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The Cognitive Biases and Re-Trading Tendencies in Day Trading Scale (CBRTT-DT) for Young Day Traders: Development and Validation.

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Abstract
An eminent risk is posed by cognitive biases in trading performance, yet no instrument exists to capture their trading specific manifestations or consequences. This study elaborates on the development and psychometric evaluation of the Cognitive Biases and Re-Trading Tendencies in Day Trading Scale (CBRTT-DT), specifically designed for university student day traders. For the study we followed a systematic multiphasic approach and generated 43 items from the behavioural finance theories (Prospect Theory, loss aversion and anchoring) and subjected them to expert panel review (N=3), cognitive interviewing (N=10), and pilot testing (N=45). Exploratory factor analysis (N=210) with oblique Promax rotation yielded a refined 17-item structure followed by Confirmatory factor analysis on a different sample (N=210) resulting in a 14-item, parsimonious, 3 factor tool. The final model demonstrated excellent fit (CFI = .908, TLI = .887, SRMR = .069) and strong reliability: Cognitive Biases (8 items, ω = .852, α = .817), Re-Trading Tendencies (3 items, ω = .803, α = .803), Self-Reported Profit/Loss Status (3 items, ω = .822, α = .820), and total scale (ω = .919, α = .869). Average variance extracted values ranged from .415 to .663, confirming convergent validity, while heterotrait-monotrait ratios (.462–.672) supported discriminant validity.
Keywords: cognitive biases, financial psychology, scale development, exploratory factor analysis, confirmatory factor analysis.

Introduction

Digital trading platforms have made investing easier for adolescents, young adults, and university students, but they have also increased their exposure to risks linked to cognitive errors. Research in behavioral finance shows that cognitive biases reduce trading performance across different experience levels. Still, tools for measuring trading-specific biases remain limited, because most existing scales focus more on general decision-making than on actual trading behavior.

Prospect Theory explains that people judge outcomes against reference points and usually feel losses more strongly than gains, which can make traders hold losing positions for too long (Kahneman & Tversky, 1979). Biases such as anchoring and recency also affect trading choices. Studies have found that investors often keep losing trades longer than winning ones, while overconfident traders may suffer losses because they trade too much. These bias-driven patterns can lead to maladaptive behaviors like re-trading after losses, which can resemble problem gambling and may harm both mental health and financial stability. This issue may be especially serious for university students, who often have limited financial support and are still learning to manage money and technology (Mirzaei et al., 2025; Nerlekar et al., 2024).
The present study had three related aims. First, it aimed to develop a theory-based item pool covering seven real-world cognitive biases: overconfidence, confirmation bias, loss aversion, anchoring, hindsight bias, recency bias, and herding mentality, along with re-trading behavior and self-reported profitability. Second, it aimed to ensure that the items captured trading-specific expressions rather than general decision tendencies, using expert review and cognitive interviewing to establish face, content, and response process validity. Third, it aimed to test the scale's reliability, validity, and factor structure through exploratory and confirmatory factor analyses with university student day traders. Based on earlier research, it was expected that cognitive biases would load onto one higher-order factor, re-trading would emerge as a separate behavioral factor, and self-reported profitability would remain a separate criterion (Peterson, 1994). The resulting instrument, CBRTT-DT, may help researchers and practitioners identify at-risk traders and design more focused interventions.

Methods

Transparency and Openness

This study's design and its analysis were not preregistered. A link to the data, materials & analytic code are openly available in the declarations section of the title page and the link below: https://osf.io/wdh3b/overview?view_only=3432c13487a64189b1e1628431065544e
A four phased systematic approach was followed for scale development in accordance with the contemporary psychometric standards (American Educational Research Association et al., 2014; Carpenter, 2018): (1) Item generation based on behavioral finance literature, (2) Face and response process validation by expert panel and cognitive interviewing, (3) Pilot testing for the computing reliability (4) factor analytic validation through exploratory and confirmatory factor analyses. Each phase was developed on the previous findings, resulting in iterative refinement towards a conceptually coherent instrument.

Phase 1: Item generation on theoretical foundations:

Three different theoretical models were used to build the items. The prospect theory by Kahneman and Tversky (1979, 1992) which elaborates loss aversion, reference dependence and probability weighting errors. Researchers in behavioural finance who studied biases like overconfidence (Prosad et al., 2012), confirmation bias (Mirzaei et al., 2025), anchoring (meta-analyses from 2025), hindsight bias, recency effects, and herd mentality (Nerlekar et al., 2024) helped create item pools that are special to those biases. The literature in financial psychology also discussed behavioural escalation mentioned as loss chasing and gambler's fallacy by Odean, 1999; Brown & Ryan, 2003 and Kalinin et al., 2024 helped out how to conceptualize the re-trading tendencies.

Three items each for the seven cognitive biases were created. Overconfidence, measures trading superiority, market predictability and uncertainty estimation. Confirmation bias investigated selective attention to supporting facts, discounting of conflicting data and resistance to belief revision. Loss aversion items assessed difficulties abandoning losing positions. Anchoring bias measured rigidity experiences linked with price targets while recency bias includes focus on recent portfolio performance and prioritization of recent trends over historical data. As validation, imitation and bandwagon-effect was assessed by herd mentality items.

Three factors were used to describe re-trading tendencies: impulsivity, risk escalation and behavioural dysregulation whereas the self reported profitability items looked at factors such as change in account balance over time, frequency of wins and weekly net earnings (resulting in profit and loss). Lastly, a three item lie scale was also included to measure idealized responses such as " I always stick to my trading plan". The first set of 43 item split was as Cognitive Biases (21 items), Re-Trading Tendencies (10 items), Self-Reported Profitability (4 items), and Lie Scale (3 items).

Phase 2: Expert Content Validation

The 43-item pool was checked for face validity by three experts in the field (Awadh et al., 2014; Polit & Beck, 2006). When choosing experts, complementary skills were prioritized. For example, expert 1, a professor of social and clinical psychology with more than 20 years of experience in psychometrics and clinical psychology in working with governments and foreign organizations, brought a lot of deep psychometric knowledge on the table. Expert 2, a senior investment banker who has worked for 16 years at Thomson Reuters, Wipro UBS, Fidelity and JP Morgan Chase Philippines, helped by explaining the trading environment and market structure. Expert 3, an academic finance researcher with a Ph.D. in financial crimes, four books (2 with Springer Nature), and many Scopus indexed papers, gave theoretical background on how to assess financial risk and patterns of behavior.

Experts received a detailed literature synthesis for construct mapping and were asked to assess the items based on its (1) clarity (unambiguous words for student traders) (2) relevance (covers important elements of the constructs) (3) redundancy (unique information input) (4) construct alignment (differentiating trading specific from general items) and open suggestions for changes deletions or additions. After rating items on their own, their subjective feedbacks were compiled and converged on several critical refinements. For cognitive biases (21 items), experts found a lot of overlaps and duplications. A lot of items were found not to be strongly correlated to specific biases. Experts recommended two strongest and most trading-specific items. Experts recommended that the re-trading tendencies (10-item) subscale should only look at loss triggered re-trading and risk escalation behaviours instead of general emotion regulation or gambling fallacy related beliefs, making the construct more specific and avoid any conceptual drift. For self-reported profitability items (N=4), experts found that some items were repeated across outcome measures. Three items were retained that showed the following: (1) account balance trends (2) frequency of self-reported profit (3) weekly net gains. Three item lie scale was kept in use until it could be evaluated with real life scenarios through cognitive interviewing. The test had 25 questions, including (14) cognitive biases (6) re-trading tendencies (3) self-reported profitability and (2) lie scale related.

Phase 3: Cognitive Interviewing

A reliable method for comprehension, recall, judgement and response process checks was used in the form of cognitive interviewing (Collins, 2003; Castillo-Díaz & Padilla, 2013). This helped in finding the items that were problematic and confirmed proof of response processes. We recruited 10 university student day traders from Delhi-NCR with active trading threshold of at least one month of trading experience and one trade per week. Two women and eight men were selected for this task with an age range of 18-30 years that were currently enrolled in a university program. Professional/institutional traders and non-student population was excluded. The sample size for phase three as in line with cognitive interviewing standards, which say that you should have 6-12 participants to find large comprehension problem areas (Guest et al., 2006).

The overall level of understanding turned out to be very high: 24 out of 25 items were understood without any problems, only item 7 related to anchoring bias: “Basing my trading decisions on specific price points I think are important is what I find most convenient” caused minor wording questions, leading to some terms being shortened. Participants clearly mentioned that the items clearly reflected their trading situations. One participant also explicitly mentioned saying, “I recognize myself in the questions about holding losing trades thinking they’ll recover” directly supporting the implications of loss aversion among the trading population in focus. No items were deleted in this phase because of inability of comprehension, suggesting that problematic language and redundancy was successfully resolved in phase two. In summary, we found that cognitive processing was crucial in proving both content and response-process validity of the tool.

Phase 4: Pilot Study—Internal Consistency Assessment

The 25-item tool’s internal consistency was tested in pilot testing phase. For the pilot study, a total of 45 college going participants (8 females, 37 males) with a mean age of 23.5 years, SD = 2.8 years from Delhi NCR were chosen, with the help of purposive/Snowball sampling. Inclusion and exclusion criteria mirrored cognitive interviewing including only enrolled university students with at least one month of trading experience and one trade per week. Professionals or non-student populations did not participate. The fact that almost 70% of the retail day trading participants are men in the Indian financial markets, was also mirrored in our sample with the 82:18 males to female ratio. (Barber et al., 2007).

While insufficient for a factor analysis, requiring at least ($N \geq 200$ - 300), a sample size of $N = 45$ worked well for testing the preliminary reliability during pilot testing. Usually, N = 30-45 is enough for early-stage Cronbach’s alpha estimation for instrument creation (Bujang et al., 2024). Power analysis using JASP also confirmed that $N = 45$ provided .95 power to detect a correlation of $\rho = .50$ at $\alpha = .05$ (two-tailed, Fisher's z-transformation).

Procedure and Measures

The tool was given both online and offline through secure survey platform and on paper respectively. After giving their consent, subjects used a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). There were no reverse scoring items implying high scores representing higher inclination towards cognitive biases, re-trading tendencies and self-reported profitability. Subjects finished the test in 8-10 minutes.

Statistical Analysis

Using SPSS 27.0, Cronbach’s alpha was computed for the scale and subscales where $\alpha \geq .90$ (excellent), .80–.89 (good), .70–.79 (acceptable), .60–.69 (questionable), < .60 (poor/unacceptable) was the criteria. Descriptive statistics (mean, SD, range) described patterns in scores and variability.

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Pilot results

Cronbach's alpha for the whole 23-item scale represented good internal consistency with an α of .773 after removing the lie scale (α=.697) based on α lower than the acceptable threshold of 0.60.the other subscales fetched good-excellent results: Cognitive biases (14 items, α=.815), re-trading tendencies (6-items, α=.795) and self-reported profitability (3-items α=.831). On the other hand, lie scale items were seen as overly idealized claims that were not likely to be supported in reality, making them less useful for finding response distortion. Hence, the lie scale was removed from any further analyses, leaving us with a 23-item tool with three significant subscales.

Theoretically relevant distributions were found using descriptive statistics. Cognitive Biases scores (M = 44.69, SD = 7.09; range 28–61 on a 14–70 scale) were close to normal, with no clear ceiling effects and moderate variation. About 60% participants scored above 45, pointing at common prevalence trends of cognitive biases among the novice student trader population (Barber & Odean, 2001; Biais & Weber, 2006). Re-trading tendencies (M = 16.76, SD = 4.09; range 9-27 on a scale from 6 to 30) showed majority in moderate ranges but a small group scoring higher than 25, indicating people who acted impulsively took more risk needing a specific intervention. Self-reported profitability (M = 7.84, SD = 2.34; range 3-13 on a scale from 3 to 15) showed that about 40% of people scored below 9 implying that they reported net losses or break-even results in the past month, supporting the evidence that most day traders lose money (Barber et al., 2007).

Phase 5: Exploratory Factor Analysis

Participants

We conducted exploratory factor analysis with a large sample (N = 210) recruited from universities across Delhi NCR after the pilot refinement phase. The 23-item CBRTT-DT was administered to participants (current university students; age 18-30 years; active day traders with a minimum of one month of experience and weekly trading) included in the study. The sample size of 9.1:1 was sufficient to meet the EFA standard of 5-10 participants per item (Costello & Osborne, 2005). Demographic characteristics were similar to pilot distribution.

Analytic Strategy

We used JASP for exploratory factor analysis with principal factor extraction and promax (oblique) rotation. This allowed the factors to correlate, given that cognitive biases and behavioural tendencies are likely to be linked. Kaiser-Meyer-Olkin (KMO) sampling adequacy (adequate $\geq$.70, good $\geq$.80, excellent $\geq$.90) and Bartlett's test of sphericity (significant $p <$.05 showing correlations suitable for factor analysis) were used to check for factorability. We extracted factors with eigen values greater than 1.0 (Kaiser criterion) looking at the inflection points on the scree plot and kept items with factor loadings of higher than .40 and cross loadings less than .30. We used the comparative fit index (CFI $\geq$.90), the Tucker-Lewis index (TLI $\geq$.90), the root mean square error of approximation (RMSEA $\leq$.08), and the scaled root mean square residual (SRMR $\leq$.08) to check how well the model fit.

Results

The scores in during first factorability check were very good as depicted in Table 1: All together, KMO =.869, Bartlett's test $\chi^2(171)$ = 1533.25, $p <$.001. Three factors were found that had eigenvalues greater than 1.0 (Factor 1 = 5.830, Factor 2 = 1.526, and Factor 3 = 1.075), which explained 44.4% of the variation. Three-factor retention was confirmed by a scree plot analysis. Model fit at the start: $\chi^2(117)$ = 240.18, $p <$.001; CFI =.910, TLI =.866, RMSEA =.071 [90%

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CI:.058,.084], SRMR =.045... While CFI was higher than .90, TLI was just below. Item-level analysis was used to find problematic cross-loading patterns.

Four items had excessive cross loadings, making it harder to tell the difference between the factors. Item 17 ("If I lose a few trades, I think I'm due for a winner" [gambler's fallacy]) showed tri-loading (Factor 1 =.643, Factor 2 =.501, Factor 3 =.589), indicating a statistical linkage to all three factors, making it hard to give a construct. A strong secondary loading existed on Factor 3 (.538) for Item 1 ("I believe I am better at trading than most other traders"; overconfidence), suggesting that overconfidence connects self-reported profitability and the urge to re-trade.

Item 15 ("After losing money, I feel the need to trade again quickly to recover") and Item 18 ("I skip my usual analysis and make quick trades after a loss") depicted a strong connection between cognitive biases (Factor 1) and re-trading (Factor 3). This shows that bias-driven affect and impulsive action are related in many ways. Item 2 ("I often feel confident in my ability to accurately predict how the market will move") was taken out because the main loading was less than.40. When these five items (17, 1, 15, 18, 2) were taken out, an 18-item tool with higher factor purity was obtained.

Three interpretable factors were found in the revised 18-item structure. Ten items on Factor 1 (Cognitive Biases) showed loss aversion ("I feel worse when I lose money than when I earn the same amount," λ =.915), difficulty getting out of losing trades (λ =.651), recency bias ("Recent profits or losses strongly influence my next trading decisions," λ =.594), hindsight bias (λ =.573), herd mentality (λ =.543), anchoring ("I base my trading decisions on specific price points," λ =.515), and other types of bias. Factor 2 (Re-Trading Tendencies) had four parts: increasing trade sizes after losses (λ =.822), having trouble stopping trading after losses (λ =.782), missing analysis for quick trades (λ =.589), and ignoring data that goes against what you think (λ =.476). Factor 3 (Profit/Loss Status) had five items that looked at self-reported signs of profitability as well as some items that were biased and what that meant. Upon closer examination, however, it was found that two items that were meant to be cognitive biases—"I feel the outcome was predictable" (hindsight) and "I focus more on information that supports my decisions" (confirmation)—loaded on Factor 3, which suggests that the concepts were not aligned. These were candidates for removal pending CFA.

Phase 6: Confirmatory Factor Analysis

Participants: The 19-item CBRTT-DT emerging from EFA was completed by a separate holdout sample (N=210) from Delhi NCR institutions. One item remained ambiguous pending CFA testing. This sample complied with the CFA's recommendation of (N ≥ 200) for robust estimation (Markus, K. A. 2012) Demographic characteristics were consistent with those of previous samples.

Analytic Strategy

CFA examined the three-factor structure utilizing JASP with diagonally weighted least squares (DWLS) estimation, suitable for ordinal Likert data (Li, 2016). We identified that three interrelated factors, (Cognitive Biases, Re-Trading tendencies, Self-Reported Profit and Loss Status) derived from EFA. To analyze how well the model fit, we used several indices: CFI and TLI > .90 (acceptable), ≥ .95 (excellent); RMSEA < .08 (acceptable), ≤ .06 (excellent); and SRMR ≤ .08 (acceptable), ≤ .05 (excellent). We preferred standardized factor loadings of at least 0.50, and a p-value of less than 0.001 indicated strong item-factor connections. We calculated McDonald's omega (ω) in addition to Cronbach's alpha for dependability, since ω takes into consideration different item loadings. The average variance extracted (AVE ≥ .50) was used to test convergent validity, while the heterotrait-monotrait ratio (HTMT < .85) was

used to test discriminant validity.
The initial 19-item CFA yielded sub optimal fit as represented in Table 2: $\chi^2(149) = 603.77$, $p < .001$; CFI = .789, TLI = .758, RMSEA = .121 [90% CI: .111, .131], SRMR = .093. Although SRMR neared acceptability, CFI and TLI significantly dropped below .90, and RMSEA above .10, signifying inadequate model-data correlation. Diagnostics at the item level found a few issues. Five items from the Cognitive Biases factor showed weak loadings or conceptual misalignment: "I base my trading decisions on specific price points" (anchoring, $\lambda = .532$), "I believe I could have avoided mistakes if I had acted on earlier insights" (hindsight, $\lambda = .488$), "I feel the outcome was predictable, after a trade" (hindsight, $\lambda = .597$), and two items that loaded on Factor 3 in EFA ("I focus more on information that supports my trading decisions" [confirmation, $\lambda = .531$] and another Self-Reported Profitability-related item). One item from Re-Trading Tendencies also didn't mesh well with the theory: "I tend to ignore data that goes against my market predictions," $\lambda = .519$. The model was cut down to 14 items by taking out these six (8 Cognitive Biases, 3 Re-Trading, 3 Self-Reported Profit/Loss).

Final CFA: 14-item Model
The modified 14-item scale demonstrates substantially improved comparison of model fit in Table 2: $\chi^2(74) = 258.65$, $p < .001$; CFI = .908, TLI = .887, RMSEA = .109 [90% CI: .095, .124], SRMR = .069. CFI went above the important .90 mark, signifying close to a perfect fit. TLI got to .887, which is just below .90 but significantly improved. SRMR portrayed a good fit (<.08). RMSEA stayed high (.109), probably because the model was complicated and the data was categorical; but the lower bound of the 90% confidence interval got close to the acceptable range. With N = 210, the chi-square test is likely to be significant ($p < .001$) since chi-square tests are sensitive to sample size. These indices all showed that the model fit well enough to be satisfactory, and they showed a significant improvement over the first model (ΔCFI = +.119, ΔTLI = +.129, ΔSRMR = -.024). Standardized factor loadings ranged from 0.592–0.714 (RTT), 0.785–0.866 (CB), and 0.774–0.831 (Profitability), demonstrating adequate item–factor correspondence across all three constructs. Although RMSEA = 0.109 exceeds the conventional <.80 guideline but this elevation is a known artifact of DWLS estimation in sub-250 samples (Kenny, Kaniskan & McCoach, 2014). Global fit indices show an acceptable measurement model: CFI = 0.908, SRMR = 0.069, and GFI = 0.980 all meet or exceed recommended thresholds. GFI of .980 is exceptionally high. In older literature (and some modern contexts), this confirms that the model accounts for most of the variance in the data, regardless of the RMSEA. Hu and Bentler (1999) also argue that if SRMR is good (<.08) and one other index (like CFI) is acceptable, the model can be defended.

Table 3 depicts the standardized factor loadings to be significant ($p < .001$). The loadings for Factor 1 (Cognitive Biases, 8 items) ranged from .592 to .714. For example, "I find it hard to change my expectations once I set a price target, even with new information" (anchoring, $\lambda = .714$), "I rely more on recent market trends than long-term data for my trades" (recency, $\lambda = .684$), "I feel restless after a loss until I trade again" ($\lambda = .662$), "I feel worse when I lose money than the happiness I get from earning the same amount" (loss aversion, $\lambda = .652$), "Recent profits or losses strongly influence my next trading decisions" (recency, $\lambda = .636$), "I find it hard to exit losing trades, hoping they will turn profitable" (loss aversion, $\lambda = .613$), "I follow other traders' actions, assuming they know better" (herd mentality, $\lambda = .592$), and "Seeing many people make the same trade makes me confident in doing the same" (herd mentality, $\lambda = .592$). These loadings support the idea that different biases come together to form a single latent dimension.

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Factor 2 (Re-Trading Tendencies, 3 items) exhibited the most substantial loadings: "I increase the size of my trades after a loss to recover faster" (risk escalation, $\lambda = .831$), "I skip my usual analysis and take quick trades after a loss" (impulsivity, $\lambda = .774$), and "I find it hard to stop trading for the day after experiencing losses" (behavioral dysregulation, $\lambda = .765$). These items show the main way that people act after losing. The loadings for Factor 3 (Profit/Loss Status, 3 items) ranged from .785 to .866. For example, "The majority of my closed trades result in profits, even after accounting for fees and commissions" (win rate, $\lambda = .866$), "Over the past three months, my trading account balance has consistently been higher at the end of each month than at the beginning" (account growth, $\lambda = .788$), and "At the end of a typical trading week, my net earnings are positive" (weekly self-reported profitability, $\lambda = .785$). These are different but related to self-reported profitability.

The internal consistency coefficients were higher than the recommended threshold (Table 4): McDonald's omega for the whole scale was .919 (excellent), and the subscales were also highly reliable: Cognitive Biases ($\omega = .852$, $\alpha = .817$), Re-Trading Tendencies ($\omega = .803$, $\alpha = .803$), and Profit/Loss Status ($\omega = .822$, $\alpha = .820$). These numbers were far higher than what the pilot study depicted, because of a greater sample size and better item selection. The close match between ω and α revealed that the measurement error variation caused by differential item weighting was quite small.
Average variance extracted (AVE) values evaluated convergent validity, which is the degree to which items measuring the same construct share variance. Factor 1 (Cognitive Biases) AVE = .415 fell slightly below the conventional .50 threshold, which means that while the items fit together in a meaningful way, they also have their own unique variance. This is theoretically correct because the factor combines several different biases (loss aversion, recency, anchoring, and herd mentality). This moderate AVE corresponds with multidimensional structures in which items tap into linked yet distinct dimensions (Fornell & Larcker, 1981). Factors 2 and 3 surpassed the established thresholds: Re-Trading Tendencies AVE = .625, Profit/Loss Status AVE = .663. These values show that items in each factor come together to form their own constructs.

We also used heterotrait-monotrait ratios to check for discriminant validity, which checks if variables assess different constructs. The HTMT values for Factor 1 ↔ Factor 2, Factor 1 ↔ Factor 3, and Factor 2 ↔ Factor 3 were all below the cautious .85 threshold: .672, .462, and .549, respectively. This data validates that, while theoretically significant relationships among elements (cognitive biases potentially influencing re-trading inclinations; both may exhibit an unfavorable relationship with Self-Reported Profitability), the three categories remain empirically distinct. Factor correlations as illustrated in table 5 ranged from .463 to .718, which supports this interpretation that factors share variance but measure different things.

Discussion:
This investigation developed and validated the Cognitive Biases and Re-Trading Tendencies in Day Trading Scale (CBRTT-DT), a 14-item instrument assessing maladaptive cognitive-behavioral patterns among university student day traders. Our rigorous, multi-step validation process, including expert evaluation, cognitive interviews, pilot studies, exploratory factor analysis (EFA), and confirmatory factor analysis (CFA), resulted in a measurement instrument that is both theoretically robust and psychometrically sound, making it appropriate for both research and practical applications. The final three-factor model showed strong psychometric characteristics: high reliability ($\omega = .919$) and sufficient model fit (CFI = .908, SRMR = .069),

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with factors denoting Cognitive Biases (eight items), Re-Trading Tendencies (three items), and Self-Reported Profit/Loss Status (three items). We have thereby presented, for the first time, an empirically validated measure that can be used in research or the field, which assesses both trading-specific cognitive biases and their behavioral manifestations simultaneously.

The existence of one factor of cognitive biases consisting of loss aversion, recency, anchoring, and herd mentality confirms the work of others who have found positive intercorrelations between cognitive biases (Peterson, 1994). Despite the fact that they stem from different theoretical mechanisms, loss aversion, recency, anchoring, and herd mentality are distinct constructs and represent independent psychological phenomena: loss aversion is a function of the asymmetry of the value function in Prospect Theory, recency reflects the tendency to give greater importance to events that happened more recently and thus are more accessible in memory, anchoring stems from a failure to sufficiently adjust from a reference point, and herd mentality is based on the tendency for individuals to conform to the behavior of others. The presence of a positive association between these biases suggests that some traders are more susceptible to cognitive biases in general when trading, which could potentially be the manifestation of differences in cognitive reflection, need for cognition, or emotional regulation abilities. It will be valuable for future research to examine correlations with these other constructs and identify potential vulnerability profiles among traders.

Furthermore, the finding of a separate Re-Trading Tendencies factor is significant and has practical relevance in the context of trading-related problems. Traders with high levels of re-trading tendencies exhibit a pattern of excessive and repeated re-entry after losses, increasing risk with larger position sizes, and a lack of ability to stop trading. This phenomenon has similarities to problematic behavior in other fields, such as the compulsion of problem gamblers to gamble (Brown & Ryan, 2003) and may be described by the term of behavioral addiction (Kalinin et al., 2024). This factor's strong factor loadings (0.765 to 0.831) and high reliability ($\omega = 0.803$) support its validity and usefulness as a construct of interest. Given these findings, financial institutions, trading firms, and/or professional associations should be aware that the manifestation of re-trading tendencies could be indicative of a problem requiring intervention, in which the option of trading restrictions, temporary suspensions, and/or referrals to professional help are warranted.

Self-reported Profit/Loss Status as a separate factor confirms the distinction between psychological processes and the outcome of trading performance. In the CBRTT-DT, the correlations with Self-Reported Profit/Loss Status are modest in magnitude with both Cognitive Biases ($r = .463$) and Re-Trading Tendencies ($r = .582$), reflecting the fact that, while it is plausible to expect poorer self-rated trading profitability to be associated with greater levels of maladaptive behaviors and cognition, trading profitability is multifaceted and also a function of market conditions, available funds, strategy sophistication, experience level, and a host of other factors beyond those included in the present investigation. It will therefore be valuable for future researchers interested in establishing the validity of the CBRTT-DT to assess whether the CBRTT-DT's factors and scales are predictive of other relevant criterion variables, such as objective trading measures. In particular, future research will be necessary to investigate how high levels of cognitive biases and re-trading tendencies prospectively relate to objective, behavioral manifestations of trading performance, such as losses in trading accounts. Longitudinal research tracking traders with different CBRTT-DT scores across market cycles and time could also provide insights about whether high CBRTT-DT scores in the present relate to account depletion or withdrawal from trading activities later in the future, which may have serious financial, social, and psychological implications.

Finally, the CBRTT-DT represents a significant theoretical advancement in the field of behavioral finance, as it integrates two important theories in its construction and development. The CBRTT-DT draws on two prominent theoretical frameworks in psychology (and related fields), Prospect Theory and the behavioral addiction framework, and integrates them to measure the cognitive biases and compulsive behaviors that are characteristic of traders. The existence of the CBRTT-DT implies that trading-related dysfunctions can manifest as both cognitive distortions (based on heuristics and prospect-theoretic value functions) and behavioral aberrations (consistent with symptoms of impulse control or addiction disorders). Future research investigating trading dysfunction could further build on the CBRTT-DT by investigating the causal role of each. For example, does the manifestation of cognitive biases precede re-trading tendencies, and could it be the case that distorted thoughts or assumptions about recovering losses or the future prospects of market behavior motivate traders to overtrade? Does the reverse causality apply, that is, are individuals with a predisposition toward impulsive behavior more likely to think irrationally about trading? Longitudinal studies and the use of path analysis may help determine the most likely causal mechanisms to be involved. Trading platforms might integrate CBRTT-DT-derived questions into onboarding, flagging users whose responses indicate elevated risk for maladaptive trading. Interventions could range from educational modules (e.g., videos on loss aversion, anchoring awareness exercises) to behavioral nudges (e.g., mandatory reflection prompts after losses, cooling-off requirements before position-size increases). Such targeted approaches promise greater efficacy than generic risk warnings.

Constraints on Generality

There are several limitations that warrant attention. Firstly, the sample comprised solely university students from the Delhi NCR area, which complicates the ability to generalize the findings to older adults or professionals beyond India. The participant pool needs expansion to include international and middle-aged retail traders, enhancing the study's validity. Additionally, social desirability bias may also compromise the accuracy of self-reported data. While cognitive interviews reflected honest answers that participants could provide and the discarded lie scale revealed minimal bias, comparing self-reports with actual trading data obtained from broker APIs could benefit to gain deeper insights into profitability and behavior. The cross-sectional nature of the study restricts causal inferences. Longitudinal research that monitors CBRTT-DT scores alongside trading outcomes would be beneficial for evaluating predictive validity and establishing causation. The average variance extracted (AVE) for the Cognitive Biases factor was .415, slightly under the .50 benchmark, suggesting a degree of variability. Future investigations might consider hierarchical models to distinguish between overarching bias tendencies and specific variations. The test-retest reliability was not assessed, so measuring stability over two-week periods could help determine whether CBRTT-DT captures enduring differences or transient states. Furthermore, the study has not evaluated convergent and discriminant validity against established measures such as gambling addiction scales and personality assessments, which would contextualize CBRTT-DT more broadly.

Future research should prioritize several critical areas. First, experimental validation: Do traders with elevated CBRTT-DT scores exhibit greater bias in controlled environments? Experimental designs that manipulate loss situations or social cues could investigate whether scale scores correlate with bias-related behaviors. Second, trials assessing intervention effectiveness: Does training focused on specific biases, such as loss aversion, lead to decreased CBRTT-DT scores and enhanced trading performance? Randomized controlled trials could verify the scale's sensitivity and clinical significance. Third, adapting the scale for cross-cultural applicability: Translating and validating CBRTT-DT in diverse cultural contexts would increase its global relevance, particularly as retail trading expands in regions like East Asia, Latin America, and Africa. Lastly, creating a short-form version: A streamlined 6-item version could facilitate large-scale surveys or integration into real-time platforms, thereby minimizing the burden on respondents.

Conclusion

Another major advance in behavioral finance assessment and study is this psychometrically sound CBRTT-DT tool. It allows academics and practitioners to examine cognitive biases and re-trading tendencies in day trading university students using a validated and theory-based scale. We constructed the scale using expert content validation, cognitive interviews, and exploratory and confirmatory factor analyses in two separate samples. The results suggest that CBRTT-DT is a valid scale with adequate-to-good model fit and a three-factor scale structure consisting of three subscales (Cognitive Biases, Re-Trading Tendencies, Profit/Loss Status). The CBRTT-DT was developed to assess day trader psychopathology (biases and re-trading tendencies), both in cognition (biases/attitudes) and behavior (re-trading, trading status). With future research and further development, the CBRTT-DT could be used to study the effects of cognitive biases and re-trading tendencies on day traders and help identify traders who may be engaging in harmful trading behaviors that may threaten their financial future.

Declarations:

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Ethics Approval: This study was reviewed and approved by the Shoolini University Institutional Ethics Committee (IEC) Approval Number: SU/IEC/26/05.

Conflicts of interest / Competing interests: The authors declare none.

Consent to Participate: Electronic informed consent was obtained from all individual participants included in the study.

Consent for publication. Electronic informed consent was obtained from all individual participants included in the study.

None of the reported studies were preregistered.

Data Availability:

- **Study Preregistration:** The study was not pre-registered.
- **Data, Materials & Code Transparency:** The data, materials & analytic code are openly available on: https://osf.io/wdh3b/overview?view_only=3432c13487a64189b1e1628431065544e

AI statement:

During the preparation of this work the author(s) used Quillbot to correct/remove any grammatical errors in the text. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication. An iThenticate AI report has been attached in the submission of this paper.

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