels of the behavior. As such, the *at-risk trading* group represents an intermediate severity level, exhibiting some problematic trading behaviors without the extensive negative outcomes observed in *disordered trading.*

One notable distinction between the *at-risk trading* and *disordered trading* classes was the lower probability of endorsing withdrawal symptoms among individuals classed

Table 3. Comparisons of demographic variables across latent classes of disordered trading symptoms and TDS categories (<5 vs. ≥5 symptoms)

	Latent classes					TDS categories			
Variables	Non-disordered trading ($n = 291$)	At-risk trading ($n = 71$)	Disordered trading ($n = 41$)	Statistic (p)	ES	Non-disordered trading (score<5) ($n = 357$)	Disordered trading (score ≥5) ($n = 46$)	Statistic (p)	ES
Mean (SD) age, in years	38.1 (11.7)^{a}	39.5 (12.9)^{a}	38.7 (13.1)^{a}	0.467 (0.792)	<0.01	38.6 (11.9)	37.6 (13.3)	−0.583 (0.560)	
% (n) Male sex	65.6 (100)^{a}	60.6 (28)^{a}	70.7 (12)^{a}	1.250 (0.535)	0.06	65.3 (233)	65.2 (30)	<0.001 (0.999)	<0.01
% (n) Marital status									
Single	54.6 (159)^{a}	36.6 (26)^{b}	46.3 (19)^{ab}	11.108 (0.196)	0.17	51.5 (184)^{a}	53.5 (20)^{a}	2.355 (0.671)	0.08
Married	36.1 (105)^{a}	54.9 (39)^{b}	43.9 (18)^{ab}			39.8 (142)^{a}	43.5 (20)^{a}		
Divorced	4.5 (13)^{a}	2.8 (2)^{a}	4.9 (2)^{a}			3.9 (14)^{a}	6.5 (3)^{a}		
Widowed	1 (3)^{a}	0 (0)^{a}	0 (0)^{a}			0.8 (3)^{a}	0 (0)^{a}		
Other	3.8 (11)^{a}	5.6 (4)^{a}	4.9 (2)^{a}			3.9 (14)^{a}	6.5 (3)^{a}		
% (n) Education level									
None	0 (0)^{a}	0 (0)^{ab}	2.4 (1)^{b}	12.935 (0.044)*	0.18	0 (0)^{a}	2.2 (1)^{b}	10.729 (0.013)*	0.16
Primary	2.4 (7)^{a}	2.8 (2)^{a}	7.3 (3)^{a}			2.5 (9)^{a}	6.5 (3)^{a}		
High School	36.4 (106)^{a}	32.4 (23)^{a}	39 (16)^{a}			35.6 (127)^{a}	39.1 (18)^{a}		
University studies	61.2 (178)^{a}	64.8 (46)^{a}	51.2 (21)^{a}			61.9 (221)^{a}	52.2 (24)^{a}		
% (n) Employment status									
Student	9.6 (28)^{a}	7 (5)^{a}	12.2 (5)^{a}	5.972 (0.426)	0.12	9 (32)^{a}	13 (6)^{a}	1.071 (0.784)	0.05
Employed	78.4 (228)^{a}	70.4 (50)^{a}	73.2 (30)^{a}			77 (275)^{a}	71.7 (33)^{a}		
Unemployed/ domestic work	9.3 (27)^{a}	16.9 (12)^{a}	12.2 (5)^{a}			10.9 (39)^{a}	10.9 (5)^{a}		
Retired	2.7 (8)^{a}	5.6 (4)^{a}	2.4 (1)^{a}			3.1 (11)^{a}	4.3 (2)^{a}		
% (n) Income									
<1000€	13.4 (39)^{a}	8.5 (6)^{a}	24.4 (10)^{a}	6.353 (0.385)	0.13	12.6 (45)^{a}	21.7 (10)^{a}	3.087 (0.378)	0.09
1000–1999€	43.3 (126)^{a}	43.7 (31)^{a}	41.5 (17)^{a}			43.4 (155)^{a}	41.3 (19)^{a}		
≥2000€	23.4 (68)^{a}	28.2 (20)^{a}	19.5 (8)^{a}			24.1 (86)^{a}	21.7 (10)^{a}		
Don't know/Prefer not to disclose	19.9 (58)^{a}	19.7 (14)^{a}	14.6 (6)^{a}			19.9 (71)^{a}	15.2 (7)^{a}		

Note: TDS categories are based on the number of disordered trading symptoms met. Endorsing ≥5 symptoms was considered as disordered trading (Guglielmo et al., 2016). Effect sizes (ES) are reported for all tests: η^2 for the Kruskal-Wallis H test (latent class comparisons) and Rosenthal's r for the Mann-Whitney U test (TDS categories comparisons) in continuous variables, and φ/Cramér's V for χ^2 tests in categorical variables. In post-hoc comparisons, significant differences are indicated with different superscript letters. $^{*}p < 0.05$, $^{**}p < 0.01$.

Table 4. Comparisons of trading-related, gambling-related and psychological correlates across latent classes of disordered trading symptoms and TDS categories (<5 vs. ≥5 symptoms)

	Latent classes					TDS categories			
Variables	Non-disordered trading (n = 291)	At-risk trading (n = 71)	Disordered trading (n = 41)	Statistic (p)	ES	Non-disordered trading (score<5) (n = 357)	Disordered trading (score ≥5) (n = 46)	Statistic (p)	ES
Trading involvement									
Disordered trading									
% (n) Met ≥5 criteria	0 (0)^{a}	8.5 (6)^{b}	97.6 (40)^{c}	339.028 (<0.001)**	**0.92**	–	–	–	–
Mean (SD) Total severity score	0.1 (0.4)^{a}	2.7 (1.1)^{b}	7.7 (2.1)^{c}	325.242 (<0.001)**	**0.88**	0.6 (1)	7.5 (2.1)	−12.746 (<0.001)**	**0.64**
Mean (SD) No. of financial assets traded	1.4 (0.7)^{a}	1.9 (1.3)^{b}	2.7 (1.8)^{c}	43.022 (<0.001)**	**0.15**	1.5 (0.9)	2.7 (1.7)	−5.838 (<0.001)**	0.29
% (n) Past-year frequency of trading†									
Less than once a month	61.9 (180)^{a}	33.8 (24)^{b}	24.4 (10)^{b}	53.052 (<0.001)**	**0.36**	57.1 (204)^{a}	21.7 (10)^{b}	37.850 (<0.001)	**0.31**
Monthly	27.8 (81)^{a}	47.9 (34)^{b}	31.7 (13)^{ab}			31.4 (112)^{a}	34.8 (16)^{a}		
Weekly	8.9 (26)^{a}	12.7 (9)^{a}	31.7 (13)^{b}			9.2 (33)^{a}	32.6 (15)^{b}		
Daily	1.4 (4)^{a}	5.6 (4)^{ab}	12.2 (5)^{b}			2.2 (8)^{a}	10.9 (5)^{b}		
Mean (SD) Mean trade size, in euros†	2,663.2 (6,749.9)^{a}	4,537.7 (10,688)^{b}	3,854.5 (10,929.3)^{a}	14.947 (<0.001)**	<0.01	3,129.2 (8,084.9)	3,002.3 (8,085.6)	−0.162 (0.872)	0.01
% (n) Shortest preferred time frame for trading†									
Seconds	31 (66)^{a}	12.5 (8)^{b}	17.5 (7)^{ab}	35.634 (<0.001)**	**0.34**	26.7 (73)^{a}	18.2 (8)^{a}	19.811 (<0.001)**	0.25
Hours	15.5 (33)^{a}	21.9 (14)^{a}	47.5 (19)^{b}			17.2 (47)^{a}	43.2 (19)^{b}		
Days	14.1 (30)^{a}	28.1 (18)^{b}	20 (8)^{ab}			16.8 (46)^{a}	22.7 (10)^{a}		
Weeks-months	39.4 (84)^{a}	37.5 (24)^{a}	15 (6)^{b}			39.2 (107)^{a}	15.9 (7)^{b}		
% (n) Frequency of daily market monitoring									
Never or not daily	66 (192)^{a}	29.6 (21)^{b}	12.2 (5)^{b}	98.244 (<0.001)**	**0.50**	59.7 (213)^{a}	10.9 (5)^{b}	72.610 (<0.001)**	**0.42**
1–3 times per day	30.9 (90)^{a}	57.7 (41)^{b}	48.8 (20)^{ab}			35.6 (127)^{a}	52.2 (24)^{b}		
Every hour	2.4 (7)^{a}	9.9 (7)^{b}	29.3 (12)^{c}			3.9 (14)^{a}	26.1 (12)^{b}		
Every few minutes	0.7 (2)^{a}	2.8 (2)^{ab}	9.8 (4)^{b}			0.8 (3)^{a}	10.9 (5)^{b}		
Mean (SD) Hours per day studying trading markets	1.3 (2.5)^{a}	3 (4.6)^{b}	3.3 (3.1)^{c}	60.032 (<0.001)**	0.07	1.6 (3.1)	3.3 (3.3)	−5.435 (<0.001)**	0.27
Gambling behaviors and psychological correlates									
% (n) Past-year gambling participation	71.8 (209)^{a}	80.3 (57)^{a}	80.5 (33)^{a}	3.078 (0.215)	0.09	73.1 (261)	82.6 (38)	1.456 (0.227)	0.07
Mean (SD) Problem gambling (PGSI) severity	0.9 (2.8)^{a}	1.9 (3.4)^{b}	9.2 (6.3)^{c}	72.252 (<0.001)**	**0.35**	1.1 (2.9)	8.4 (6.5)	−7.512 (<0.001)**	0.37
% (n) Problem gambling (PGSI ≥5)	3.4 (10)^{a}	9.9 (7)^{a}	58.5 (17)^{b}	119.398 (<0.001)**	**0.54**	4.5 (16)	54.3 (25)	110.879 (<0.001)**	**0.53**

(continued)

Table 4. Continued

Variables	Latent classes: Non-disordered trading (n = 291)	Latent classes: At-risk trading (n = 71)	Latent classes: Disordered trading (n = 41)	Statistic (p)	ES	TDS categories: Non-disordered trading (score<5) (n = 357)	TDS categories: Disordered trading (score ≥5) (n = 46)	Statistic (p)	ES
Mean (SD) Impulsivity (UPPS-P)									
Total score	41.3 (8.3)[a]	43.8 (7.7)[b]	49.3 (6.9)[c]	35.183 (<0.001)**	0.09	41.7 (8.16)	49 (7.8)	−5.529 (<0.001)**	0.28
Negative urgency	9.3 (2.9)[a]	9.8 (2.6)[a]	11.2 (2.1)[b]	17.347 (<0.001)**	0.04	9.4 (2.80)	11.1 (2.2)	−3.801 (<0.001)**	0.19
Lack of premeditation	6.7 (2.1)[a]	7 (2.3)[a]	8.3 (2.2)[b]	20.497 (<0.001)**	0.05	6.7 (2.08)	8.3 (2.5)	−4.269 (<0.001)**	0.21
Lack of perseverance	7 (2.2)[a]	7.4 (2.3)[a]	8.5 (2)[b]	16.631 (<0.001)**	0.04	7 (2.2)	8.5 (2.1)	−4.306 (<0.001)**	0.21
Sensation seeking	9.3 (2.7)[a]	9.9 (2.8)[ab]	10.8 (2)[b]	12.135 (0.002)**	0.03	9.5 (2.7)	10.5 (2.5)	−2.679 (<0.001)**	0.13
Positive urgency	8.9 (2.5)[a]	9.7 (2.3)[b]	10.5 (2.3)[b]	18.058 (<0.001)**	0.04	9.1 (2.5)	10.5 (2.5)	−3.551 (<0.001)**	0.18
% (n) Substance use									
Alcohol	87.6 (255)[a]	90.1 (64)[a]	80.5 (33)[a]	2.267 (0.322)[a]	0.08	88.2 (315)	80.4 (37)	1.593 (0.207)	0.08
Tobacco	23 (67)[a]	29.6 (21)[a]	53.7 (22)[b]	17.221 (<0.001)**	0.21	24.1 (86)	52.2 (24)	14.811 (<0.001)**	0.20
Cannabis	10.3 (30)[a]	14.1 (10)[ab]	29.3 (12)[b]	11.601 (0.003)**	0.17	10.9 (39)	28.3 (13)	9.410 (0.002)**	0.16
Cocaine	2.1 (6)[a]	9.9 (7)[b]	12.2 (5)[b]	14.522 (<0.001)**	0.19	3.1 (11)	15.2 (7)	11.365 (<0.001)**	0.18
Hallucinogens	2.1 (6)[a]	4.2 (3)[ab]	14.6 (6)[b]	15.912 (<0.001)**	0.20	2.2 (8)	15.2 (7)	15.698 (<0.001)**	0.22

Note: TDS categories are based on the number of disordered trading symptoms met. Endorsing ≥5 symptoms was considered as disordered trading (Guglielmo et al., 2016). Effect sizes (ES) are reported for all tests: η^2 for the Kruskal-Wallis H test (latent class comparisons) and Rosenthal's r for the Mann-Whitney U test (TDS categories comparisons) in continuous variables, and φ/Cramér's V for χ^2 tests in categorical variables. In post-hoc comparisons, significant differences are indicated with different superscript letters. Large effect sizes are shown in bold.

[†]Trading frequency is based on the financial asset in which participants engaged most frequently. Mean trade size refers to the average amount of money invested per trade across all assets. The preferred time frame reflects the shortest duration participants held positions in financial assets.

$^{*}p < 0.05$, $^{**}p < 0.01$.

as *at-risk trading*. This is consistent with previous research, where gamblers or gamers who experienced withdrawal symptoms less frequently or with milder intensity, were less likely to be classified as disordered, particularly when is not accompanied by loss of control and negative consequences (Pontes, Schivinski, Brzozowska-Woś, & Stavropoulos, 2019). The distinction between individuals with *at-risk trading* and *disordered trading* was further supported by the application of the disordered trading classification based on Guglielmo et al.'s (2016) proposed cut-off. Nearly all individuals classified in the *disordered* group (97.6%) met the cut-off of five or more criteria, compared to only 8.5% of those belonging to the *at-risk trading* group and none of the *non-disordered trading* class. These findings, together with the consistency of results in both latent class and cut-off-based comparisons, appear to demonstrate the effectiveness of this threshold in identifying severe cases of disordered trading.

In the cross-class comparisons, the *disordered trading* class exhibited higher overall severity scores, traded more frequently, and spent more time monitoring trading markets than both *at-risk trading* and *non-disordered trading* classes. Interestingly, despite their higher trading frequency and use of shorter holding periods (i.e., the length of time that a trader had ownership of a financial asset, with shorter periods indicating short-term investment strategies), individuals in this class reported lower mean trade size values (i.e., the average amount of money invested per trade) than participants in the *at-risk trading* class. This suggests a compulsive engagement in trading (Mosenhauer et al., 2021), which parallels patterns observed among frequent gamblers, who tend to place smaller bets compared to less frequent gamblers who make larger individual bets (Gainsbury, Sadeque, Mizerski, & Blaszczynski, 2012; Petry, 2016).

In addition, individuals in the *disordered trading* class exhibited higher levels of impulsivity and substance use compared to the other groups, factors that have been consistently associated with gambling problems and trading-related behaviors (Leslie, Shaw, & McGrath, 2024; Mallorquí-Bagué et al., 2019; Moreira, Azeredo, & Dias, 2023; Oksanen, Mantere, et al., 2022; Sonkurt & Altınöz, 2021). In fact, more than half of the participants in this class met the PGSI cut-off for problem gambling (58.5%). All these findings remained consistent when comparisons were performed using the ≥5 cut-off for the TDS, highlighting the clinical relevance of this group and supporting the classification of disordered trading as a construct with meaningful psychological and behavioral correlates.

The TDS's validity was reinforced by its strong correlations with related constructs. TDS score showed a strong positive correlation with PGSI score, which assesses problematic gambling behaviors, demonstrating good concurrent validity. Moreover, significant correlations were found with trading-engagement variables, such as past-year frequency of trading, the number of assets traded, and daily market monitoring (Delfabbro, King, & Williams, 2021), supporting the scale's convergent validity. Importantly, when disordered trading was treated as a continuous measure (i.e., overall TDS scores), no significant correlations were found with financial metrics such as mean trade size values or preferred holding periods. In contrast, when traders were grouped based on specific combinations of symptoms though latent class analysis, an association was detected between disordered trading and the adoption of riskier strategies, such as shorter holding periods coupled with lower amounts of money invested. This suggests that the relationship between disordered trading and financial metrics becomes clearer when considering distinct behavioral profiles rather than assuming a linear progression with increasing severity. The effect sizes for these financial variables were smaller compared to other trading-related variables, particularly for the mean trade size variable, which further indicates that the scale primarily captures the psychological and behavioral dimensions of trading rather than financial outcomes.

These findings are particularly important given that a recent criticism of this type of work is the potential for pathologizing typical aspects of trading behavior (Billieux, Schimmenti, Khazaal, Maurage, & Heeren, 2015). It can be posited that specific trading behaviors may be characterized by intense involvement, which could potentially explain why the preoccupation item exhibited slightly lower (albeit still satisfactory) discriminative power. However, the findings suggest that disordered trading, as assessed using the TDS, is not exclusively characterized by engagement metrics, but also by clinically relevant harm-related indicators, including financial, relational, emotional, and health-related consequences. Moreover, the cross-class comparisons showed that individuals in the *disordered trading* class displayed compulsive trading behaviors and significant negative outcomes that extended beyond mere engagement in the activity. This supports the notion that higher scores on the TDS do not merely reflect a strong commitment to trading but are indicative of a maladaptive and harmful pattern.

As has occurred with the expansion of gambling products into the online environment, new technologies have significantly altered how individuals engage in trading activities. Many trading apps and platforms incorporate design elements commonly used by the gambling industry, aiming to increase user engagement (Davies & Ferris, 2022; Newall & Weiss-Cohen, 2022). These gamblified features may encourage the practice of trading in a manner that is analogous to gambling (Lee, 2022; Macey, Hamari, & Adam, 2024; Newall & Weiss-Cohen, 2022) and contribute to the emergence of harmful patterns of engagement (Andrade & Newall, 2023; Håkansson, Fernández-Aranda, & Jiménez-Murcia, 2021; Newall & Weiss-Cohen, 2022). This is further reflected in the increasing number of gambling helpline consultations related to cryptocurrency trading issues (Marionneau, Kristiansen, & Wall, 2024), highlighting the growing intersection between trading and gambling-related harms.

However, in order to determine whether disordered trading should be considered a form of gambling, or a distinct phenomenon, it is essential to rely on assessment tools specifically designed to capture the unique characteristics of trading-related impairment. The development of reliable and valid measures is also crucial for advancing research in this area and improving clinical identification and intervention strategies for problematic trading behaviors. To date, existing psychometric instruments have been limited in their applicability across different financial assets and investor profiles. The present study is the first to validate a scale for disordered trading among a sample of amateur investors and to evaluate the psychometric properties of a diagnostic threshold for identifying such behaviors. Despite these strengths, several limitations should be noted. First, the sample was recruited from an online panel, which may affect the generalizability of the findings. Although quotas were used to match the demographic characteristics of the sample to the Spanish population, panel members might have differed from the general population in terms of internet use, education, and socioeconomic status (Hays, Liu, & Kapteyn, 2015). While online panels are generally considered reliable for examining similar behaviors (Lee et al., 2023; Wardle & Tipping, 2023), caution is warranted when extrapolating these results to the larger populations of retail investors.

Moreover, the cross-sectional design of the study did not allow the testing of predictive validity or temporal stability of the scale. The present study did not employ test-retest reliability, and no longitudinal analyses were conducted, which limited the possibility of assessing the ability of the TDS to identify individuals at risk of developing severe trading problems, or to monitor changes during the treatment of disordered trading. While a sample size five to ten times the number of items is typically deemed sufficient for factorial analysis, particularly when the questionnaire structure is unidimensional (Wolf, Harrington, Clark, & Miller, 2013; Wu, 2010), further studies with larger samples are recommended to confirm the factorial structure identified in this study. Finally, the accuracy of the diagnostic cut-off point used to define disordered trading was primarily tested through LCA, given the absence of an established gold standard.

While the results underscore the ability of the TDS cut-off in effectively distinguishing disordered trading, which was the primary focus of the study, the specific characteristics observed in the *at-risk* class identified in the LCA, provide a foundation for future studies to consider incorporating intermediate severity levels, similar to those used in gambling research (e.g., PGSI categories). Such an approach could assist in more accurately identifying individuals at moderate risk who may not yet meet the threshold for disordered trading but exhibit patterns of problematic behavior. Moreover, given that all measures comprised self-report data, which may have been influenced by social-desirability and recall biases (Heirene, Wang, & Gainsbury, 2022), additional research is needed to validate this threshold using external benchmarks or expert clinical assessments to confirm its reliability.

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SUPPLEMENTARY MATERIAL

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APPENDICES

Appendix A. Trading Disorder Scale – English version

In relation to your participation in trading activities, please indicate if, in the PAST 12 MONTHS, you have experienced any of the following situations (yes/no).	Yes	No
1. Have you often found your mind occupied with investment and/or trading activities (e.g., reliving past investment experiences, analyzing, or planning the next investment, reading literature or online forums related to the financial world, making investments/trading the main activity of your daily life)?		
2. Have you felt the need to invest and/or trade increasingly larger amounts of money to achieve the desired excitement?		
3. Have you felt the need to spend more and more time making investments/trading and/or looking for new financial instruments to invest in?		
4. Have you been nervous or irritable when you tried to reduce or stop investing and/or trading?		
5. Has your sleep pattern been disrupted by investment and/or trading activities (e.g., staying up at night to be online at the opening of foreign financial markets)?		
6. Have you made repeated efforts to control, reduce, or stop investing and/or trading, always without succeeding?		
7. Except for investments and/or trading, have you lost interest in social and/or recreational activities that you previously enjoyed because of investments/trading?		
8. Have you often invested and/or traded when you felt distressed (e.g., helplessness, guilt, anxiety, depression)?		
9. After losing money in investments and/or trading, have you immediately or another day invested again to try to recover the losses?		
10. Have you lied to conceal your level of involvement with investments and/or trading (e.g., lying about financial losses, only talking about investments where you made money)?		
11. Have you jeopardized or lost an important relationship, your job, or opportunities in your studies or career because of investments and/or trading activities?		
12. Do you rely on others to give you money to relieve your desperate financial situation caused by investments and/or trading?		
13. Due to investments and/or trading, have you had thoughts about taking your own life, with or without planning, or have you attempted to take your own life?		

Scoring: Yes=1, No=0. Total score*: ___________

*A score of ≥5 indicates the possible presence of disordered trading.

Appendix B. Trading Disorder Scale – Spanish version

En relación con tu participación en actividades de trading, por favor indica si, durante los ÚLTIMOS 12 MESES, te ha ocurrido (sí/no) alguna de las situaciones que se describen a continuación.	Sí	No
1. ¿A menudo has tenido la mente ocupada en actividades de inversión y/o trading – compraventa - (p.ej. reviviendo experiencias de inversiones pasadas, analizando o planificando la próxima inversión, leyendo literatura o foros online relacionados con el mundo financiero, convirtiéndose las inversiones/trading en la actividad principal de tu vida cotidiana…)?		
2. ¿Has tenido la necesidad de invertir y/o realizar trading (compraventa) de cantidades de dinero cada vez mayores para conseguir la excitación deseada?		
3. ¿Has tenido la necesidad de pasar cada vez más tiempo realizando inversiones/trading y/o buscando nuevos instrumentos financieros en los que invertir?		
4. ¿Has estado nervioso/a o irritado/a cuando has intentado reducir o abandonar las inversiones y/o el trading?		
5. ¿Has visto alterado tu patrón de sueño por realizar actividades de inversión y/o trading (p.ej. quedarte despierto/a por la noche para estar conectado/a en la apertura de mercados financieros extranjeros)?		
6. ¿Has hecho esfuerzos repetidos por controlar, reducir o abandonar las inversiones y/o el trading, siempre sin éxito?		
7. A excepción de las inversiones y/o el trading, ¿has perdido interés en actividades sociales y/o recreativas que previamente realizabas, a causa de las inversiones/trading?		
8. ¿A menudo has invertido y/o realizado trading cuando sentías desasosiego (p.ej. desamparo, culpabilidad, ansiedad, depresión…)?		
9. Después de perder dinero en las inversiones y/o el trading, ¿has vuelto a invertir inmediatamente u otro día para intentar ganar y así recuperar las pérdidas?		
10. ¿Has mentido para ocultar tu grado de implicación con las inversiones y/o el trading (p.ej. mentir sobre pérdidas financieras, hablar solo de las inversiones en las que has ganado dinero,…)?		
11. ¿Has puesto en peligro o has perdido alguna relación importante, tu empleo u oportunidades en tus estudios o en tu carrera profesional a causa de las inversiones y/o actividades de trading?		
12. ¿Cuentas con los demás para que te den dinero para aliviar tu situación financiera desesperada provocada por las inversiones y/o el trading?		
13. Debido a las inversiones y/o el trading, ¿has tenido pensamientos sobre quitarte la vida, con o sin planificación, o has intentado quitarte la vida?		

Corrección: Sí=1, No=0 Puntuación total*: __________

*Una puntuación ≥5 es indicativa de un posible trastorno del trading.