NBER WORKING PAPER SERIES

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Working Paper 35345
http://www.nber.org/papers/w35345

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
June 2026

We thank Hui Chen, Lauren Cohen, Davidson Heath, Nengjiu Ju, Yongxiang Wang, Hong Yan, Naide Ye, Songfa Zhong, Ning Zhu, and conference/seminar participants of the 20th International Behavioural Finance Conference, National Chengchi University, and Zhejiang University for helpful comments. The fieldwork received approval from the Institutional Review Boards (IRBs) of the University of Michigan. All errors are our own. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 35345
June 2026
JEL No. C80, C89, D91, G11, G41, J24

ABSTRACT

The emergence of wearable electroencephalography (EEG) technologies presents new opportunities to identify and quantify neural correlates of decision-making in real-time, financially consequential settings. We report a field study in which we use wearable EEG devices to record brainwave activity from professional day traders during real-world, high-stakes trading. Using these signals, we construct an established psychophysiological Engagement Index (EI), which is defined as beta wave power divided by the sum of alpha and theta wave power, and document clear spike-and-decay patterns around trade execution. Linking EI dynamics to trading performance, we find that more successful trades are preceded by larger EI spikes in the 30 seconds before execution, while baseline or background EI levels have no predictive power and, if anything, are negatively associated with performance. We further show that higher EI is associated with attenuated behavioral biases in trading, including the round number heuristic and the disposition effect.

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1. Introduction

Psychological factors are of first-order importance in economic decision-making (e.g., Simon, 1955; Kahneman and Tversky, 1979; Thaler, 1980; Shiller, 2003; DellaVigna, 2009). This thesis has made the most progress in behavioral finance, where human tendencies and biases are amplified in the presence of financial incentives and risk (e.g., Shleifer and Vishny, 1997; De Bondt and Thaler, 1985; Hirshleifer, 2001; Barberis and Thaler, 2003). A crucial step forward in this literature is identifying and quantifying psychophysiological signals associated with behavior. These *neurofinance* measures are useful because they help tie behavior to biology, reveal unconscious processes that shape choice, and may even offer guidance on possible interventions to reduce costly biases (e.g., Lo and Repin, 2002; Camerer et al., 2005; Kuhnen and Knutson, 2005; Coates and Herbert, 2008; Frydman and Camerer, 2016; Bossaerts et al., 2024).

A major challenge for this research is that most traditional psychophysiological tools are expensive and difficult to operate. For example, standard electroencephalogram (EEG) setups require extensive electrode arrays and trained technicians, and functional magnetic resonance imaging (fMRI) demands costly scanners and tight experimental control. These constraints make it virtually impossible to study real-world, high-stakes financial decisions among professional traders (e.g., Camerer et al., 2005; Frydman et al., 2014; Kuhnen and Knutson, 2005). To date, clinical studies in neurofinance have been conducted primarily in laboratory environments with simplified tasks and non-professional subjects, often in hypothetical settings.

The primary objective of this paper is to assess the feasibility of utilizing newly available wearable EEG technology to investigate financial decision-making in a real trading environment. Unlike traditional EEG systems, which record brain activity through a dense network of electrodes attached to the scalp, wearable EEG devices collect brain-wave information using a minimal set of sensors integrated into a headset. These recordings are not quantitatively identical to clinical systems, but they greatly improve cost efficiency and ease of use. The device, manufactured by a leading company, takes the form of an ordinary headset and retails for a fraction of the cost of clinical equipment.

Our paper reports field data collected using wearable EEG devices from a group of professional day traders as they engage in real-world stock trading under high-stakes and rapid decision-making pressure. We collaborate with a proprietary trading firm specializing in high-frequency intraday scalping in the Chinese A-share market, where traders execute simulated "T+0" round-trip trades (also known as *scalp trading*). The firm maintains a hedged base inventory of highly liquid, volatile stocks, allowing traders to either buy and then sell into inventory or sell inventory shares first and repurchase them later in the session. Because the firm offsets the inventory's market exposure with index futures, profits primarily arise from traders' ability to capture short-lived price dislocations, rather than from directional market movements.

As a result, trading occurs in a highly volatile environment in which most round-trip trades complete within minutes, average trade sizes are large relative to retail activity, and per-trader daily volume often reaches tens of millions of RMB. Individual profit and loss are, therefore, driven by execution speed and precision, not by longer-horizon price trends. This structure yields a relatively clean study setting: the trading task is tightly constrained, with minimal external hedging concerns or inventory management decisions distracting from moment-to-moment choice and performance.

Our field study includes 16 *day traders* from this firm. On each trading day, a participating trader records two hours of EEG data, with one hour in the morning session and one hour in the afternoon, both beginning shortly before the market opens. Each trader contributes data for five consecutive trading days, then pauses for a week, and then records another five days of trading. This cycle repeats a second time before full exit from the study. By repeatedly measuring EEG signals from the same individuals across different days and weeks, this empirical design enables us to identify within-individual variation in neural activity tied to specific decisions. We also stagger the 16 traders into two cohorts (eight traders in weeks 1, 3, and 5 of our study periods and eight traders in weeks 2, 4, and 6) so that our analysis is less influenced by temporal or market seasonality. This field study yields a substantial dataset: we observe valid EEG-linked measures over 9,544 executed and filled trades (buys and sells), producing 954,692 trader-by-second observations of EEG signals.

To analyze these data, we follow the psychophysiological EEG literature and construct a cognitive Engagement Index (EI) defined as the ratio of Beta band power to the sum of Alpha and Theta band power. In EEG spectral terms, Beta activity (typically in the 13–30 Hz range) is linked to active, alert mental states and focused cognitive effort, while Alpha activity (8–13 Hz) dominates during relaxed wakefulness and tends to decrease with increasing attentional demands, and Theta activity (4–7 Hz) varies with memory processing and task-related control demands. Therefore, our EI captures the relative predominance of high-frequency, task-related cortical activation over lower-frequency rhythms associated with relaxed or internally directed processing, or simply put, how intensively a trader is engaged with the decision task.

We begin by documenting EI patterns around the moment of trade execution. EI remains flat until about one minute before a trade, then rises sharply in the seconds leading up to execution, peaks at the trade moment, and returns quickly to baseline. The pre-trade increase in EI appears comparable for both entry and exit trades; however, their post-trade dynamics diverge markedly. Following an entry trade, EI declines gradually back to baseline. Following an exit trade, EI drops much more sharply, overshooting the pre-trade increase before slowly returning to baseline. These patterns offer an encouraging sign that the EI we build can capture cognitive engagement. Engagement rises as traders monitor conditions and commit to a trade decision, and falls once the trade is executed. The sharper post-trade response following exit trades is also intuitive, as exits close positions and eliminate risk, whereas entries initiate exposure and leave uncertainty in place.

Several other characteristics of EI also support its validity as a measure of investor engagement. First, EI tends to be higher in the morning than in the afternoon, consistent with intra-day patterns of cognitive resource depletion found in other studies. Second, we cross-validate the neural metrics using the d2 Test of Attention, a standardized behavioral assessment of selective and sustained attention (Bates and Lemay, 2004). We find that traders with higher d2 scores tend to exhibit higher EI during the task, and second-level regressions show a positive association between EI and d2 correctness. This alignment between a validated neuropsychological benchmark and our trading-derived metrics supports the interpretation that high EI reflects heightened cognitive focus, rather than mere physiological arousal or noise. Finally, we compare trading behavior and performance during periods when traders wear the EEG equipment and when they do not. We find no significant differences, ruling out a Hawthorne effect.

In the second part of our analysis, we assess whether EI relates to trading performance. We first show that higher EI signals predict a greater propensity to trade. More importantly, the magnitude of the EI increase immediately prior to a trade is positively correlated with trade outcomes. In contrast, baseline EI levels before or after trade execution do not positively predict performance; if anything, higher background EI is associated with worse trade outcomes. Similarly, when relating daily performance to daily EI patterns, we find no positive association and, in several specifications, a negative one. The consistent pattern indicates that it is the surge in engagement immediately before a decision, not the level of background engagement, that links to better performance.

How does cognitive engagement affect performance? We provide two examples of how EI relates to behavioral biases in trading. First, we examine the round number heuristic, the tendency to quote prices at round integers, which is a commonly observed cognitive shortcut among financial traders (e.g., Harris, 1991; Kuo, Lin, and Zhao, 2015). We document that the round number heuristic is present in our data and economically costly: trades executed at "strong round prices" (those ending in .00 or .50) yield lower returns than those at precise, non-round prices. Linking this to EEG-measured engagement, we document a striking asymmetry in performance: the profitability penalty associated with round-number pricing is concentrated in trades executed under low engagement.

Second, we examine the disposition effect, that is, traders holding losing stocks longer than winning ones (e.g., Frydman et al., 2014). This is another well-documented behavioral bias present in our data: losing positions are held for about 60.4 seconds on average, compared with 55.9 seconds for profitable positions. Merging trade behavior with moment-by-moment EI patterns, we find that higher engagement during the holding and exit windows is associated with a significant mitigation of the disposition effect. A one-standard-deviation increase in engagement reduces the additional holding duration of loss trades by roughly 4 to 5 seconds, depending on the engagement window. Engaged traders are therefore more likely to cut losses promptly, which may help reduce losses associated with the disposition bias.

Importantly, the high-frequency and repeated nature of our EI measurement allows us to include trader-by-date-hour fixed effects in the main regression specifications. The identifying variation is therefore very local: we compare the same trader within the same trading hour and ask whether trades preceded by relatively higher EI, or a larger EI run-up, are associated with different trading decisions and outcomes. These fixed effects absorb all time-invariant trader characteristics as well as trader-specific conditions within a given date-hour, including broad market conditions and other intraday shocks. As a result, the estimates are not driven by cross-trader differences or by common shocks at a particular point in time, but by within-trader, within-hour fluctuations in cognitive engagement.

We acknowledge that our analyses are mostly associational and do not establish a strong causal inference. Some of our findings could be subject to alternative interpretations. For example, a larger pre-trade increase in EI may reflect the presence of better trade opportunities, which could both *induce* a larger EI spike and lead to better realized trading performance. Our extensive controls for trading opportunities at the tick and order level go some way toward addressing this concern, though they cannot eliminate it entirely. Nonetheless, we hope that the descriptive patterns documented in this paper are informative and interesting enough to motivate future work that introduces experimental interventions on EI, or other EEG measures, to address these causal relationships.

In addition, while our results show that higher engagement is associated with lower degrees of behavioral biases, this effect is unlikely to be universal. We conjecture that engagement primarily reduces biases that arise from limited attention, heuristic processing, or failures of cognitive control. In contrast, biases rooted in distorted beliefs or stable preferences may persist even under high engagement, as they reflect how individuals interpret information rather than whether they process it attentively, e.g., memory-induced biased beliefs and subsequent choices (Bordalo et al., 2023; Enke et al., 2024; Bordalo et al., 2025; Jiang et al., 2025; Gödker et al., 2025). These questions also call for further studies.

Related Literature. Our work contributes to the neurofinance literature, which integrates cognitive neuroscience, psychology, and behavioral finance to study the biological foundations of financial decision-making (e.g., Kuhnen and Knutson, 2005; Camerer, Loewenstein, and Prelec, 2005; Frydman and Camerer, 2016). We are most closely related to research on the biophysiology of trading expertise, which introduces biometric measures such as heart rate variability (HRV) and galvanic skin response (GSR) into the study of professional traders (Lo and Repin, 2002; Lo, Repin, and Steenbarger, 2005; Coates and Herbert, 2008).

A related experimental literature further shows that biological states can causally affect trading behavior and market outcomes. For example, Nadler et al. (2018) exogenously increase testosterone in experimental asset markets and find that testosterone leads to higher bids and larger, longer-lasting price bubbles. A central insight from this line of work is that effective regulation of sympathetic arousal by the parasympathetic nervous system constitutes a form of learned expertise. In this view, "learning the market" involves not only acquiring informational or strategic skill but also training the body's autonomic response to volatility (Bechara et al., 1997; Fenton-O'Creevy et al., 2012; Kandasamy et al., 2016). This literature also emphasizes persistent individual differences.[1] Neurobiological traits, such as the integrity of the amygdala, and psychological characteristics, such as neuroticism or extraversion, help explain variation in risk tolerance and vulnerability to behavioral biases, including the round number heuristic (e.g., Harris, 1991; Kuo, Lin, and Zhao, 2015; Lin and Pursiainen, 2021) and disposition effect (e.g., Shiv et al., 2005; Grinblatt and Keloharju, 2009; Cesarini et al., 2010; De Martino, Camerer, and Adolphs, 2010; Jung et al., 2018; Quispe-Torreblanca et al., 2026).

Our contribution to this literature is both methodological and substantive. Methodologically, our paper is the first to use brain-based measurement to monitor neural activity in a real-world high-stakes financial setting. Existing neurofinance studies rely almost exclusively on clinical EEG or fMRI to study neural mechanisms in laboratory environments (e.g., Kuhnen and Knutson, 2005; De Martino et al., 2006; Knutson and Bossaerts, 2007; Frydman et al., 2014; Smith et al., 2014; Coates and Gurnell, 2017). The operational constraints of these technologies make them largely infeasible for deployment in real-time trading contexts, particularly among professional traders. As a result, prior field work, most notably Lo and Repin (2002), relies on peripheral physiological measures such as heart rate, blood pressure, and skin conductance to capture traders' emotional responses. While informative, these signals reflect broad autonomic activation and are responsive to various emotional states. They do not directly capture central executive processes associated with attention and cognitive control. EEG provides a closer measure of the cognitive effort and attentional focus that precede trade execution. We show that wearable EEG devices allow real-time neural monitoring in active trading environments, with signal quality sufficient to test theory-driven predictions about decision timing and performance.

[1] For a more comprehensive review of the extensive literature on biology and finance, see Burnham and Cronqvist (2026).

Substantively, our findings shift attention from cross-sectional differences to within-individual dynamics. Much of the existing literature, on both mainstream and the neural sides, emphasizes persistent traits, learning over career horizons, or seniority-based differences in expertise (e.g., List, 2003; Feng and Seasholes, 2005; Haigh and List, 2005; Seru, Shumway, and Stoffman, 2010; Dohmen et al., 2011). Our results instead point to short-run fluctuations in neural engagement within the same individual. Performance differences arise most clearly during brief and well-defined periods immediately preceding decision execution. These findings point to the importance of critical windows in decision-making rather than stable trader types alone. From this perspective, improving task performance involves identifying and cultivating effective engagement at key moments, not only selecting individuals with desirable long-run characteristics.

Looking forward, wearable EEG opens new possibilities for economic and financial research. It is particularly well-suited to questions that require opening the decision-making black box in real operating environments, where laboratory abstraction is costly. Because neural signals can be observed in real time, this technology also allows scope for interventions that respond to cognitive state, including neuro-aware decision aids or adaptive trading systems designed to support more stable and disciplined performance (e.g., Parasuraman, 2003; Zander and Kothe, 2011; Aricò et al., 2016; Lo, 2017; Di Flumeri et al., 2019). More broadly, the low cost and ease of deployment of wearable EEG make it a practical tool for neuroeconomic research in settings where in-situ measurement of brain activity has previously been infeasible (e.g., Debener et al., 2012; Krigolson et al., 2017; Dikker et al., 2021).

Finally, our paper speaks to the economic value of real-time investor engagement. Trades preceded by a steeper rise in neural engagement perform better ex post, even though background engagement levels have little predictive content for performance. This finding parallels the findings by Gargano and Rossi (2018) that retail investors who allocate more attention to the trading platform, proxied by browsing time on the brokerage website, achieve superior trading outcomes. Relative to their work, we provide direct neurophysiological evidence that elevated engagement in the moments just before execution is linked to better performance. More broadly, our results suggest that real-time neural engagement may help investors override heuristic, System 1-type responses and make more disciplined high-stakes decisions under pressure.

The rest of the paper is organized as follows. Section 2 provides background on EEG and related psychophysiological research. Section 3 describes the field study design, data, and EI measurement. Section 4 links EI to financial performance. Section 5 concludes.

2. Background

2.1 EEG Vocabulary

Electroencephalography (EEG) is a non-invasive method that records the electrical activity of the brain by capturing voltage fluctuations at the scalp. These signals originate primarily from synchronous postsynaptic currents in populations of aligned cortical pyramidal neurons. Any single neuron's activity is weak, but when large groups of cortical neurons fire in synchrony, their combined electrical fields propagate through the skull and scalp to produce a measurable signal (Buzsáki et al., 2012).

Traditional laboratory EEG systems use a cap or array with numerous electrodes (often 20 or more in the standard 10–20 placement system) to sample these signals from multiple brain regions (Appendix Figure 1). The electrodes are typically wetted using conductive gel or paste to ensure low impedance contact with the skin for high-quality recording. Each electrode captures the difference in voltage between its site and a reference electrode, and these analog signals are amplified and filtered to isolate the frequency range of interest. The result is a set of continuous voltage time series, also known as "brain waves," which can be analyzed for their spectral content. This spectral analysis allows researchers to decompose the EEG into distinct frequency bands that have well-established links to mental states (Buzsáki and Draguhn, 2004).

EEG signals are conventionally divided into five frequency bands, identified by their oscillating frequency. Delta waves (0.5–4 Hz) are the slowest and tend to dominate during deep, dreamless sleep or unconscious states. Theta waves (4–7 Hz) are associated with drowsiness, light sleep, and relaxed or meditative states; excess theta activity in waking EEG typically signals reduced alertness, for example, during monotonous tasks or fatigue. Alpha waves (8–13 Hz) are prominent in relaxed wakefulness, especially when the eyes are closed, and the mind is unfocused. Alpha rhythm is often described as the idling state of the awake brain. Beta waves (13–30 Hz) reflect active thinking, focus, and intense cognitive processing. Higher beta activity is observed when individuals concentrate, make decisions, or engage with external stimuli. Finally, Gamma waves (30+ Hz) represent the highest-frequency band. Gamma activity is often linked to states of peak concentration, multi-sensory integration, or other forms of heightened and coordinated brain activity. However, the gamma band can be difficult to measure with scalp EEG reliably.

Broadly speaking, faster brainwaves (beta and gamma) are often associated with heightened vigilance and information processing demands, whereas the slower waves (alpha, theta, and delta) are typically associated with relaxed, drowsy, or sleep-like states. These frequency-band associations allow EEG researchers to interpret changes in the power of each band and/or their combinations as indicative of shifts in cognitive state (Ray and Cole, 1985; Steriade et al., 1993; Buzsáki and Draguhn, 2004).

2.2 Wearable EEG

We measure our traders' neural activity using a portable single-channel EEG headset produced by NeuroSky.[2] Unlike a full clinical EEG setup, which requires an array of electrodes, extensive skin preparation, and gel application by a trained technician, this wearable device uses a few dry electrodes integrated into a lightweight headset. The primary sensor rests on the trader's forehead at the left frontopolar position, and a reference electrode clips onto the earlobe.[3] This configuration enables the device to record a single EEG channel from the forehead, a region sensitive to changes in alertness and executive processing, while the ear reference provides a baseline and helps cancel out ambient electrical noise.

The use of dry electrodes means the headset can be donned quickly without any skin abrasion or gel applications. Once the headset is in place, the on-board amplifier continuously measures the voltage difference between the forehead sensor and the ear clip. The raw signal is immediately cleaned and processed, and a Fast Fourier Transform is applied on successive one-second epochs of the EEG, which generates the power levels in each of the Delta, Theta, Alpha, Beta, and Gamma frequency bands.

Despite its advantages in portability and ease of use, the wearable EEG system does face important limitations compared to a clinical-grade EEG system. First, signal quality is inherently lower. Dry electrodes typically exhibit higher impedance than gel-based electrodes, which can translate into a lower signal-to-noise ratio. Small movements, cable shifts, or facial muscle contractions (e.g., frowns and eye blinks) can introduce artifacts that a multi-electrode setup might better identify and reject. Most consumer-grade wearables include an embedded high-pass filter (often with a cutoff around 3 Hz) to mitigate the impact of low-frequency movement noise. This filter effectively attenuates

[2] https://neurosky.com/

[3] The placement corresponds approximately to the FP1 site in the traditional 10–20 EEG system.

much of the delta band. In our study, we avoid using slow-wave oscillations and instead analyze higher-frequency rhythms like theta, alpha, and beta.

Second, with only one channel, we have no way to localize activity. A spike in beta power could reflect genuine frontal lobe engagement, but we cannot tell if, say, the visual cortex or other regions are also activated at that moment. Last, reliability over long sessions can be a concern. Dry electrodes can lose good contact if the participant moves too much or if the headset shifts position. Fortunately, in our application, traders mostly keep relatively still with their eyes on screens, and there is minimal gross movement. The recording periods (1 hour per session) are also short enough that signal dropouts were rare. Appendix Figure 1 shows a comparison of clinical wet EEG versus wearable dry EEG devices.

The correspondence between wearable devices and clinical EEG has been a subject of extensive validation. NeuroSky's own analysis of simultaneous recordings with the Biopac traditional wet EEG system shows that the two systems produce highly correlated power spectra of frequency bands with an average correlation coefficient of about 0.8 (NeuroSky, 2009). Peer-reviewed academic studies have also produced promising results. Kam et al. (2019) compare a wireless 31-channel dry-electrode EEG system with a conventional wired wet-electrode EEG system and find that key electrophysiological measures are highly correlated across systems with a correlation coefficient ranging between 0.54 and 0.89. Hinrichs et al. (2020) report that a 19-channel dry EEG system produced comparable alpha and beta power readings to a traditional wet system, with only small differences in theta and delta power. The same study reported that even event-related potentials recorded with dry vs. wet electrodes had similar amplitudes and latencies, suggesting that dry electrodes can capture meaningful neural signals for both spectral analysis and time-locked responses.

2.3 Measuring Cognitive Engagement using EEG Signals

The application of EEG to measure cognitive engagement rests on the observation that the distribution of power across different frequency bands reflects the depth of an individual's immersion in a task. We are mainly interested in cognitive engagement, which refers to the degree of active mental involvement, focus, and effort that an individual directs toward a task. Our interest is specifically in task engagement: a heightened state of arousal and concentration in which a person is "tuned in" to their actions and environment.

Neuroscience research has shown that certain brainwave patterns are correlated with levels of alertness and attention. Generally, when a person becomes mentally absorbed in a demanding activity, the EEG signal tends to exhibit increased high-frequency power (Beta and Gamma) and decreased lower-frequency power (Alpha and Theta). Conversely, lapses in engagement (boredom, fatigue, mind-wandering) often manifest as a rise in alpha/theta activity and a decrease in beta activity. These physiological signatures provide a basis for quantifying engagement. By comparing the relative power in "task-positive" fast waves versus "task-negative" slow waves, one can derive an index that tracks the intensity of cognitive engagement on a moment-to-moment basis.

A well-established metric in this vein is the so-called Engagement Index, typically defined as the ratio of beta power to the sum of alpha and theta power. This index was originally developed in Pope et al. (1995) to monitor NASA pilots' and operators' attention in real time. Pope et al. (1995) first demonstrated that this EEG-based engagement index could be used in a closed-loop "bio-cybernetic" system: they feed the index into an automated task allocation program, which would reduce a pilot's workload if the EEG indicates that engagement is dropping (to prevent lapses due to fatigue). In that study, using the EEG engagement feedback improves performance. For example, pilots maintain vigilance longer and commit fewer errors when the system dynamically responds to their brain state. EEG measures of cognitive engagement have been applied across a range of fields (e.g., Freeman et al., 1999; Berka et al., 2007; Knyazev, 2012; Helfrich et al., 2014; Chaouachi et al., 2010; Attar, 2022), yet have received little attention among economic and finance scholars.

3. Measurement

3.1 Trading Environment

We collaborate with a professional proprietary trading firm that specializes in high-frequency intraday scalping in the Chinese A-share market. The Chinese equity market operates under a strict "T+1" settlement mandate, which prohibits investors from selling stocks purchased on the same calendar day. To enable their traders to make high-frequency round-trip trading, the firm relies on a base inventory mechanism. Under this framework, the firm maintains pre-existing long positions in a set of high-volume, volatile stocks. This inventory serves as a liquidity pool that allows traders to conduct "T+0," i.e., same-day round-trip transactions. Specifically, when the traders identify an intraday opportunity, they can execute a "long-first" sequence by purchasing shares and subsequently selling an equivalent amount from the existing inventory within a few minutes or even seconds. Alternatively, they may execute a "short-first" sequence by selling inventory shares near a price peak and repurchasing them later in the session at a lower price.

To insulate the firm's capital from broader market fluctuations, the underlying base inventory is systematically hedged using corresponding stock index futures. By maintaining a short position in futures contracts that offsets the long exposure of the stock basket, the firm achieves a market-neutral (also referred to as "delta-neutral") risk profile. Under this arrangement, price movements of the base inventory itself do not contribute to the traders' profits and losses. Instead, revenue is derived primarily from traders' execution efficiency, specifically their ability to capture transient price imbalances through frequent buy-and-sell cycles. This institutional setting is ideal for us to analyze the traders' cognitive states before each trade and their success in generating intraday alpha.

Appendix Figure 2 shows a typical setup for a trader. Each trader operates a workstation equipped with four monitors. The top-left screen displays broad market indices, the top-right tracks sector price trends, the bottom-left shows real-time candlestick charts for the focal stock, and the bottom-right enables order entry. Throughout the trading session, traders engage in rapid-fire execution that often involves holding positions for only a few minutes or even seconds. This practice is often known as scalp trading. Traders receive 50% of their net trading profits as a performance bonus. Over our study period, on average, a trader earns a daily bonus of approximately CNY 2,000 (about $290 USD per trading day).[4] The setup, therefore, features a high-intensity environment characterized by the constant need to monitor order books and make rapid decisions under high personal financial stakes.

3.2 Study Setup

Recruitment. As our study is conducted in partnership with the trading firm and receives approval from the management board, all traders at the firm are involved in the study. In total, 16 professional traders participate in the study.

Training. All traders receive instructions on how to use the EEG device at least one week prior to the launch of the study. We arrive on site to demonstrate how to wear the headset and how to connect the device to the data terminal. Traders are given explicit assurance that the EEG device poses no risk to their physical or mental well-being and does not interfere with their trading activities.

[4] Note that our data cover two one-hour trading sessions per day, and the reported profits and bonuses reflect outcomes within these observed windows only. Full-day amounts would be approximately twice as large.

Schedules. Our study spans six weeks between October 22nd and December 2nd, 2025. The Chinese stock market operates from 09:30 to 11:30 in the morning session and from 13:00 to 15:00 in the afternoon session on each trading day. The study is conducted in the firm's trading room, with traders operating in their regular workspace. We ask each subject trader to wear the EEG headband and begin EEG data transmission at least 5 minutes prior to the start of each trading session, and to continue wearing it for at least 60 minutes. We assign a research project manager on-site to monitor the study field. Given the high-stakes trading environment, the project manager does not intervene in cases of noncompliance. In Section 3.3 below, we statistically assess the extent to which traders adhere to the guideline and whether monitoring timing may be endogenous, for example, whether monitoring correlates with performance.

We use a weekly crossover design in which each subject trader participates in the study for five consecutive trading days, does not participate in the following week, and then participates again in subsequent weeks. This cycle then repeats one more time for the trader to provide a third week of data. In practice, we randomly divided the 16 subject traders into two groups. Eight traders participate in the 1st, 3rd, and 5th weeks of the study, while the other eight participate in the 2nd, 4th, and 6th weeks. This design helps mitigate potential seasonal influences, such as factors that differ across earlier versus later periods within the October to December window, while also reducing the traders' experimental fatigue. Appendix Figure 3 illustrates the schedule.

Data Linkage. We built a real-time synchronization between the EEG headsets, the EEG data acquisition software, and the firm's trading terminal. Each successful order is logged by the server using local timestamps (UTC+8) at the second level. The EEG data stream is recorded at a frequency of 1 Hz, that is, one observation per second, and is subsequently aligned with the trading logs.

Trader Survey. We administer a survey asking traders to report basic demographics (age and handedness), lifestyle habits (whether they engage in gym activity, consume caffeine, smoke, or drink alcohol on an almost daily basis), and sleep patterns (average daily sleep hours and self-rated sleep quality on a Likert scale from 1, poor, to 5, excellent). Fifteen of the sixteen traders complete the survey and provide full responses to all questions. We later examine the correlation between measured cognitive engagement patterns and these characteristics.

3.3 Data Quality Checks

Our subject traders are generally cooperative throughout the field study. Nonetheless, the high-pressure environment of real-time trading occasionally introduces complications. Unlike controlled laboratory settings, the intensity of pre-market preparations sometimes leads to delayed equipment deployment, and technical demands occasionally require adjustments during active trading sessions. It is also plausible that, when traders are under extreme pressure, they may choose to adjust or even remove the experimental headset if they feel it adds to discomfort. This latter behavior may introduce endogenous bias, as it could cause data to be differentially missing as a function of underlying engagement levels and trading performance. As mentioned earlier, due to the high-stakes setting, we do not interfere with traders once trading sessions begin.

To mitigate these potential concerns, we conduct several data quality checks. First, we examine the extent to which traders adhere to the experimental guidelines, i.e., starting EEG signal recording several minutes before the beginning of both the morning trading session at 9:30 am and the afternoon trading session at 1:00 pm, and maintaining each recording session for at least one hour. Appendix Figure 4 presents the statistics. Panel A shows that, for the morning session, a majority of traders (86.58%) begin recording several minutes before the 9:30 am market opening. Compliance in the afternoon session is more concentrated during the time window around 1:00 pm, as most traders prefer to take a nap during the lunch break and wake up around 12:50–12:55 pm. Panel B shows the distribution of recording duration per trader-session. The figure exhibits a pronounced concentration at exactly 60 minutes, which suggests that most traders adhere to the guideline for monitoring duration. In addition, we remove observations with substantial data gaps exceeding 30 minutes from the formal analysis.

Second, we test for endogenous monitoring: whether the presence of EEG recording is systematically related to traders' behavior and performance. In our setting, this concern is akin to a Hawthorne effect. For example, traders may change their trading style when the headset is on, or remove or delay wearing the device during periods of heavy trading pressure. To address this concern, we examine trades executed in the 15 minutes before and after each EEG session, as well as sampled trading records from the week after the study ends.

We conduct the analysis at the batch level. The dependent variables include batch holding duration, batch profit, batch return, an indicator for whether the batch is profitable, and the number of trades in the batch. We regress these outcomes on an indicator equal to one if the batch begins during an EEG session and zero otherwise. All specifications include trader by date-hour fixed effects. Appendix Table 1 reports the results. Wearing the device is not statistically associated with changes in any of the trading outcomes we examine.

3.4 Results

Raw EEG Signals. Panel A of Table 1 presents summary statistics for the raw EEG spectral power across five frequency bands, Delta, Theta, Alpha, Beta, and Gamma, based on 954,692 trader-by-second observations. Note that the EEG signals are recorded as *band power values*, which represent relative amplitudes of each frequency band after filtering and scaling of the raw brain waves. As a result, their magnitudes differ from the scales of brain wave amplitudes typically reported in clinical settings, such as $\mu V^2/Hz$. Although the exact algorithms used for filtering and scaling are proprietary and not publicly disclosed, NeuroSky notes that the band power values provide "an indication of whether each particular band is increasing or decreasing over time, and how strong each band is relative to the other bands." As a result, band power values, rather than raw brain wave amplitudes, are commonly used in psychophysiological research to quantify psychological states (e.g., Pope et al., 1995; Gevins and Smith, 2003; Berka et al., 2007).

Engagement Index. Following Pope et al. (1995), we construct an Engagement Index (EI), defined as the ratio of Beta power to the sum of Alpha power and Theta power:

$$\text{Engagement Index} = \frac{\text{Beta power}}{\text{Alpha power+Theta power}} \quad (1)$$

As discussed in Section 2.1, higher Beta power corresponds to more active information processing, attention, and task involvement. Lower Alpha power corresponds to reduced idling or disengagement, and lower Theta power reflects less drowsiness or fewer attentional lapses. This ratio effectively normalizes attention-related signals (beta) by idling-related ones (alpha+theta). This construction has two advantages. First, it reduces the impact of individual baseline power differences, for example, those arising from equipment or measurement variation, thereby substantially reducing noise in the metric. Second, it captures relative dominance across frequency bands. Higher values of EI indicate a brain state dominated by beta activity relative to alpha and theta activity, which Pope et al. (1995) interpret as greater mental engagement in the task, or, in their original words, a state in which "*the operator is mentally involved enough to maintain situation cognizance and attentively supervise the system*."

Panel A of Table 1 also reports summary statistics for the EI, and Panel B presents the pairwise correlation matrix between the EI and the raw EEG signals. We use the EI based on Pope et al. (1995) as our primary measure of engagement. For robustness, we also use (1) the Theta-to-Beta ratio, an inverse metric of attentional control linked to mind wandering (Putman et al., 2010; van Son et al., 2019), and (2) the Gamma-to-Alpha ratio, which reflects feature binding and cognitive processing (Jensen et al., 2007). We note that the latter should be interpreted with caution due to the lower reliability of wearable EEG measurement in the Gamma band. Results from both alternative specifications remain qualitatively similar to our baseline estimates.

Appendix Figure 5 shows a ridge plot of the distribution of EI separately by trader. For each trader, we plot the distribution of EI observed during the trading periods. We define trading periods as valid EEG observations within 60 seconds before or after a trade execution timestamp. Non-trading periods include all remaining valid EEG observations outside these trade-execution windows. Several intriguing patterns emerge. First, EI varies widely within the same individual, suggesting that mental engagement is transient in nature. Second, for many traders, there is a visually apparent rightward shift in the EI distribution, i.e., higher overall EI levels during the trading window relative to the non-trading window. We test these differences more systematically below. Third, the overall shape of the EI distribution differs substantially across traders, with some individuals exhibiting a long right tail of EI realizations. Among the 16 traders in our study, the median EI ranges from 0.18 to 0.35, and the standard deviation of EI ranges from 0.14 to 0.54.

The EEG headsets used in the study are of an identical model and technical specifications, and their operation is straightforward. We thus expect that only a small portion of this cross-individual heterogeneity is driven by operational artifacts, with most reflecting genuine differences in individual engagement patterns. Accordingly, we include trader fixed effects in most analyses below and thus examine the relationship between cognitive engagement and trading behavior within the same individual.

Several other patterns corroborate the interpretation of EI as a measure of engagement. First, we administered a d2 Test of Attention, which is a standardized, easy-to-implement neuropsychological assessment of selective and sustained attention, immediately following the trading session. An example of the test is provided in Appendix B. This external benchmark allows us to compare the physiological signatures of trading against a controlled task explicitly designed to demand high cognitive focus. Appendix Table 2 reports trader-level summary statistics and second-level regression evidence from the d2 testing period. In Panel A, traders are ranked by d2 performance, measured as the number of correct responses out of 100, alongside their mean EI during the task. We find a clear positive relationship: traders with higher d2 scores tend to exhibit higher engagement levels. In Panel B, using second-level EEG observations recorded during the task, we regress d2 correctness on neural measures and find that EI is positively associated with performance. That is, traders who display stronger neural engagement during the attention task also perform better behaviorally. Taken together, these results suggest that EI captures meaningful individual differences in sustained cognitive focus, rather than nonspecific arousal or background physiological noise. Second, in Panel A of Appendix Figure 6, we show that traders' cognitive resources vary within the same day. The average EI in the morning is 0.45, whereas it decreases to 0.42 in the afternoon session. Third, we find an intuitive correlation between EI and trader demographic, physiological, and lifestyle characteristics. We discuss these additional findings later.

Trading Outcomes. Table 2 reports summary statistics for the stock trading data. We first report statistics at the trade-order level. Over the study period, we observe a total of 9,544 trades, and we report average statistics on trading amount, trading volume, and associated transaction costs, including commissions and taxes.

We then report statistics at the batch level. A batch is defined as a complete intraday round-trip trading cycle. From each trader's daily inventory, we identify batch initiation as the moment when a position, either long or short, is opened, and we identify batch completion as the moment when the cumulative net inventory returns to zero. The average Batch Investment Amount is 262,472 CNY, approximately 37,500 USD, and the mean Batch Return is 0.11 percent, with a standard deviation of 0.42 percent. The average number of Trades Per Batch is 2.95, with a median of 2, suggesting that while the modal strategy involves a simple entry and exit pair, traders frequently scale into or out of positions.

Finally, we report statistics at the trader-day level, aggregating trading activities for each trader within our observed trading windows on a given day. Importantly, our data cover only two one-hour trading sessions per day, one in the morning and one in the afternoon, rather than the full trading day. Within this two-hour observed window, the average trader executes 17.57 batches and 52.20 distinct transactions per day. This corresponds to an average trading volume of approximately 9.25 million CNY (≈1.32 million USD) over the observed sessions. In terms of performance, the average net profit during these observed trading windows is 4,816 CNY (≈690 USD). Given that traders typically receive a substantial share of this profit as a performance bonus (i.e., 50%), this implies a remarkably high level of compensation relative to the average daily income in China (approximately 340 CNY, or ≈50 USD).

Engagement Patterns around Trades. We next document how the subject traders' EI behaves shortly before and after trade execution. We conduct an event-study-style analysis in which each trade execution is treated as an event. We align a trader's EI data to describe the average pattern in the 150 seconds before and 150 seconds after one transaction.[5]

Panel A of Figure 1 presents the results. We find that traders' EI follows a flat trend until approximately one minute before the trade execution, at which point it begins to increase. The increase accelerates during the final 30 seconds before execution. EI peaks exactly at the moment of trade execution, corresponding to $t = 0$ in the figure, and then declines sharply. Following the trade, EI again exhibits a flat pattern, but at a level that is slightly lower than the pre-trade period. The magnitude of the EI swing is substantial. The spike is approximately 0.07 units, which corresponds to roughly 14 percent of the standard deviation of EI reported in Table 1.

[5] We use a window of ±150 seconds (a total span of 5 minutes) around each trade. This choice is motivated by the observation that the average trader executes approximately 50 trades per day and most of the trades take place in the first hours of each trading session, which falls into our sample. Cumulatively, 50 trades with a 5-minute window amount to 250 minutes (about 4 hours), which closely aligns with the total daily trading hours of the Chinese stock market. For robustness, we also verify our findings using narrower windows (e.g., ±60 and ±30) and find the results to be qualitatively unchanged. We also restrict the sample to non-overlapping trades, defined as trades that are not preceded by another trade by the same trader within 150 seconds. See Appendix Figure 8.

In Panel B of Figure 1, we split the sample into entry trades, defined as the first trade of a batch, and exit trades, defined as the last trade of a batch. A clear difference emerges. While both entry and exit trades are associated with a pronounced increase in EI shortly before execution, the post-trade dynamics differ markedly. Following entry trades, EI declines gradually and returns to its pre-trade level. In contrast, exit trades are followed by an immediate and large decline in EI that overcompensates for the pre-trade increase, before EI slowly returns to its pre-trade level. These patterns are consistent with the psychological demands faced by traders: After opening a position, the trader assumes risk and must maintain continued vigilance and monitoring. In contrast, executing an exit trade resolves uncertainty and releases cognitive load.

To understand what determines EI around trade execution, Table 3 examines three sets of predictors. We define EI level as the average Engagement Index during the immediate pre-trade decision window, from 30 seconds before execution to the execution time. EI change is defined as the difference between EI in this decision window and EI in the earlier baseline window, measured from 150 to 30 seconds before execution. Panel A examines recent trading history, Panel B examines market and technical indicators constructed from tick-level and order-level data, and Panel C examines trader characteristics and lifestyle habits. Panels A and B include trader-by-date-hour fixed effects, so the estimates absorb trader-specific opportunity conditions within each trading hour. Panel C includes date-hour fixed effects, because trader characteristics are time-invariant and would otherwise be absorbed by trader fixed effects.

Panel A shows that recent trading history explains only a limited portion of the variation in EI. Cumulative trading activity, measured by cumulative completed batches, cumulative losing batches, cumulative trade count, and cumulative trading amount, is not systematically related to either EI level or EI change. Trade size and execution price are also not significant predictors. A few variables are informative, however. Cumulative prior profit is negatively associated with EI change, suggesting that traders exhibit a smaller pre-trade engagement increase after accumulating more profits earlier in the day.

The indicator for whether the last completed trade generated a loss is positively associated with EI change, consistent with the idea that recent losses may sharpen attention before the next execution. The time elapsed since the previous trade is negatively associated with both EI level and EI change, indicating that engagement is higher when trades occur closer together. These results suggest that EI is not merely a mechanical reflection of recent trading intensity, although recent outcomes and trading tempo appear to matter at the margin.

Panel B examines whether EI is driven by observable market conditions before trade execution. The evidence again does not point to a single mechanical explanation. Short-run momentum is positively associated with EI in the 180-second window, especially for EI change, but the relation is weaker in shorter windows. Realized volatility, the number of trades, trade volume, and the number of submitted orders do not show a stable relationship with either EI level or EI change. Price-path efficiency is positively related to EI change in the 30- and 60-second windows, suggesting that traders' engagement rises more when the pre-trade price path is directionally cleaner. Distance to the recent high is negatively related to EI level and EI change in the 180-second window, while distance to the recent low and relative price are generally insignificant. Taken together, the market-signal results indicate that EI responds to some features of the trading environment, but the pattern is selective. The pre-trade EI spike documented in Figure 1 is therefore unlikely to be explained solely by standard measures of market activity, volatility, or liquidity.

Panel C relates EI to trader characteristics and lifestyle measures. Age is negatively associated with both EI level and EI change, consistent with clinical evidence that aging is associated with a shift toward lower-frequency EEG activity and weaker high-frequency activation. Left-handedness is negatively associated with EI level, though not with EI change. Regular gym activity is positively associated with both EI level and EI change, consistent with evidence that physical fitness supports executive function and attentional control. Smoking is positively associated with EI change, while alcohol use is negatively associated with EI change. Sleep quality is positively associated with EI change, whereas sleep hours enters positively but is not statistically significant at conventional levels. These correlations are descriptive and should not be interpreted causally, but they provide further validation that EI captures meaningful variation in traders' cognitive state rather than only measurement noise.

Taken together, Table 3 supports the interpretation that EI is a psychophysiological measure of engagement that is related to, but not fully determined by, observable trading conditions. Recent trading history and market signals explain some variation, and trader characteristics are correlated with both EI levels and EI changes. However, no single observable factor accounts for the sharp pre-trade engagement dynamics shown in Figure 1. In particular, the pre-trade increase in engagement does not appear to be mechanically generated by standard measures of trading opportunities. EI growth responds only selectively to market conditions, while EI level is largely unrelated to them. This mitigates the concern that the predictive power of pre-trade EI in our main results merely reflects traders reacting to obviously superior trading signals. The evidence is more consistent with the view that the short-run increase in EI captures an additional dimension of traders' internal cognitive state that is only imperfectly linked to observable market conditions, in the same vein as "trader intuition" (Bruguier et al., 2010; Corgnet et al., 2018)[6]. This motivates the analysis below, where we ask whether these short-run EI dynamics are related to trading behavior and performance.

The Appendix reports several extensions. Appendix Figure 7 presents results using alternative EI specifications from the literature, including the theta/beta ratio, which captures mind wandering and reduced attentional control, and the gamma/alpha

[6] More broadly, these findings suggest limits to full algorithmic substitution in short-horizon discretionary trading (which is also the view held by the partnering trading firm). The predictive content of the pre-trade EI spike appears only imperfectly linked to observable market signals, consistent with the idea that part of trader performance reflects context-sensitive judgment and intuition rather than purely mechanical signal extraction. In that sense, our evidence favors complementarity between human discretion and algorithmic tools (Cao et al., 2024), rather than a strict "man versus machine" view (van Binsbergen et al., 2023).

ratio, which captures cognitive engagement and focused information processing (e.g., Putman et al., 2010; van Son et al., 2019). The findings are qualitatively similar.

Appendix Figure 9 documents EI dynamics within each batch by tracing neural engagement over the normalized holding period of round-trip trades. In Panel A, which pools all batches, EI is slightly elevated at the moment a position is opened, declines modestly soon after, and then remains broadly stable for the remainder of the holding period. In other words, once a position has been initiated, traders appear to maintain a relatively steady level of cognitive engagement rather than exhibiting a continued rise or fall as the trade unfolds. This pattern complements the event-time evidence around trade execution: the sharp EI fluctuations documented in Figure 1 are concentrated around discrete decision points, whereas engagement during the holding period is comparatively flat.

A natural next question is whether EI patterns differ between winning and losing trades. We explore this issue in Section 4, where we examine the relationship between EI dynamics and trader performance.

4. Cognitive Engagement and Trade

In this section, we examine the extent to which EI explains traders' behavior and performance. Section 4.1 associates traders' propensity to execute trades with their EI patterns. Section 4.2 examines the correlation between traders' performance and EI. Section 4.3 discusses the mitigating role of EI in behavioral biases, including round-number heuristic and disposition effect.

4.1 EI and the Propensity to Trade

We begin with a distributed lag analysis to examine how the likelihood of trade execution is related to a trader's cognitive state in the moments before a trade. We specify a linear probability model in which the dependent variable is a binary indicator equal to one if a transaction occurs for trader i at second t:

$$1(\mathrm{Trade}_{i,t}) = \sum_{\tau} \beta^{\tau} \cdot \overline{\mathrm{EI}}_{i,t\in\tau} + \Gamma \cdot X_{i,t}^{pre} + \alpha_{i-date-hour} + \varepsilon_{i,t} \tag{2}$$

The explanatory variables of interest $\overline{\mathrm{EI}}_{i,t\in\tau}$ are lagged values of EI averaged over non-overlapping time windows τ ranging from 1 to 150 seconds before t. We include trader-by-date-hour fixed effects ($\alpha_{i-date-hour}$) to pin down within-trader temporal variation within each trading hour, and we control for prior trader-state variables $X_{i,t}^{pre}$ measured before time t, including the cumulative number of completed batches, the cumulative number of losing batches, the cumulative number of previous executions, cumulative trading amount, cumulative realized profit from completed batches, an indicator for whether the most recently completed batch generated a loss, and the log time elapsed since the trader's previous execution. These controls absorb recent trading intensity, accumulated gains and losses, and short-run trading tempo before the current second. Standard errors are clustered at both trader and date-hour levels to account for potential serial correlation within traders and common intraday market conditions.

Table 4 presents the β^{τ} coefficient estimates. Column (1) reports results using the full sample. Consistent with the descriptive patterns shown in Figure 1, the coefficient estimates indicate a pronounced increase in EI before trade execution. The coefficients for the most recent lags, from 0–1 seconds to 10–15 seconds before execution, are positive and statistically significant. The magnitude of the coefficient is largest in the 5–10 second window. As we move further back in time, to 15–150 seconds prior to the trade, the coefficients lose statistical significance and, in some cases, become negative.

Columns (2) through (5) of Table 4 decompose the sample into (i) entry trades, defined as the first trade of a round-trip trade batch, (ii) exit trades, defined as the last trade of a batch, (iii) buy trades, and (iv) sell trades, respectively. A similar pattern of increasing EI prior to trade execution persists across all subsamples. The predictive relationship is particularly evident for entry and exit trades in Columns (2) and (3). The similarity of the EI patterns for buy trades in Column (4) and sell trades in Column (5) suggests that EI largely captures the cognitive demands of the decision-making process itself, rather than reflecting the direction of the trading action.

4.2 EI and Trading Performance

Can a trader's pre-trade EI pattern predict trade performance, or is daily performance instead related to the trader's average EI level over the day? We revisit the analysis in Figure 2, but partition the transaction sample based on ex post profitability. Each trade is classified into one of two groups: "Profit" if the associated batch yields a positive return, or "Loss" if the return is zero or negative. Figure 2 plots the mean EI for these two subsamples within a window of ±150 seconds relative to trade execution (t = 0). Shaded bands indicate 95% confidence intervals.

Two patterns emerge. First, both groups exhibit a similar structural increase in engagement as the trade execution time approaches, with EI peaking at t = 0. Second, Profit trades are associated with significantly lower baseline EI, approximately from t = −150 to t = −30, but a substantially larger spike in EI immediately prior to execution than the Loss trades. After execution, the EI for Profit trades declines more rapidly and to a lower level than for Loss trades. These patterns suggest that differences between Profit and Loss trades are explained more by the magnitude of the short-run spike in engagement before trade execution than by the overall level of engagement.[7]

[7] By contrast, Panel B of Appendix Figure 9 suggests that EI dynamics during the holding period differ only modestly between profit and loss batches, even though the two groups exhibit clearer differences around trade execution. Loss batches tend to display slightly higher and more volatile EI over much of the holding period, whereas profit batches show a somewhat lower and smoother profile. However, the difference is small, with substantial overlap in the confidence intervals, so we interpret it cautiously. One possible interpretation is that losing positions require more monitoring or generate greater cognitive tension while they remain open, whereas profitable positions are managed in a more stable cognitive state. Taken together, these findings suggest that the most pronounced neural dynamics arise at the moments of

We next ask whether the profit-loss heterogeneity documented in Figure 2 differs with the traders' position. To examine this, we partition the sample into the first trade and the last trade of each batch, and within each subsample, classify trades according to whether the corresponding batch ultimately ends in a profit or a loss. Figure 3 plots the mean EI for these groups within a window of ±150 seconds around trade execution.

Several differences stand out. For the first trade of a batch, both Profit and Loss groups exhibit the familiar increase in EI as execution approaches, but the increase is noticeably sharper for Profit trades. By contrast, Loss trades display a flatter pre-trade pattern and a more muted spike immediately before execution, consistent with weaker task-focused engagement at the moment when the batch is initiated. More importantly, for Loss trades, EI reaches its peak only *after* trade execution, suggesting that traders become more cognitively engaged only after the order is submitted, possibly because they are evaluating or reacting to a poor trading decision.

For the last trade of a batch, the pattern is different. Loss trades exhibit a higher EI level throughout most of the event window, and their EI is slightly higher than that of Profit trades exactly at the moment of execution. This pattern is also consistent with traders in loss-making batches being in a tenser or stressed cognitive state when closing out the batch. At the same time, the fact that Loss trades maintain a higher average EI level overall is also consistent with the full-sample evidence in Figure 2.

Table 5 presents a more formal regression analysis linking Profit trades to traders' EI patterns. The dependent variable is a binary indicator equal to one if the corresponding trading batch yields a positive realized profit. Columns (1) and (2) use the ratio of average EI in the decision window ([−30, 0]) to average EI in earlier baseline windows, namely [−150, −30] seconds and [−60, −30] seconds before execution (e.g., this ratio is calculated

trade initiation and completion, while cognitive engagement during the intervening holding period is relatively persistent and only weakly differentiated by eventual performance.

as $\bar{EI}_{i,t=-30\to 0}/\bar{EI}_{i,t=-150\to -30}$).[8] Columns (3) through (5) use absolute pre-trade EI levels in the [−30, 0], [−60, −30], and [−150, −30] second windows. Columns (6) and (7) use post-trade EI levels in the [0, 30] and [30, 150] second windows. All regressions control for transaction characteristics, window-matched tick- and order-level market controls, and trader-by-date-hour fixed effects. Standard errors are two-way clustered at the trader and date-hour levels.

$$1(\mathrm{ProfitTrade}_{i,t}) = \beta \cdot (\bar{EI}_{i,t=-30\to 0}/\bar{EI}_{i,t=-\tau 1\to \tau 2}) + \Gamma \cdot X_{i,t}^{pre} + \alpha_{i-date-hour} + \varepsilon_{i,t} \qquad (3)$$

In Columns (1) and (2), the coefficients on decision-window EI relative to earlier baseline windows are positive and statistically significant. In contrast, the absolute EI level in the decision window is not statistically significant in Column (3). Baseline EI in the [−150, −30] second window is negatively associated with performance in Column (5), and post-trade EI in the [30, 150] second window is also negative in Column (7). These estimates are consistent with Figure 2: performance is related to the short-run increase in EI immediately before execution, not to a high level of EI in general.

The inclusion of market controls helps address the concern that the EI spike simply reflects the arrival of better trading opportunities. These controls are constructed from tick- and order-level data and include short-run price movements, realized volatility, trading and order activity, price-path efficiency, and the stock's position within its recent high-low range. The positive association between relative pre-trade EI and trading success remains after adding these controls.

These controls cannot fully rule out all alternative interpretations. However, the estimates make it less likely that the EI spike is only a proxy for observable market conditions. Instead, EI appears to capture an additional dimension of the trader's cognitive state around execution.

[8] We run separate regressions because including both EI level during the 30-second decision window and relative change will incur mechanical correlation between the covariates.

The lack of explanatory power of EI levels is noteworthy. This finding suggests that an average mental state without consistently high alertness or engagement, for example, feeling somewhat "off" on a given day, may not materially impair performance, provided that high engagement is briefly activated immediately before trade execution. To directly test this implication, we conduct a trader-by-day level analysis linking daily trading performance to different measures of a trader's EI patterns over the course of the day, while controlling for trader fixed effects and date fixed effects, and clustering robust standard errors on these levels as well.

$$\%\mathrm{ProfitTrade}_{i,date} = \beta_1 \cdot \mathrm{DailyMean}_{i,date} + \beta_2 \cdot \mathrm{DailyStd}_{i,date} + \beta_3 \cdot \mathrm{DailyHigh}_{i,date} + \beta_4 \cdot \mathrm{DailyMean}_{i,date-1} + \beta_5 \cdot \mathrm{AllTimeMean}_i + \Gamma \cdot X_{i,date} + \alpha_i + \alpha_{date} + \varepsilon_{i,date} \quad (4)$$

Table 6 presents the regression results. Panel A reports results at the daily level, where the dependent variable is the proportion of Profit trades for trader i on $date$. Column (1) shows that a higher average level of EI over the day is negatively associated with performance on that day $\mathrm{DailyMean}_{i,date}$. Column (2) shows that the standard deviation of EI $\mathrm{DailyStd}_{i,date}$ is not significantly correlated with performance. Column (3) shows that the daily 95th percentile of EI $\mathrm{DailyHigh}_{i,date}$ is also negatively associated with performance. Column (4) shows that the mean EI on the prior day $\mathrm{DailyMean}_{i,date-1}$ is negatively associated with today's performance. Column (5), while not controlling for α_{date}, shows that the average EI levels during the whole sample $\mathrm{AllTimeMean}_i$ are likewise not predictive of current-day performance. Panel B repeats the analysis at the trade level by linking individual trade outcomes to the trader's daily EI patterns. Consistent with the event-study results presented earlier, most of the measures capturing overall daily EI patterns significantly negatively predict the outcomes of specific trades.

Overall, our findings suggest that trade performance is most strongly related to the magnitude of the EI spikes immediately before trade execution. Outside these critical windows, the overall EI characteristics play a limited role, and persistently high levels of EI are negatively correlated with performance.

4.3 EI and Behavioral Biases

Even though higher background levels of EI do not predict overall performance, they may still play a role in mediating behavioral biases. In this section, we examine whether EI helps explain well-documented behavioral biases in financial decision-making, such as the round number heuristic (Harris, 1991; Kuo, Lin, and Zhao, 2015) and disposition effect (Frydman et al., 2014).

Round Number Heuristic. Asset prices tend to cluster at specific round values, such as those ending in .00 or .50, rather than being uniformly distributed across all possible decimals. This pattern has been documented in equity, foreign exchange, and commodity markets (Harris, 1991; Grossman et al., 1997) and is commonly attributed to a round number heuristic, in which traders rely on cognitive shortcuts in price setting. In high-frequency trading, decisions are made under time pressure and heavy information load. Round numbers provide a simple anchor that reduces mental effort. We therefore hypothesize that reliance on round numbers is more likely when cognitive engagement is low, whereas higher engagement enables traders to price more precisely.

We first document the prevalence of price clustering in our sample. For each transaction, we extract the decimal component of the execution price and compute the frequency distribution across all 100 possible cent values, from .00 to .99. Panel A of Figure 4 plots the histogram. Consistent with prior evidence, we observe substantial concentration at focal points. Trades cluster heavily at what we label "Strong Round" numbers, namely .00 and .50, indicating a clear preference for these anchors.

We then assess the financial consequences of this heuristic. Transactions are grouped into three categories: (1) Strong Round trades, executed at .00 or .50; (2) Other Round trades, executed at other multiples of 10, such as .10 or .20, excluding .00 and .50; and (3) All trades. Panel B of Figure 4 reports the average batch profit for all trades, other round trades, and strong round trades. Relative to the full-sample benchmark, profitability is lower for trades executed at round prices, especially for strong round prices ending in .00 or .50. Other round trades also earn lower average profits than the full-sample average, but the decline is smaller. This pattern suggests that clustering at salient round numbers is costly in our setting. The convenience of anchoring appears to come at the expense of pricing precision and profits.[9]

We next examine the relation between EEG-measured engagement and round-number pricing. In Appendix Figure 10, we sort trades into deciles based on the average Engagement Index over the 150 seconds prior to execution and then plot the fraction of trades executed at different round-number prices. Panel A focuses on Strong Round prices (.00 or .50). The pattern is largely flat across EI deciles, with the strong-round ratio fluctuating within a relatively narrow range and with substantial overlap in the confidence intervals. Thus, there is little evidence of a clear monotonic relation between pre-trade engagement and reliance on the most salient round-number anchors. Panel B turns to Other Round prices, defined as prices ending in .10, .20, ..., .90, excluding .00 and .50. Here, the relationship is more clearly non-monotonic. The fraction of Other Round trades declines from the low-EI deciles toward the middle of the EI distribution, and then rises again in the higher deciles, with the highest-EI group exhibiting the greatest use of such prices.

We then examine how cognitive engagement interacts with price clustering in shaping trading performance. Figure 5 partitions trades into three execution-price categories: Not Round, Other Round, and Strong Round, and further splits each category by whether the trader's standardized pre-trade Engagement Index is above or below zero. This figure reports average batch profit with 95% confidence intervals.

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[9] Although one might suspect that strong round-number trades reflect clustering of counterpart orders, our data suggest otherwise. Strong round trades account for only about 9.1% of all trades (870 out of 9,544), and other rounds for 21.9% (2,093 out of 9,544), so the majority of trades occur at non-round prices. More importantly, the performance penalty for round prices is concentrated among trades executed under low engagement (Figure 5). High-engagement trades at round prices perform just as well as non-round trades. This is consistent with the profitability cost being related to traders' inattention and low cognitive state.

Two patterns emerge. First, among high-EI trades, profitability is broadly similar across price categories. Strong Round trades do not appear to underperform materially relative to non-round trades. Second, among low-EI trades, profitability declines sharply with roundedness: Not Round trades earn the highest average profit, Other Round trades perform somewhat worse, and Strong Round trades generate by far the lowest profit. Thus, the performance cost of round-number trading is concentrated in low-engagement states, especially for the most salient anchors, .00 and .50. One possible interpretation is that when EI is low, rounded prices are more likely to reflect heuristic processing or inattention, leading traders to rely on salient but suboptimal price points. When EI is high, by contrast, the use of round prices may be more deliberate and conditioned on market circumstances, which helps explain why Strong Round trading is not especially costly in those states.

Disposition Effect. We begin by documenting the presence of the disposition effect among our professional traders, defined as the tendency to hold losing positions longer than winning ones. Figure 6 shows the difference in holding periods by trading outcome. Panel A compares the average round-trip holding duration, measured in seconds, for trades that resulted in a profit versus those that resulted in a loss. Panel B restricts the sample to losing trades and plots the absolute realized loss amount against holding duration, with holding duration on the x-axis and absolute loss amount on the y-axis. This scatter plot examines whether longer holding periods are associated with larger realized losses among loss-making trades.

The results in Panel A show that the average holding duration for losing trades is approximately 60.4 seconds, compared with 55.9 seconds for profitable trades. This difference is marginally significant at the 10% level (p-value = 0.071). The duration gap indicates a slight reluctance to realize losses, as traders tend to keep losing positions open in the hope of a price reversal. Panel B provides complementary evidence. Among losing trades, the fitted trend indicates that larger realized losses are associated with longer holding periods. This pattern suggests that the tendency to delay exit is more pronounced when losses become larger.

We finally test whether cognitive engagement during the holding and exit periods helps mitigate the tendency to hold losing positions for too long. Table 7 reports batch-level regression results for multi-leg trading batches with a well-defined holding period from the first execution to the last execution. The dependent variable is Holding Duration in seconds. The key explanatory variable is IsLoss, which equals one if the batch ends in a realized loss. Column (1) tests the baseline disposition effect. Column (2) interacts IsLoss with average EI during the holding period. Columns (3) and (4) interact IsLoss with EI measured over the 30-second and 60-second windows before batch exit. All specifications control for pre-entry EI, transaction characteristics, tick- and order-level market signals, and trader-by-date-hour fixed effects.

The results suggest that engagement moderates the relationship between losses and holding duration. In Column (1), the coefficient on IsLoss is positive but statistically insignificant after controls and fixed effects. In Columns (2) through (4), however, the interaction terms between IsLoss and engagement are negative and statistically significant. A one-standard-deviation increase in holding-period EI reduces the additional duration associated with losing positions by 4.4 seconds. The estimates are similar when engagement is measured in the 30-second and 60-second windows before exit. These results support the interpretation that engagement facilitates more disciplined exit decisions and helps traders cut losses more promptly.

Overall, the evidence indicates that cognitive engagement is not simply related to holding duration in a mechanical way, but instead matters specifically through its interaction with losing states, where it appears to reduce the behavioral tendency to ride losses for too long.

5. Conclusion

This paper demonstrates that wearable EEG technology can be used to study the neural underpinnings of high-stakes economic decision-making in the real world. By recording brain activity from 16 professional day traders over multiple weeks, we constructed a real-time index of cognitive engagement and linked it to key trading behavior and outcomes. Our study is set in a high-frequency proprietary trading firm, which enables us to observe thousands of trades under real financial consequences, providing novel evidence on how traders' momentary mental state relates to their performance.

Our analysis provides several main findings. First, traders exhibit a pronounced pattern of neural engagement right before trade execution. The Engagement Index remains flat until shortly before a trade, then climbs sharply in the seconds leading up to the decision, peaking at the moment of execution and dropping back to baseline afterward. This dynamic, including a steeper post-trade drop in engagement for exit trades than for entry trades, is consistent with traders intensifying focus as they commit to a position and relaxing once uncertainty is resolved.

Second, we find that these engagement fluctuations have predictive power for performance: trades preceded by larger pre-trade engagement spikes result in higher profits on average. In contrast, a trader's overall or baseline engagement level outside of these decision windows has no positive association with success. If anything, persistently high engagement in the absence of imminent decisions is linked to diminished performance, suggesting that it is not raw arousal but the timely deployment of cognitive resources that benefits trading outcomes.

Third, heightened engagement is associated with a lower degree of behavioral biases. We document two sources of distortions in our sample: the tendency to cluster trades at round numbers and the disposition effect. On the round number heuristic, we show that the performance penalty associated with rounding is concentrated in low-engagement trades, suggesting that heuristics are costly. Similarly, for the disposition effect, we observe that losing positions are typically held about 8% longer than winning ones. However, elevated engagement attenuates this asymmetry, as engaged traders cut their losses more promptly. Together, these results align with the notion that greater cognitive recruitment counteracts both cognitive shortcuts and emotion-driven biases, enabling more disciplined and precise decision-making.

We note important caveats and directions for future research. Our findings are correlational and do not by themselves establish causality. Although the use of trader fixed effects and high-frequency data helps ensure we are capturing within-individual fluctuations rather than spurious cross-sectional differences, it remains possible that unobserved factors (such as the presence of an exceptionally good trading opportunity) drive both high engagement and better outcomes. However, even if this is the case, the bottom line is that it takes high engagement to grasp such a good trading opportunity. Future studies could address this by experimentally manipulating engagement or providing real-time cognitive feedback to traders to test for causal effects.

Additionally, while our single-channel EEG device captures an aggregate engagement signal, more advanced multi-channel wearables could identify specific neural circuits involved and provide richer measures of attention, stress, or emotion during trading. Expanding this line of inquiry to other financial contexts (e.g., longer-term investment decisions or automated trading settings) and to other populations (such as less experienced traders) would help determine the generality of our results. Despite these limitations, our work provides novel empirical evidence that momentary neural engagement is linked to performance in high-stakes markets. It underscores the value of incorporating insights from neuroscience into finance and suggests that managing one's cognitive state may be an important factor in financial decision-making success.

References

Aeschbach, D., Cajochen, C., Landolt, H.-P., & Borbély, A. A. (1996). Homeostatic sleep regulation in habitual short sleepers and long sleepers. American Journal of Physiology-Regulatory, Integrative and Comparative Physiology, 270(1), R41–R53.

Aricò, P., Borghini, G., Di Flumeri, G., Colosimo, A., Bonelli, S., Golfetti, A., Pozzi, S., Imbert, J. P., Granger, G., Benhacene, R., & Babiloni, F. (2016). Adaptive automation triggered by EEG-based mental workload index: a passive brain-computer interface application in realistic air traffic control environment. Frontiers in Human Neuroscience, 10, 217761.

Attar, E. T. (2022). Review of electroencephalography signals approaches for mental stress assessment. Neurosciences, 27(4), 207–215.

Bali, T. G., Cakici, N., & Whitelaw, R. F. (2011). Maxing out: Stocks as lotteries and the cross-section of expected returns. Journal of Financial Economics, 99(2), 427-446.

Barberis, N., & Thaler, R. (2003). A survey of behavioral finance. Handbook of the Economics of Finance 1, 1053-1128.

Barberis, N., & Xiong, W. (2012). Realization utility." Journal of Financial Economics, 104(2), 251-271.

Bates, M. E., & Lemay, E. P. (2004). The d2 Test of attention: Construct validity and extensions in scoring techniques. Journal of the International Neuropsychological Society 10(3), 392-400.

Bechara, A., Damasio, H., Tranel, D., & Damasio, A. R. (1997). Deciding advantageously before knowing the advantageous strategy. Science, 275(5304), 1293-1295.

Berka, C., Levendowski, D. J., Lumicao, M. N., Yonta, A., Zivkovic, V. T., Olmstead, R. E., Tremoulet, P. D., & Orne-Levendowski, G. (2007). EEG correlates of task engagement and mental workload in vigilance, learning, and memory tasks. Aviation, Space, and Environmental Medicine, 78(5), B231–B244.

Bordalo, P., Burro, G., Coffman, K., Gennaioli, N., & Shleifer, A. (2025). Imagining the future: memory, simulation, and beliefs. Review of Economic Studies, 92(3), 1532-1563.

Bordalo, P., Conlon, J. J., Gennaioli, N., Kwon, S. Y., & Shleifer, A. (2023). Memory and probability. The Quarterly Journal of Economics, 138(1), 265-311.

Bossaerts, P., Fattinger, F., Rotaru, K., & Xu, K. (2024). Emotional engagement and trading performance. Management Science, 70(6), 3381-3397.

Bruguier, A. J., Quartz, S. R., & Bossaerts, P. (2010). Exploring the nature of "trader intuition". The Journal of Finance, 65(5), 1703-1723.

Burnham, T., & Cronqvist, H. (2026). Biology and Finance. Available at SSRN 6049376.

Buzsáki, G., Anastassiou, C. A., & Koch, C. (2012). The origin of extracellular fields and currents—EEG, ECoG, LFP and spikes. Nature Reviews Neuroscience, 13(6), 407-420.

Buzsáki, G., & Draguhn, A. (2004). Neuronal oscillations in cortical networks. Science, 304(5679), 1926-1929.

Camerer, C., Loewenstein, G., & Prelec, D. (2005). Neuroeconomics: How neuroscience can inform economics. Journal of Economic Literature, 43(1), 9-64.

Cao, S., Jiang, W., Wang, J., & Yang, B. (2024). From man vs. machine to man+ machine: The art and AI of stock analyses. Journal of Financial Economics, 160, 103910.

Cesarini, D., Johannesson, M., Lichtenstein, P., Sandewall, Ö., & Wallace, B. (2010). Genetic variation in financial decision-making. The Journal of Finance, 65(5), 1725–1754.

Chaouachi, M., Chalfoun, P., Jraidi, I., & Frasson, C. (2010). Affect and mental engagement: Towards adaptability for intelligent systems. In Proceedings of the Twenty-Third International Florida Artificial Intelligence Research Society Conference (FLAIRS 2010).

Chen, H., Cohen, L., Gurun, U., Lou, D., & Malloy, C. (2020). IQ from IP: Simplifying search in portfolio choice. Journal of Financial Economics, 138(1), 118-137.

Coates, J. M., & Herbert, J. (2008). Endogenous steroids and financial risk taking on a London trading floor. Proceedings of the National Academy of Sciences, 105(16), 6167-6172.

Coates, J., & Gurnell, M. (2017). Combining field work and laboratory work in the study of financial risk-taking. Hormones and behavior, 92, 13-19.

Corgnet, B., Desantis, M., & Porter, D. (2018). What makes a good trader? On the role of intuition and reflection on trader performance. The Journal of Finance, 73(3), 1113-1137.

Da, Z., Engelberg, J., & Gao, P. (2011). In search of attention. The Journal of Finance, 66(5), 1461-1499.

Debener, S., Minow, F., Emkes, R., Gandras, K., & De Vos, M. (2012). How about taking a low-cost, small, and wireless EEG for a walk? Psychophysiology, 49(11), 1617–1621.

De Bondt, W. F. M., & Thaler, R. (1985). Does the stock market overreact? The Journal of Finance, 40(3), 793–805.

De Martino, B., Camerer, C. F., & Adolphs, R. (2010). Amygdala damage eliminates monetary loss aversion. Proceedings of the National Academy of Sciences, 107(8), 3788–3792.

De Martino, B., Kumaran, D., Seymour, B., & Dolan, R. J. (2006). Frames, biases, and rational decision-making in the human brain. Science, 313(5787), 684-687.

DellaVigna, S. (2009). Psychology and economics: Evidence from the field. Journal of Economic Literature, 47(2), 315–372.

Dikker, S., Michalareas, G., Oostrik, M., Serafimaki, A., Kahraman, H. M., Struiksma, M. E., & Poeppel, D. (2021). Crowdsourcing neuroscience: inter-brain coupling during face-to-face interactions outside the laboratory. NeuroImage, 227, 117436.

Di Flumeri, G., De Crescenzio, F., Berberian, B., Ohneiser, O., Kramer, J., Aricò, P., Borghini, G., Babiloni, F., Bagassi, S., & Piastra, S. (2019). Brain–computer interface-based adaptive automation to prevent out-of-the-loop phenomenon in air traffic controllers dealing with highly automated systems. Frontiers in Human Neuroscience, 13, 296.

Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J., & Wagner, G. G. (2011). Individual risk attitudes: Measurement, determinants, and behavioral consequences. Journal of the European Economic Association, 9(3), 522-550.

Duffy, F. H., Albert, M. S., McAnulty, G., & Garvey, A. J. (1984). Age-related differences in brain electrical activity of healthy subjects. Annals of Neurology: Official Journal of the American Neurological Association and the Child Neurology Society, 16(4), 430-438.

Enke, B., Schwerter, F., & Zimmermann, F. (2024). Associative memory, beliefs and market interactions. Journal of Financial Economics, 157, 103853.

Feng, L., & Seasholes, M. S. (2005). Do investor sophistication and trading experience eliminate behavioral biases in financial markets? Review of Finance, 9(3), 305–351.

Fenton-O'Creevy, M., Lins, J. T., Vohra, S., Richards, D. W., Davies, G., & Schaaff, K. (2012). Emotion regulation and trader expertise: Heart rate variability on the trading floor. Journal of Neuroscience, Psychology, and Economics, 5(4), 227.

Finelli, L. A., Baumann, H., Borbély, A. A., & Achermann, P. (2000). Dual electroencephalogram markers of human sleep homeostasis: correlation between theta activity in waking and slow-wave activity in sleep. Neuroscience, 101(3), 523-529.

Freeman, F. G., Mikulka, P. J., Prinzel, L. J., & Scerbo, M. W. (1999). Evaluation of an adaptive automation system using three EEG indices with a visual tracking task. Biological Psychology, 50(1), 61-76.

Frydman, C., Barberis, N., Camerer, C., Bossaerts, P., & Rangel, A. (2014). Using neural data to test a theory of investor behavior: An application to realization utility. The Journal of Finance, 69(2), 907-946.

Frydman, C., & Camerer, C. (2016). Neural evidence of regret and its implications for investor behavior. The Review of Financial Studies, 29(11), 3108-3139.

Gargano, A., & Rossi, A. G. (2018). Does it pay to pay attention?. The Review of Financial Studies, 31(12), 4595-4649.

Gevins, A., & Smith, M. E. (2003). Neurophysiological measures of cognitive workload during human-computer interaction. Theoretical issues in Ergonomics Science, 4(1-2), 113-131.

Gödker, K., Jiao, P., & Smeets, P. (2025). Investor memory. The Review of Financial Studies, 38(6), 1595-1640.

Grinblatt, M., & Keloharju, M. (2009). Sensation seeking, overconfidence, and trading activity. The Journal of Finance, 64(2), 549–578.

Grossman, S. J., Miller, M. H., Cone, K. R., Fischel, D. R., & Ross, D. J. (1997). Clustering and competition in asset markets. The Journal of Law and Economics, 40(1), 23-60.

Haigh, M. S., & List, J. A. (2005). Do professional traders exhibit myopic loss aversion? An experimental analysis. The Journal of Finance, 60(1), 523–534.

Harris, L. (1991). Stock price clustering and discreteness. The Review of Financial Studies, 4(3), 389-415.

Helfrich, R. F., Schneider, T. R., Rach, S., Herrmann, C. S., & Engel, A. K. (2014). Entrainment of brain oscillations by transcranial alternating current stimulation. Current Biology, 24(3), 333–339.

Hillman, C. H., Erickson, K. I., & Kramer, A. F. (2008). Be smart, exercise your heart: exercise effects on brain and cognition. Nature reviews neuroscience, 9(1), 58-65.

Hinrichs, H., Scholz, M., Baum, A. K., Kam, J. W. Y., Knight, R. T., & Heinze, H.-J. (2020). Comparison between a wireless dry electrode EEG system with a conventional wired wet electrode EEG system for clinical applications. Scientific Reports, 10(1), 5218.

Hirshleifer, D. (2001). Investor psychology and asset pricing. The Journal of Finance, 56(4), 1533–1597.

Jensen, O., Kaiser, J., & Lachaux, J. P. (2007). Human gamma-frequency oscillations associated with attention and memory. Trends in Neurosciences, 30(7), 317-324.

Jiang, Z., Liu, H., Peng, C., & Yan, H. (2025). Investor memory and biased beliefs: Evidence from the field. The Quarterly Journal of Economics, 140(4), 2749-2804.

Jung, W. H., Lee, S., Lerman, C., & Kable, J. W. (2018). Amygdala functional and structural connectivity predicts individual risk tolerance. Neuron, 98(2), 394–404.

Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. Econometrica, 47(2), 263–291.

Kam, J. W. Y., Griffin, S., Shen, A., Patel, S., Hinrichs, H., Heinze, H.-J., Deouell, L. Y., & Knight, R. T. (2019). Systematic comparison between a wireless EEG system with dry electrodes and a wired EEG system with wet electrodes. NeuroImage, 184, 119–129.

Kandasamy, N., Garfinkel, S. N., Page, L., Hardy, B., Critchley, H. D., Gurnell, M., & Coates, J. M. (2016). Interoceptive ability predicts survival on a London trading floor. Scientific Reports, 6(1), 32986.

Knutson, B., & Bossaerts, P. (2007). Neural antecedents of financial decisions. Journal of Neuroscience, 27(31), 8174-8177.

Knyazev, G. G. (2012). EEG delta oscillations as a correlate of basic homeostatic and motivational processes. Neuroscience & Biobehavioral Reviews, 36(1), 677-695.

Krigolson, O. E., Williams, C. C., Norton, A., Hassall, C. D., & Colino, F. L. (2017). Choosing MUSE: Validation of a low-cost, portable EEG system for ERP research. Frontiers in Neuroscience, 11, 109.

Kuhnen, C. M., & Knutson, B. (2005). The neural basis of financial risk taking. Neuron, 47(5), 763-770.

Kuo, W. Y., Lin, T. C., & Zhao, J. (2015). Cognitive limitation and investment performance: Evidence from limit order clustering. The Review of Financial Studies, 28(3), 838-875.

Lin, T. C., & Pursiainen, V. (2021). The round number heuristic and entrepreneur crowdfunding performance. Journal of Corporate Finance, 68, 101894.

List, J. A. (2003). Does market experience eliminate market anomalies? The Quarterly Journal of Economics, 118(1), 41–71.

Lo, A. W. (2017). Adaptive markets: Financial evolution at the speed of thought. Princeton University Press.

Lo, A. W., & Repin, D. V. (2002). The psychophysiology of real-time financial risk processing. Journal of Cognitive Neuroscience, 14(3), 323-339.

Lo, A. W., Repin, D. V., & Steenbarger, B. N. (2005). Fear and greed in financial markets: A clinical study of day-traders. American Economic Review, 95(2), 352-359.

Nadler, A., Jiao, P., Johnson, C. J., Alexander, V., & Zak, P. J. (2018). The bull of Wall Street: Experimental analysis of testosterone and asset trading. Management Science, 64(9), 4032-4051.

NeuroSky, Inc. (2009). Brain wave signal (EEG) of NeuroSky, Inc. Sleep Shepherd LLC.

https://sleepshepherd.com/wp-content/uploads/2016/02/neurosky-vs-medical-eeg.pdf

Parasuraman, R. (2003). Neuroergonomics: Research and practice. Theoretical Issues in Ergonomics Science, 4(1–2), 5–20.

Pfurtscheller, G., & Aranibar, A. (1977). Event-related cortical desynchronization detected by power measurements of scalp EEG. Electroencephalography and clinical neurophysiology, 42(6), 817-826.

Pfurtscheller, G., & Lopes da Silva, F. H. (1999). Event-related EEG/MEG synchronization and desynchronization: basic principles. Clinical neurophysiology, 110(11), 1842-1857.

Polich, J. (1997). On the relationship between EEG and P300: individual differences, aging, and ultradian rhythms. International journal of psychophysiology, 26(1-3), 299-317.

Pope, A. T., Bogart, E. H., & Bartolome, D. S. (1995). Biocybernetic system evaluates indices of operator engagement in automated task. Biological Psychology, 40(1-2), 187-195.

Putman, P., van Peer, J., Maimari, I., & van der Werff, S. (2010). EEG theta/beta ratio in relation to fear-modulated response-inhibition, attentional control, and affective traits. Biological psychology, 83(2), 73-78.

Quispe-Torreblanca, E., Hume, D., Gathergood, J., Loewenstein, G., & Stewart, N. (2026). At the top of the mind: Peak prices and the disposition effect. Journal of Political Economy Microeconomics, 4(1), 265-315.

Ray, W. J., & Cole, H. W. (1985). EEG alpha activity reflects attentional demands, and beta activity reflects emotional and cognitive processes. Science, 228(4700), 750-752.

Seru, A., Shumway, T., & Stoffman, N. (2010). Learning by trading. The Review of Financial Studies, 23(2), 705–739.

Shiller, R. J. (2003). From efficient markets theory to behavioral finance. Journal of Economic Perspectives, 17(1), 83–104.

Shiv, B., Loewenstein, G., Bechara, A., Damasio, H., & Damasio, A. R. (2005). Investment behavior and the negative side of emotion. Psychological Science, 16(6), 435–439.

Shleifer, A., & Vishny, R. W. (1997). The limits of arbitrage. The Journal of Finance, 52(1), 35–55.

Simon, H. A. (1955). A behavioral model of rational choice. The Quarterly Journal of Economics, 99–118.

Smith, A., Lohrenz, T., King, J., Montague, P. R., & Camerer, C. F. (2014). Irrational exuberance and neural crash warning signals during endogenous experimental market bubbles. Proceedings of the National Academy of Sciences, 111(29), 10503–10508.

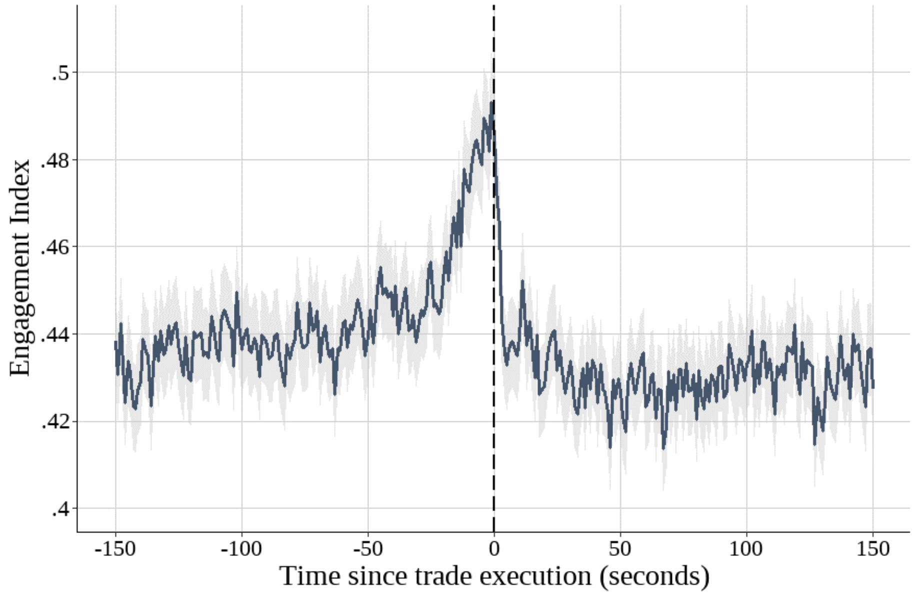
Steriade, M., McCormick, D. A., & Sejnowski, T. J. (1993). Thalamocortical oscillations in the sleeping and aroused brain. Science, 262(5134), 679-685.

Thaler, R. (1980). Toward a positive theory of consumer choice. Journal of economic behavior & organization, 1(1), 39-60.

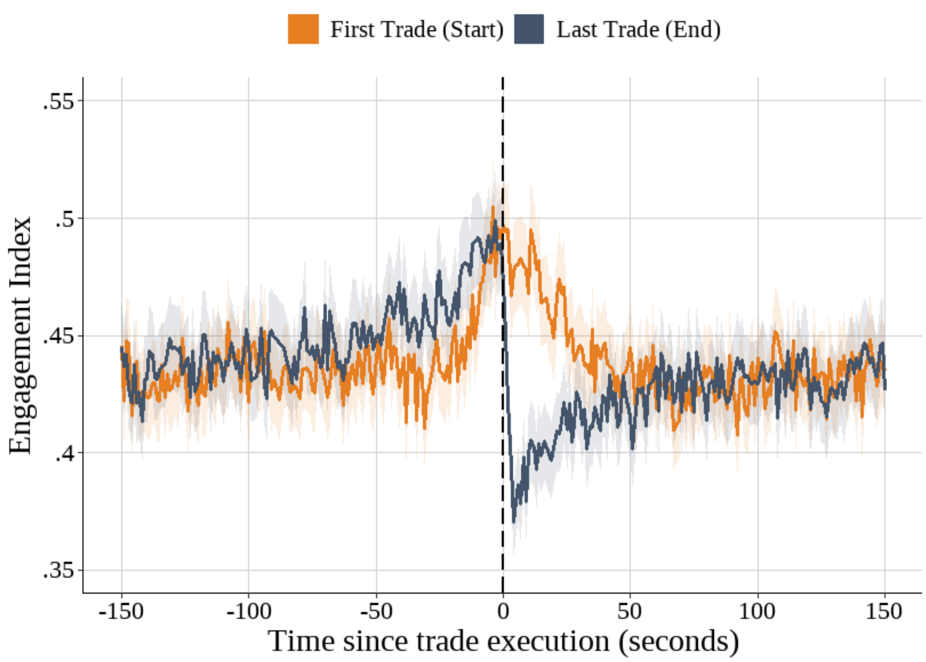
Van Binsbergen, J. H., Han, X., & Lopez-Lira, A. (2023). Man versus machine learning: The term structure of earnings expectations and conditional biases. The Review of Financial Studies, 36(6), 2361-2396.

Van Son, D., De Blasio, F. M., Fogarty, J. S., Angelidis, A., Barry, R. J., & Putman, P. (2019). Frontal EEG theta/beta ratio during mind wandering episodes. Biological Psychology, 140, 19-27.

Zander, T. O., & Kothe, C. (2011). Towards passive brain–computer interfaces: Applying brain–computer interface technology to human–machine systems in general. Journal of Neural Engineering, 8(2), 025005.



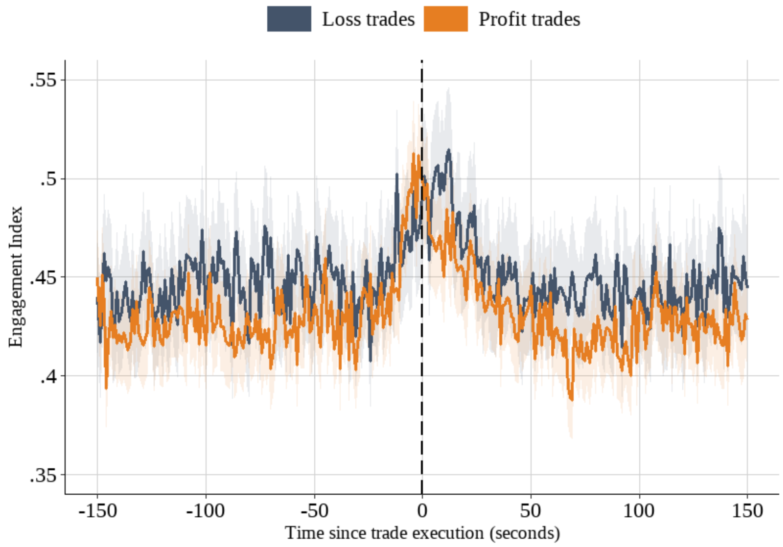
A. Engagement Index around Trade Execution



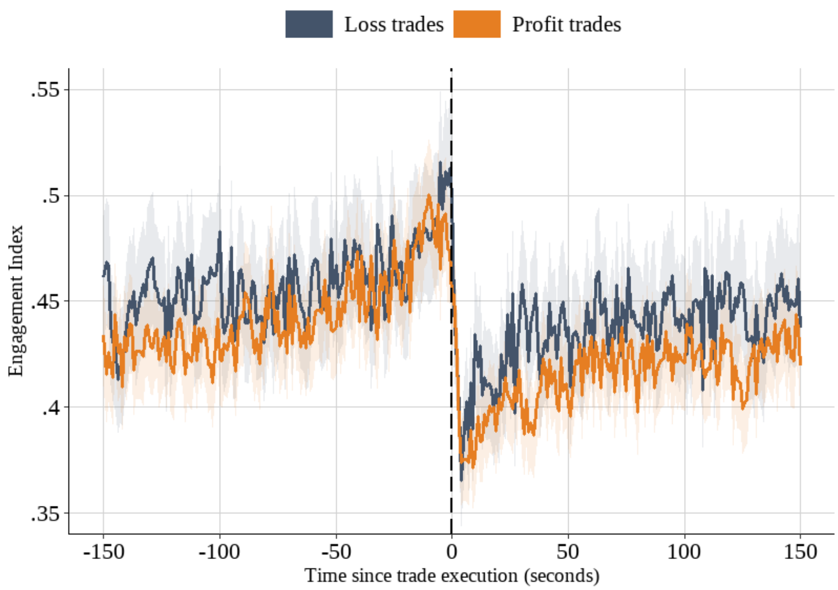
B. Engagement Index around Entry versus Exit Trades

Figure 1. Engagement Index around Trade Execution. This figure reports the results of an event study analyzing the evolution of the Engagement Index within ±150 seconds surrounding trade execution. Panel A displays the aggregate results for all trades, where the solid line represents the sample mean and the shaded area denotes the 95% confidence interval. The vertical dashed line represents the exact second of trade execution (t=0). Panel B decomposes the sample to compare the cognitive patterns associated with the entry trade and the exit trade of a trading batch. For both panels, the underlying engagement data are winsorized at the 1% and 99% levels to limit the impact of outliers, and standard errors are calculated based on the number of observations in each relative time bin.

Figure 2. Engagement Index around Profit versus Loss Trades. This figure examines the heterogeneity in cognitive engagement patterns based on the performance of trading batches. The sample is split into trades associated with a realized profit (labeled "Profit") and those associated with a realized loss (labeled "Loss"). The vertical dashed line at t=0 marks the time of trade execution. This figure presents the aggregate event study for all trades that compares the mean Engagement Index evolution for profitable versus unprofitable transactions across the entire sample. The solid lines represent the cross-sectional means, while the shaded ribbons indicate the 95% confidence intervals. All data points are winsorized at the 1% and 99% levels to mitigate the influence of outliers.

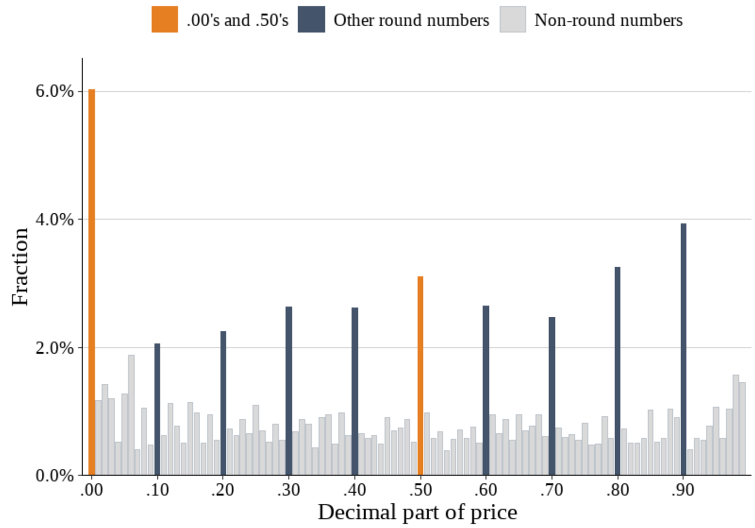


A. First trade of every batch

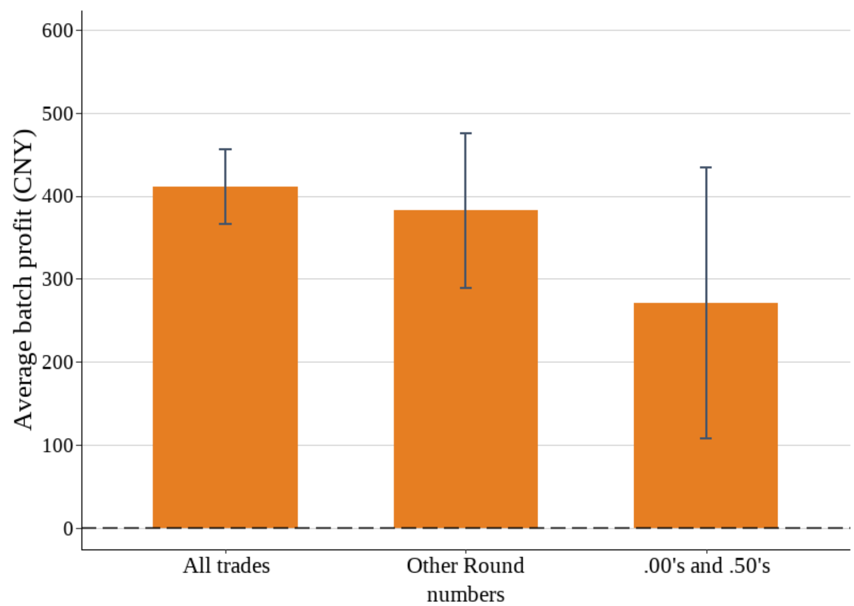


B. Last trade of every batch

Figure 3. Engagement Index around Profit versus Loss Trades. This figure examines the heterogeneity in cognitive engagement patterns by both trading-batch performance and trade position within the batch. The sample is split into the first trade and the last trade of each trading batch. Within each subgroup, trades are further classified according to whether the corresponding batch ends in a realized profit ("Profit") or a realized loss ("Loss"). The vertical dashed line at t = 0 marks the time of trade execution. The figure reports the event-study evolution of the mean Engagement Index around trade execution for profit and loss batches separately, with Panel A focusing on the first trade of each batch and Panel B focusing on the last trade. The solid lines represent the cross-sectional means, while the shaded ribbons indicate the 95% confidence intervals. All data points are winsorized at the 1% and 99% levels to mitigate the influence of outliers.



A. Price clustering



B. Price clustering and trading performance

Figure 4. Price Clustering and Trading Performance. The sample consists of all executed trades with valid transaction prices. Panel A presents the frequency distribution of the decimal components of execution prices. The x-axis represents the decimal part of the transaction price, ranging from 0 to 99 cents. The y-axis displays the relative frequency of each decimal point across the full sample. Panel B compares the average realized profit across transactions executed at different levels of price decimals. Trades are categorized into three groups based on their execution price decimals: (1) "Strong Round" (ending in .00 or .50), (2) "Other Round" (ending in other multiples of 10, e.g., .10, .20, excluding .00/.50), and (3) "All trades" (all sample). The height of each bar represents the mean realized profit per batch (in CNY) for that category. The vertical error bars indicate 95% confidence intervals. The horizontal dashed line at zero serves as the break-even benchmark.

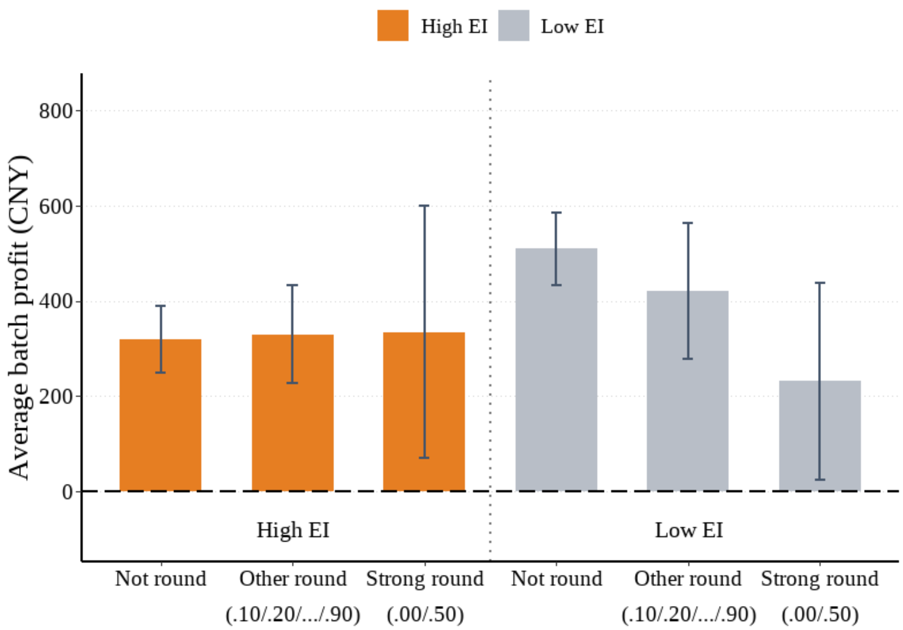
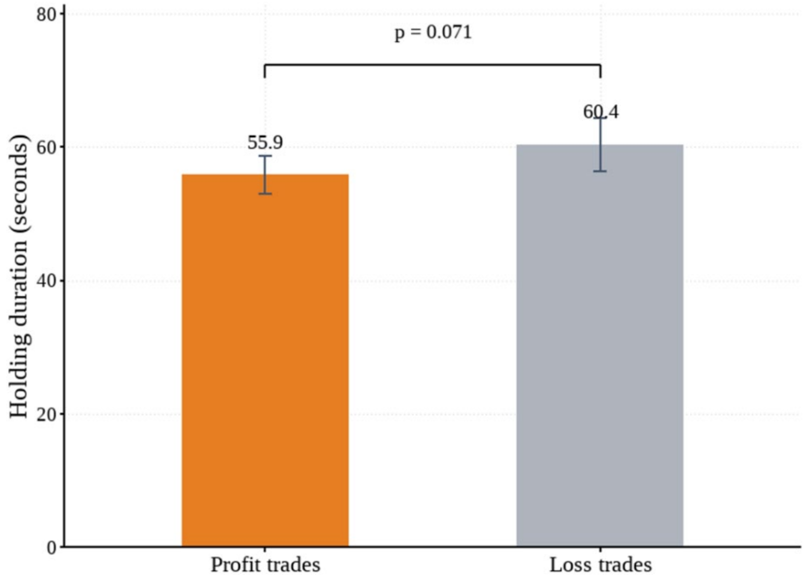
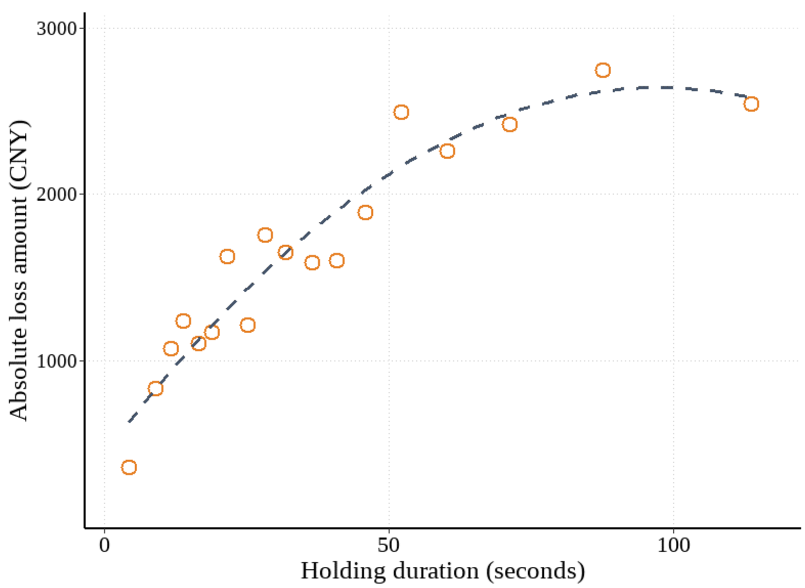


Figure 5. Cognitive Engagement, Round number orders, and Trading performance. This figure illustrates heterogeneity in trading performance across execution-price categories and trader engagement states. The sample is divided into two dimensions. First, trades are classified into three groups based on the decimal component of the execution price: Not Round, Other Round, and Strong Round. Strong Round trades are those executed at prices ending in .00 or .50, while Other Round trades are those executed at prices ending in .10, .20, ..., .90, excluding .00 and .50. Not Round includes all remaining prices. Second, within each price category, trades are split into High EI and Low EI subgroups. High EI is defined as trades for which the trader-specific standardized Engagement Index over the 150-second pre-trade window is above zero, and Low EI otherwise. The y-axis reports the average batch profit in CNY. The vertical error bars represent 95% confidence intervals for the mean.



A. Holding duration by profit and loss trades



B. Holding Duration and Loss Severity among Loss Trades

Figure 6. Disposition Effect. This figure illustrates the asymmetry in holding periods and the relation between holding duration and loss severity. Panel A compares the average round-trip holding duration, measured in seconds, for profitable trades versus losing trades. The bars report mean duration, and the error bars indicate 95% confidence intervals. Longer holding duration for losing trades is consistent with the disposition effect, whereby traders tend to hold losing positions longer than winning ones. Panel B restricts the sample to loss trades and plots the absolute realized loss amount against holding duration. The x-axis is holding duration in seconds, and the y-axis is the absolute loss amount in CNY. The dashed curve shows a fitted trend, indicating that larger realized losses are associated with longer holding periods among loss trades.

Table 1. Summary Statistics: EEG Data. This table presents summary statistics (Panel A) and Pearson correlation matrices (Panel B) for the brainwave variables used in the sample. Brainwave data are collected at a sampling rate of 1 Hz (i.e., one observation per second). The variables include Delta, Theta, Alpha, Beta, and Gamma waves. Note that for Alpha, Beta, and Gamma, the reported values sum the corresponding low- and high-frequency sub-band readings. In panel B, we report the correlation matrices of the six variables.

Panel A: Summary stats								
Variable	N	Mean	Std	Min	Q25	Median	Q75	Max
Delta power	954,692	527,808	617,088	1,376	46,519	269,252	816,196	2,604,528
Theta power	954,692	133,582	210,337	2,016	18,481	53,491	148,926	1,228,499
Alpha power	954,692	56,643	84,181	1,730	12,243	26,646	60,511	512,193
Beta power	954,692	41,701	48,323	1,808	12,729	25,396	51,228	290,188
Gamma power	954,692	31,344	39,356	895	7,874	17,916	38,354	234,875
Engagement Index	954,692	0.43	0.51	0.05	0.15	0.26	0.48	3.08
Panel B: Correlation Matrices								
	delta	theta	alpha	beta	gamma	engagement		
Delta power	1.00							
Theta power	0.51	1.00						
Alpha power	0.46	0.66	1.00					
Beta power	0.46	0.66	0.74	1.00				
Gamma power	0.44	0.65	0.72	0.78	1.00			
Engagement Index	–0.24	–0.21	–0.16	0.03	–0.03	1.00		

Table 2. Summary Statistics: Trading Data. This table reports summary statistics for investor trading activity at three levels. First, at the order level, we report the trading amount, share volume, average price, commission fees, and taxes for each transaction. Second, we report statistics at the batch level, where a batch represents a round-trip trading cycle. We identify a batch based on the high-frequency dynamics of an investor's intraday inventory. Specifically, for a given investor and stock within a trading day, we track the cumulative net position transaction by transaction. A new batch begins when the investor opens a position (either long or short) and ends at the exact timestamp when the cumulative inventory returns to zero, provided that the complete round-trip cycle is completed within 10 minutes. For each batch, we report batch profit, return rate, total investment, the number of trades included in the cycle, and the holding period in seconds. Third, we report statistics at the trader-day level by aggregating trading activity for each trader across the two observed one-hour trading sessions on a given day. Because our data cover only one hour in the morning and one hour in the afternoon, these measures should be interpreted as reflecting trading activity within the observed two-hour window rather than over the full trading day. At this level, we report trading intensity using the total number of completed batches and individual transactions, and we summarize trading scale and performance using total trading volume—calculated as the sum of the absolute value of all transactions—and total net profit within the observed sessions.

Variable	Unit	N	Mean	Std	Min	Q25	Median	Q75	Max
TradingAmnt	Yuan	9,544	175,716.02	110,922.05	11,311.00	94,487.35	148,014.97	259,302.78	560,414.11
TradingVol	Share	9,544	2,215.40	3,922.52	100.00	300.00	800.00	2,500.00	25,000.00
AveragePrice	Yuan	9,544	355.93	445.01	5.58	49.88	178.23	425.50	1,500.53
CommssnFee	Yuan	9,544	95.04	81.56	4.63	35.96	70.73	125.00	412.25
Tax	Yuan	9,544	43.55	59.59	0.00	0.00	0.00	74.19	258.63
BatchProfit	Yuan	3,209	248.96	1,172.57	−3,492.97	−209.55	92.79	536.91	5,337.78
BatchRet	%	3,209	0.11	0.42	−0.96	−0.12	0.06	0.26	1.76
BatchInvestAmnt	Yuan	3,209	262,472.95	208,022.43	22,032.72	117,069.43	211,640.59	323,085.41	1,167,148.94
TradesPerBatch	#	3,209	2.95	1.54	1.00	2.00	2.00	4.00	9.00
DurationSec	Second	3,209	56.83	62.78	0.00	18.00	36.00	70.00	344.92
DailyBatches	#	182	17.57	10.28	2.00	10.00	17.00	23.00	47.14
DailyTradesCnt	#	182	52.20	34.06	4.81	27.25	43.00	71.75	152.95
DailyTradeVol	Yuan	182	9,254,952.64	6,780,150.74	810,453.00	4,493,202.97	7,665,049.81	12,677,357.28	31,462,520.27
DailyProfit	Yuan	182	4,816.57	7,290.48	−8,095.72	−296.70	3,102.94	7,309.73	29,050.92

Table 3. Determinants of the Engagement Index.

This table examines what predicts traders' cognitive engagement around trade execution. The dependent variables are the Engagement Index level and the change in the Engagement Index. EI level is defined as the average Engagement Index during the immediate pre-trade decision window, from 30 seconds before execution to the execution time. EI change is defined as the difference between EI in the decision window and EI in the baseline window, measured from 150 to 30 seconds before execution. Panel A examines trading-history determinants. The explanatory variables capture the trader's prior trading state within the same trading day before the current execution. Cumulative batch count is the cumulative count number of completed trading batches, cumulative batch loss is the cumulative number of completed losing batches, cumulative trade count is the number of previous executions, cumulative trade amount is the cumulative trading amount, and cumulative profit is the cumulative realized profit from previously completed batches. Last trade loss is an indicator equal to one if the most recently completed batch generated a loss. LastTimeGap is the log time elapsed since the trader's previous execution. Price is the logarithm of the execution price, and Vol is the logarithm of transaction size. Panel B examines market and technical indicators constructed from tick- and order-level data before each execution. Columns report signals measured over 30-second, 60-second, and 180-second pre-trade windows. Momentum is the cumulative stock return over the corresponding window. Realized volatility is the realized return volatility over the same window. #Trades is the number of tick-level trades, Trade Vol is total traded volume, and #Order is the number of submitted orders during the window. Efficiency ratio is the absolute net price change divided by the sum of absolute tick-by-tick price changes, with higher values indicating a cleaner directional price path. Distance to high and distance to low measure the distance between the current price and the highest and lowest prices observed during the corresponding window. Relative price measures the current price's position within the pre-trade high-low price range. Panel C examines cross-sectional trader characteristics and lifestyle habits. Age and trading experience are measured in years. Left hand is an indicator equal to one if the trader is left-handed. Gym, caffeine, smoke, and alcohol are binary indicators for the corresponding self-reported habits. Sleep hours is the self-reported average daily sleep duration, and sleep quality is a self-assessed score from 1 to 5. Panels A and B include trader-by-date-hour fixed effects, absorbing trader-specific opportunity conditions within each trading hour. Panel C includes date-hour fixed effects only, because trader characteristics are time-invariant and would be absorbed by trader fixed effects. Standard errors are clustered at the trader and date-hour levels in Panels A and B, and at the trader level in Panel C. Continuous EEG and financial variables are winsorized at the 1st and 99th percentiles. T-statistics are reported in parentheses.

	Panel A: Trading history			Panel B: Technical Indicators							Panel C: Personal traits	
Dep. Var.	EI level	EI chg		EI level	EI chg	EI level	EI chg	EI level	EI chg		EI level	EI chg
			Time horizon	30s		60s		180s				
	(1)	(2)		(3)	(4)	(5)	(6)	(7)	(8)		(9)	(10)
CumBatch Cnt	0.0184	-0.0131	MOM	0.7040	0.5219	0.8655	1.5978	1.1030*	1.0485**	Age	-0.0371**	-0.0153***
	(0.51)	(-0.47)		(0.61)	(0.40)	(0.88)	(1.26)	(1.78)	(2.25)		(-2.64)	(-5.64)
CumBatch Loss	-0.0183	-0.0002	Realized Volatility	-0.1698	0.4891	-0.4497	0.1690	-0.4650	0.0188	TradExp	0.0262	0.0138***
	(-0.51)	(-0.01)		(-0.31)	(0.69)	(-1.16)	(0.39)	(-1.61)	(0.07)		(1.54)	(4.67)
CumTrad Cnt	-0.0030	0.0014	#Trades	-0.0046	0.0074	-0.0037	0.0076	-0.0141	-0.0063	LeftHand	-0.2603***	-0.0097
	(-0.07)	(0.06)		(-0.19)	(0.52)	(-0.15)	(0.50)	(-0.53)	(-0.41)		(-5.38)	(-0.75)
CumTrad Amnt	0.0026	0.0013	Trade Vol	-0.0093	-0.0081	-0.0100	-0.0079	-0.0116	-0.0049	Gym	0.0794**	0.0536***
	(0.78)	(0.59)		(-0.79)	(-1.33)	(-0.81)	(-1.49)	(-1.02)	(-0.80)		(2.79)	(8.56)
CumProfit Amnt	-0.0016	-0.0018*	#Order	0.0215	0.0046	0.0232	0.0044	0.0327	0.0108	Caffeine	-0.1280	0.0161
	(-1.19)	(-1.83)		(1.30)	(0.34)	(1.22)	(0.27)	(1.53)	(0.64)		(-1.44)	(1.03)
LastTrad Loss	0.0134	0.0063*	Efficiency Ratio	0.0840	0.1281*	0.0895	0.1334**	-0.0499	0.1508	Smoke	-0.0260	0.0721***
	(1.53)	(1.97)		(1.17)	(1.86)	(1.22)	(2.68)	(-0.31)	(0.79)		(-0.36)	(6.28)
LastTime Gap	-0.0039***	-0.0015*	DistanceTo High	-1.0896	-0.0762	-2.0700	-1.8190	-3.1604***	-1.8095**	Alcohol	0.0522	-0.0774***
	(-3.00)	(-2.11)		(-0.30)	(-0.03)	(-0.94)	(-0.94)	(-4.27)	(-2.84)		(0.67)	(-6.26)
Price	0.0067	0.0032	DistanceTo Low	-2.1268	-1.1903	-0.9168	-1.5928	-0.2224	-0.7821	SleepHr	-0.0305	0.0205
	(1.58)	(0.89)		(-1.68)	(-0.60)	(-1.12)	(-1.65)	(-0.18)	(-0.80)		(-0.69)	(1.69)
Vol	0.0081	-0.0003	Relative Price	0.0126	0.0019	0.0116	0.0044	0.0299	0.0137	Sleep Quality	-0.0167	0.0170**
	(1.06)	(-0.07)		(1.18)	(0.17)	(1.34)	(0.37)	(1.73)	(0.83)		(-0.54)	(3.00)
Trader × DateHr FE	√	√		√	√	√	√	√	√			
DateHr FE											√	√
Num.Obs.	9544	9509		9501	9466	9505	9470	9508	9473		7558	7535

Table 4. Engagement Index and the Propensity to Trade. This table reports event-study regressions estimating whether prior cognitive engagement predicts trade execution. The dependent variable is an indicator equal to one if trader i executes a transaction at second t, and zero otherwise. Columns (1) through (5) report results for the full sample of trades, entry trades (the first trade of a batch), exit trades (the last trade of a batch), buy trades, and sell trades, respectively. The key independent variables are lagged measures of the Engagement Index, averaged over non-overlapping windows before time t, ranging from t−1 second to t−150 seconds. All specifications include trader-by-date-hour fixed effects, which absorb time-invariant trader characteristics as well as trader-specific conditions within each trading hour. All specifications also control for prior trader-state variables measured before time t, including recent trading intensity, accumulated gains or losses, and elapsed time since the previous execution. Standard errors are two-way clustered at the trader and date-hour levels. The Engagement Index is winsorized at the 1st and 99th percentiles to mitigate the influence of outliers. T-statistics are reported in parentheses.

Dep. Var.			1(Trade)		
Engagement t=	All	First trade	Last Trade	Buy	Sell
	(1)	(2)	(3)	(4)	(5)
0-1s	0.0014***	0.0005***	0.0003*	0.0006***	0.0007***
	(3.44)	(3.28)	(1.82)	(3.18)	(3.22)
1-3s	0.0013***	0.0006**	0.0005*	0.0008***	0.0006*
	(3.20)	(2.81)	(2.13)	(3.92)	(1.79)
3-5s	0.0016***	0.0009***	0.0005**	0.0010**	0.0006***
	(4.11)	(3.58)	(2.69)	(2.92)	(2.97)
5-10s	0.0021***	0.0009***	0.0007**	0.0007***	0.0014**
	(3.29)	(3.23)	(2.67)	(2.99)	(2.49)
10-15s	0.0017***	0.0000	0.0008***	0.0004	0.0013***
	(3.25)	(0.13)	(3.53)	(1.45)	(3.81)
15-30s	-0.0009**	-0.0005**	-0.0001	-0.0002	-0.0007
	(-2.46)	(-2.44)	(-0.33)	(-1.12)	(-1.66)
30-60s	-0.0007	-0.0002	0.0002	0.0000	-0.0006**
	(-0.76)	(-0.35)	(0.72)	(-0.06)	(-2.57)
60-100s	-0.0007	-0.0002	-0.0003	-0.0004	-0.0002
	(-0.85)	(-0.52)	(-0.83)	(-0.87)	(-0.39)
100-150s	-0.0009	-0.0004	-0.0006*	-0.0005	-0.0004
	(-1.24)	(-1.08)	(-2.04)	(-0.89)	(-0.89)
Controls	√	√	√	√	√
Trader × DateHr FE	√	√	√	√	√
Num.Obs.	952292	952292	952292	952292	952292

Table 5. Cognitive Engagement and Trading Performance. This table examines whether traders' cognitive engagement around trade execution predicts trading performance. The dependent variable is a binary indicator equal to one if the corresponding trading batch yields a positive realized profit, and zero otherwise. EI[a,b] denotes the average Engagement Index from a to b seconds relative to trade execution, with negative values indicating pre-trade windows. Columns (1)–(2) use relative EI ratios: EI[-30,0]/EI[-150,-30] and EI[-30,0]/EI[-60,-30]. Columns (3)–(5) use absolute pre-trade EI levels in the [-30,0], [-60,-30], and [-150,-30] windows. Columns (6)–(7) use post-trade EI levels in the [0,30] and [30,150] windows. All specifications include transaction controls, window-matched tick/order-level market controls, and trader-by-date-hour fixed effects. Standard errors are two-way clustered at the trader and date-hour levels. Continuous variables are winsorized at the 1st and 99th percentiles. T-statistics are reported in parentheses.

Dep. Var.	1 (Profit Trade)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Decision/Base EI	0.2316***						
	(4.79)						
Decision/Recent EI		0.1516***					
		(4.08)					
Decision EI			0.0489				
			(0.29)				
Recent EI				-0.2672			
				(-1.31)			
Base EI					-0.5131**		
					(-2.17)		
Post EI [0,30]						-0.3010	
						(-1.51)	
Post EI [30,150]							-0.6638**
							(-2.05)
Controls	√	√	√	√	√	√	√
Trader × DateHr FE	√	√	√	√	√	√	√
Num.Obs.	8828	8793	8859	8825	8828	8857	8811

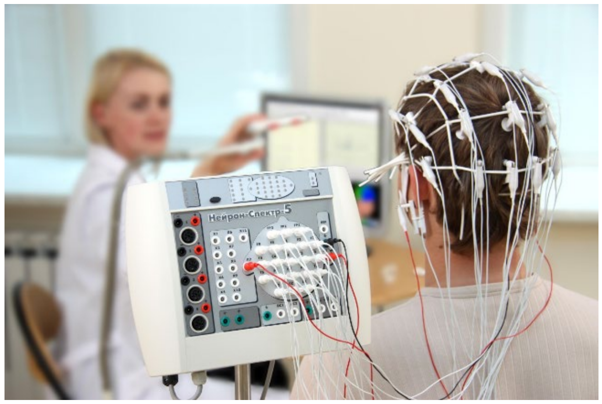
Table 6. Daily Engagement and Trading Performance. This table examines the relationship between daily cognitive engagement and trading performance at both the trader-day level and the transaction level. In Panel A, the unit of observation is the trader-day, and the dependent variable is the daily win rate, defined as the proportion of trading batches yielding a positive realized profit on that day. In Panel B, the unit of observation is the transaction, and the dependent variable is an indicator equal to one if the corresponding trading batch yields a positive realized profit, and zero otherwise. DailyMean is the average Engagement Index during the trading day. DailyStd is the standard deviation of the Engagement Index, capturing within-day cognitive variability. DailyHigh is the 95th percentile of the Engagement Index, capturing peak engagement. LastDayMean is the trader's average Engagement Index on the previous trading day. HistoricAverage is the trader's historical average Engagement Index. All specifications control for aggregated 30-second pre-trade market signals constructed from tick- and order-level data over the trader's executed trades on that day. The first four specifications include trader fixed effects and date fixed effects. The last specification excludes trader fixed effects because HistoricAverage is time-invariant at the trader level. Standard errors are two-way clustered at the trader and date levels. Continuous variables are winsorized at the 1st and 99th percentiles. T-statistics are reported in parentheses.

	Panel A: Daily-level results				
Dep. Var.	Winrate				
	(1)	(2)	(3)	(4)	(5)
DailyMean	-0.1804**				
	(-2.87)				
DailyStd		-0.0888			
		(-1.72)			
DailyHigh			-0.0474***		
			(-3.19)		
LastDayMean				-0.0884	
				(-1.24)	
HistoricAverage					0.1078
					(0.53)
Controls	√	√	√	√	√
Trader FE	√	√	√	√	
Date FE	√	√	√	√	√
Num.Obs.	182	182	182	166	182
	Panel B: Transaction-level results				
Dep. Var.	1(IsProfit)				
	(1)	(2)	(3)	(4)	(5)
DailyMean	-0.7708**				
	(-2.40)				
DailyStd		-0.4710**			
		(-1.99)			
DailyHigh			-0.2374***		
			(-2.69)		
LastDayMean				-0.7918**	
				(-2.28)	
HistoricAverage					0.6501
					(0.82)
Controls	√	√	√	√	√
Trader FE	√	√	√	√	
Date FE	√	√	√	√	√
Num.Obs.	9544	9544	9544	8391	9544

Table 7. Engagement Index and Disposition Effect. This table investigates whether cognitive engagement moderates the disposition effect. The sample includes multi-leg trading batches with more than one execution, so that each batch has a well-defined holding period from the first execution to the last execution. The dependent variable is holding duration in seconds. The key independent variable is the Loser dummy IsLoss, equal to one if the batch results in a realized loss, and zero otherwise. Column (1) tests the baseline disposition effect, examining whether losing batches are held longer than winning batches. Column (2) interacts the Loser dummy with average EI during the holding period. Columns (3) and (4) interact the Loser dummy with EI measured over the 30-second and 60-second windows before batch exit, respectively. All specifications control for pre-entry EI, transaction characteristics, and tick/order-level market signals. All models include trader-by-date-hour fixed effects. Standard errors are two-way clustered at the trader and date-hour levels. Continuous variables are trimmed at the 1st and 99th percentiles. T-statistics are reported in parentheses.

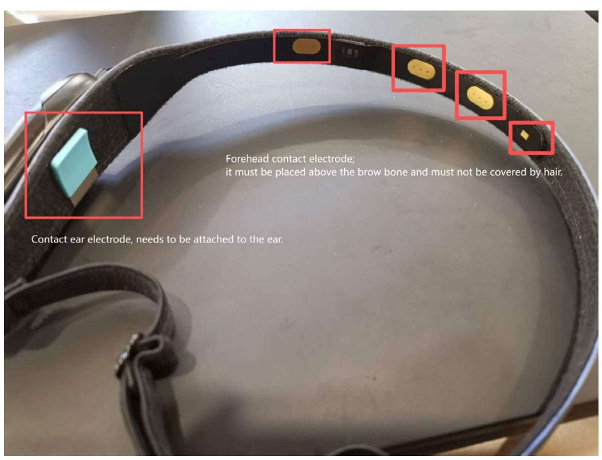
	Duration			
	(1)	(2)	(3)	(4)
IsLoss	4.8216	4.8989	4.8432	4.9714
	(1.09)	(1.19)	(1.19)	(1.23)
Holding period EI		-3.8668***		
		(-3.41)		
IsLoss × Holding period EI		-4.4050**		
		(-2.29)		
Pre Exit 30 EI			-5.1416*	
			(-1.77)	
IsLoss × Pre Exit 30 EI			-4.9194**	
			(-2.35)	
Pre Exit 60 EI				-6.5795
				(-1.54)
IsLoss × Pre Exit 60 EI				-4.5750**
				(-2.31)
Controls	√	√	√	√
Trader × DateHr FE	√	√	√	√
Num.Obs.	2694	2694	2694	2694

Appendix A. Additional Figures and Tables.



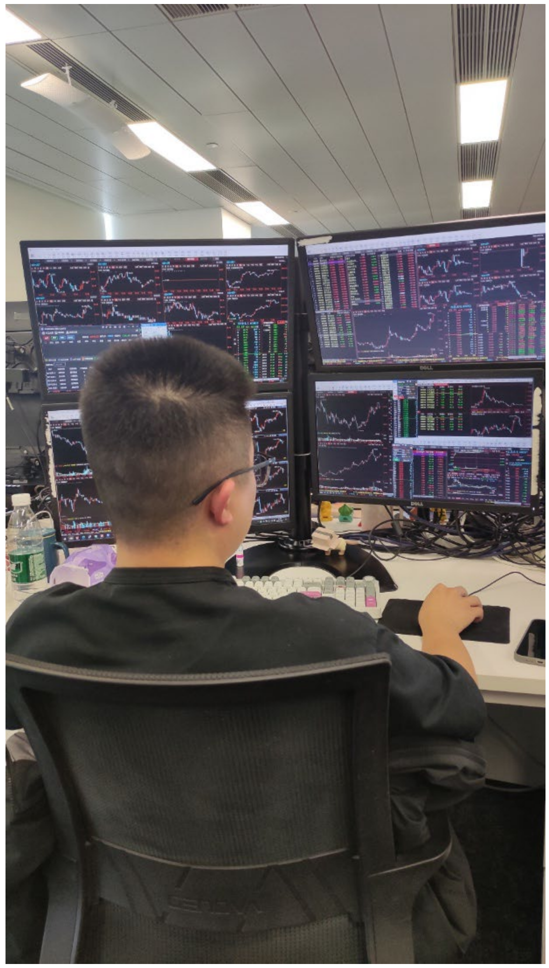
A. Clinical ("Wet") EEG device

B. Wearable ("Dry") EEG device

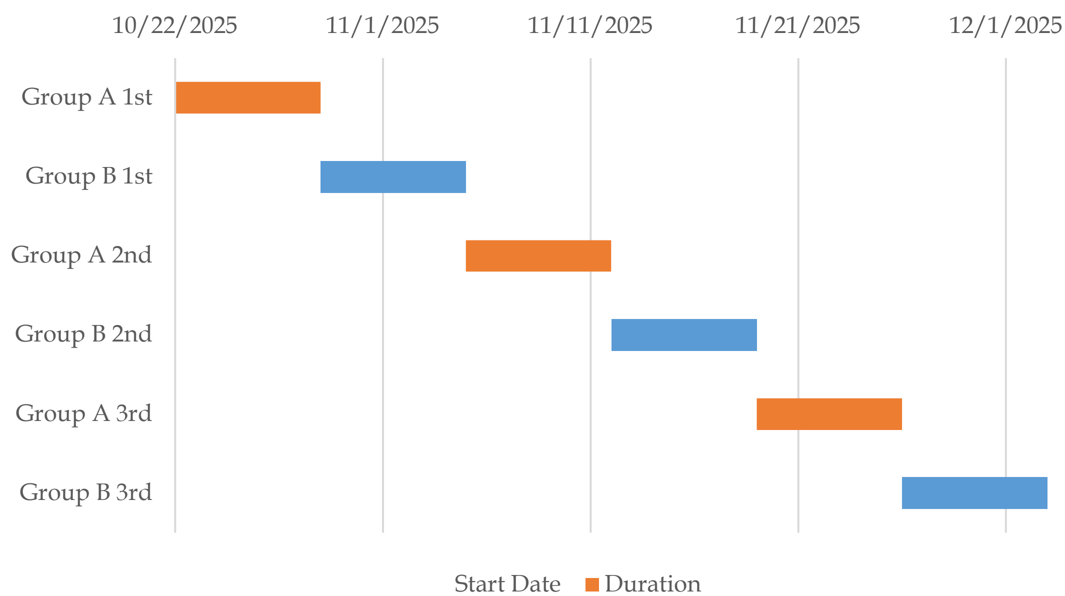


C. Wearable EEG sensors

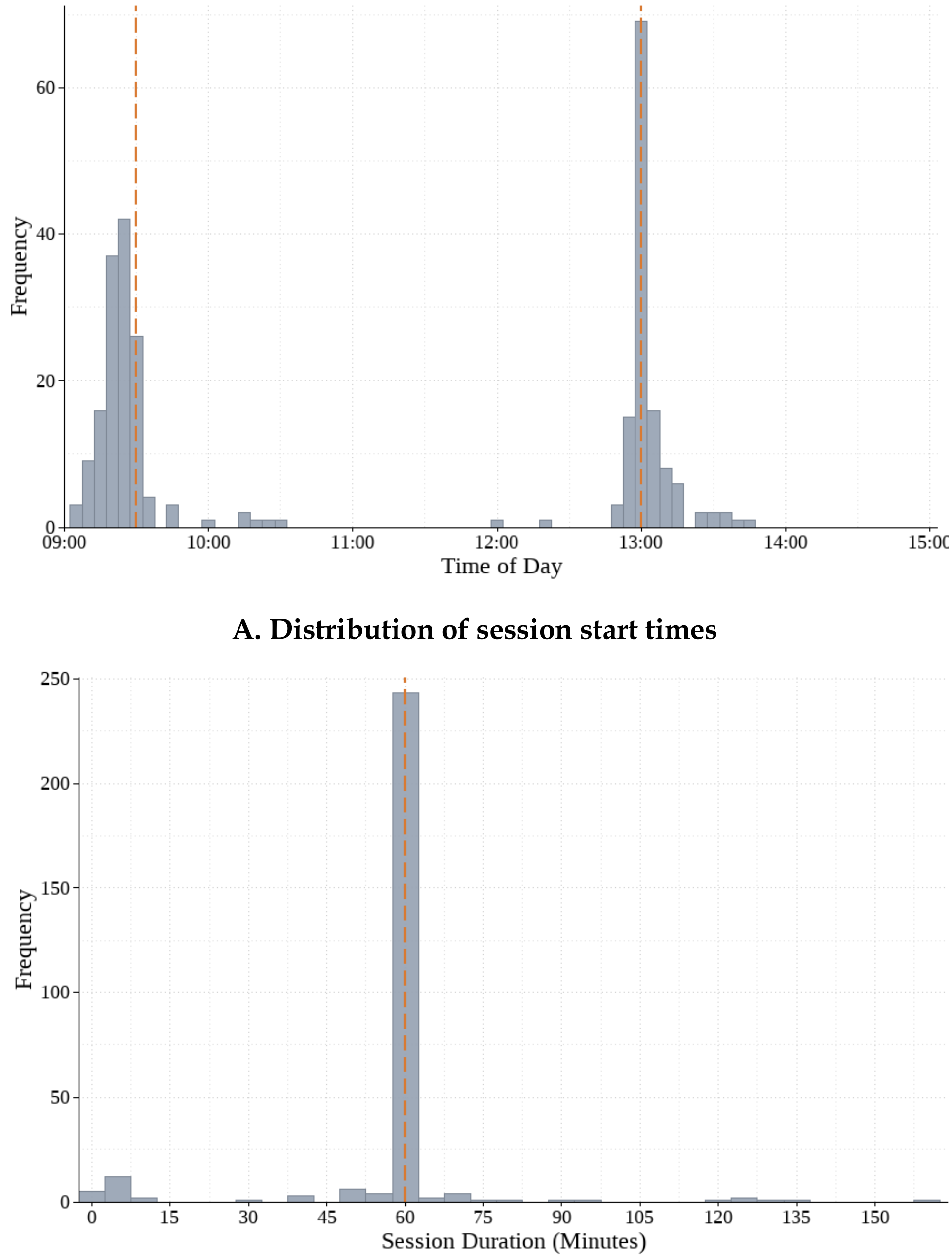
Appendix Figure 1. EEG devices comparison. Panel A illustrates clinical EEG devices (Image source: Wikimedia Commons). Panels B and C illustrate the wearable EEG device developed by NeuroSky.



Appendix Figure 2. Trading environment. This figure shows an example of the workspace of the traders. Each trader operates a workstation equipped with four monitors. The top-left screen displays broad market indices, and the top-right screen tracks sector-level price trends. The bottom-left monitor shows real-time candlestick charts for the focal stock, while the bottom-right screen is usually for order entry.



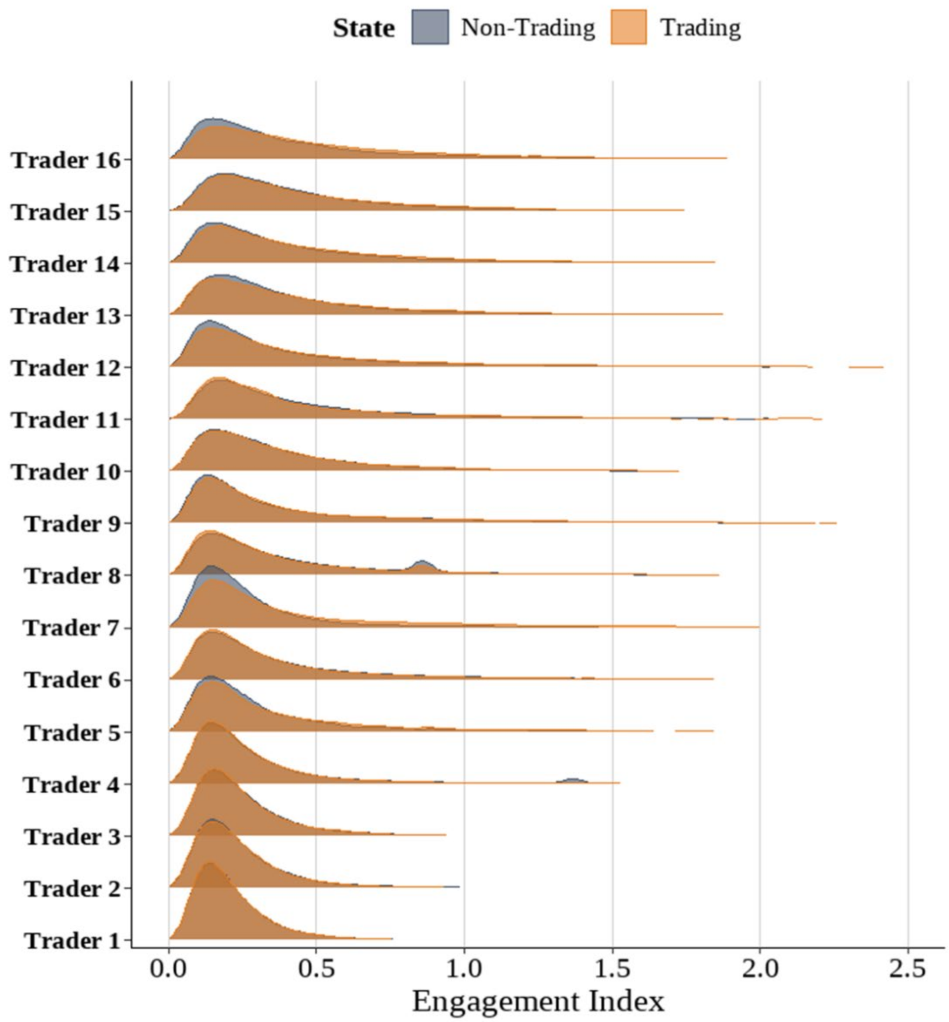
Appendix Figure 3. Study Schedule. Our study spanned a six-week period between October 22nd and December 2nd, 2025. In practice, we randomly divided the 16 subject traders into two groups. Eight traders participated in the 1st, 3rd, and 5th weeks of the study, while the other eight participated in the 2nd, 4th, and 6th weeks.



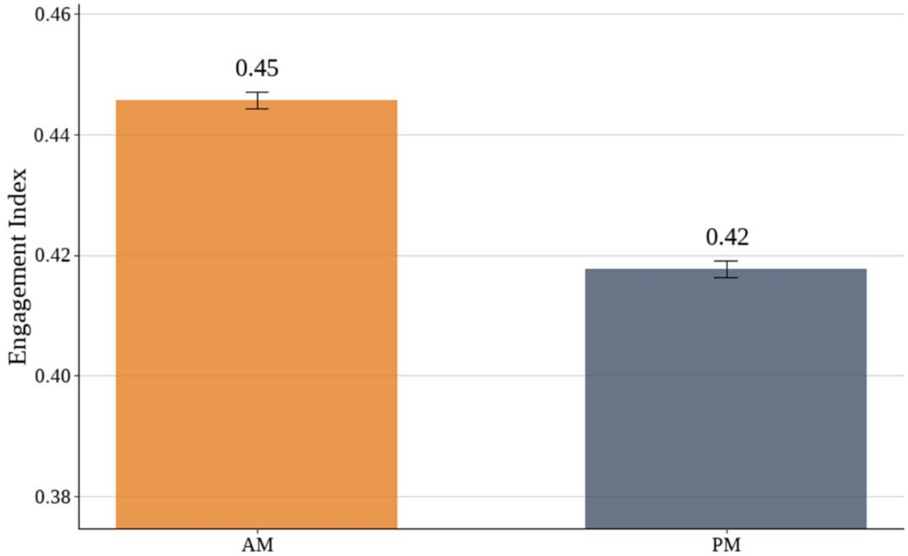
A. Distribution of session start times

B. Distribution of session durations

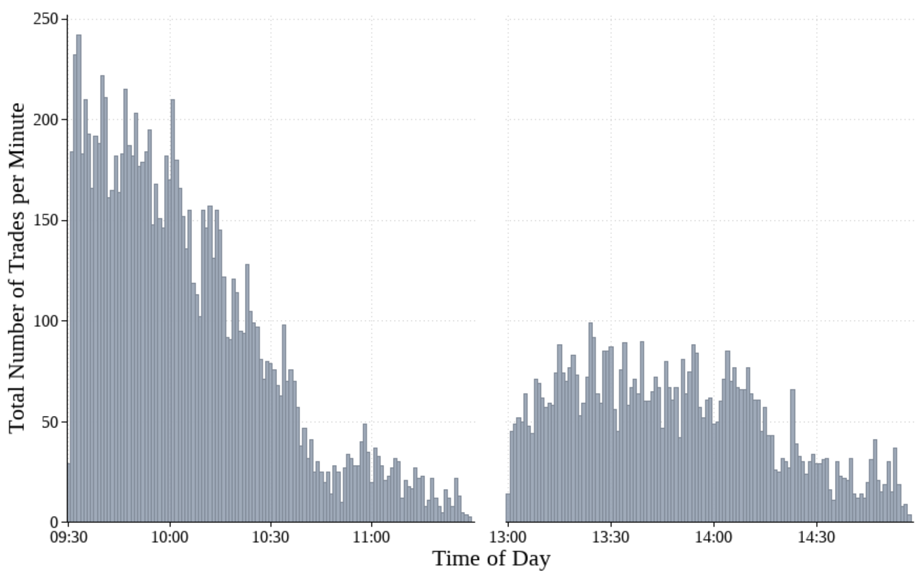
Appendix Figure 4. Compliance Statistics. This figure reports compliance statistics for EEG recording sessions. Panel A plots the distribution of session start times, defined as the first EEG recording time in the morning and afternoon for each trader-day. Vertical dashed lines mark the official market opening times for the morning and afternoon sessions. Panel B plots the distribution of session durations, calculated as session end time minus session start time. The vertical dashed line marks 60 minutes, the experimental guideline for session length. Frequencies are shown as counts.



Appendix Figure 5. Distribution of brainwaves. Distribution of the Engagement Index During Trading and Non-Trading Periods. This figure displays ridgeline plots comparing the distribution of the Engagement Index for each trader during trading and non-trading periods. Trading observations are valid EEG observations within 60 seconds before or after a trade execution timestamp; non-trading observations are all remaining valid EEG observations outside these windows. The Engagement Index is winsorized at the 1st and 99th percentiles. Traders are ordered vertically based on their median engagement levels during trading periods.

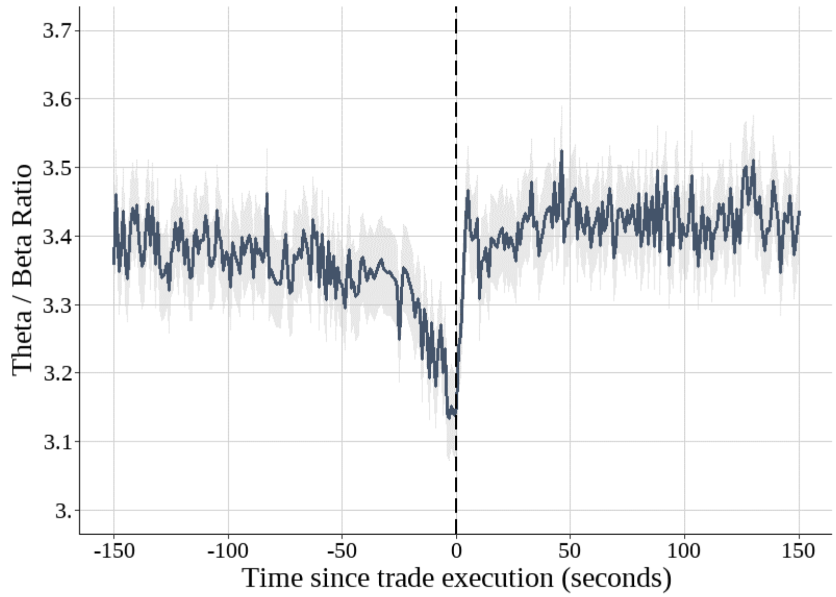


A. Engagement Index: Morning vs. Afternoon

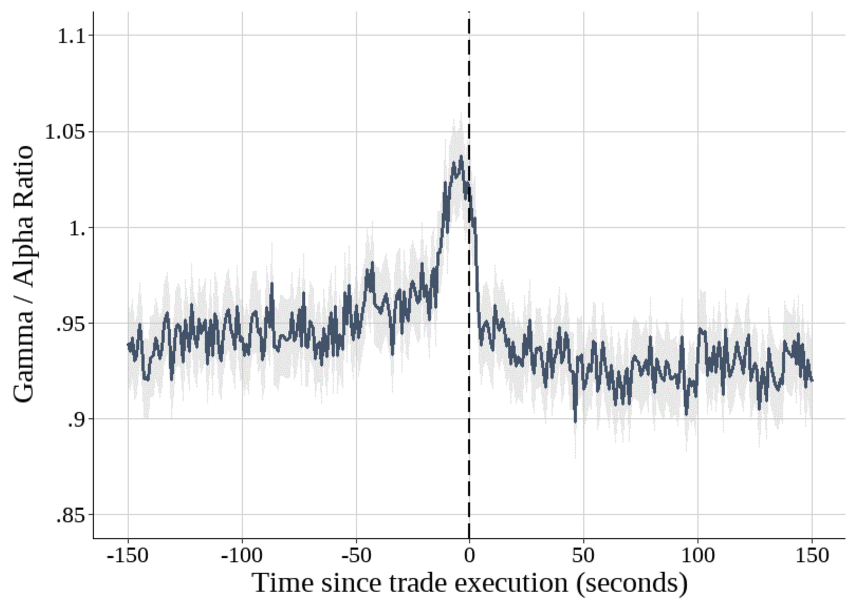


B. Intraday trading rhythm

Appendix Figure 6. Engagement index in the morning and afternoon. Panel A displays bar plots comparing the mean Engagement Index across two distinct temporal periods, where "AM" represents the trading session prior to 12:00 PM and "PM" represents the session thereafter. To mitigate the impact of outliers, the engagement data are winsorized at the 1st and 99th percentiles prior to aggregation. The height of the bars corresponds to the average engagement level, while the error bars represent the 95% confidence intervals. Panel B displays total number of trades per minute over the days for all traders.

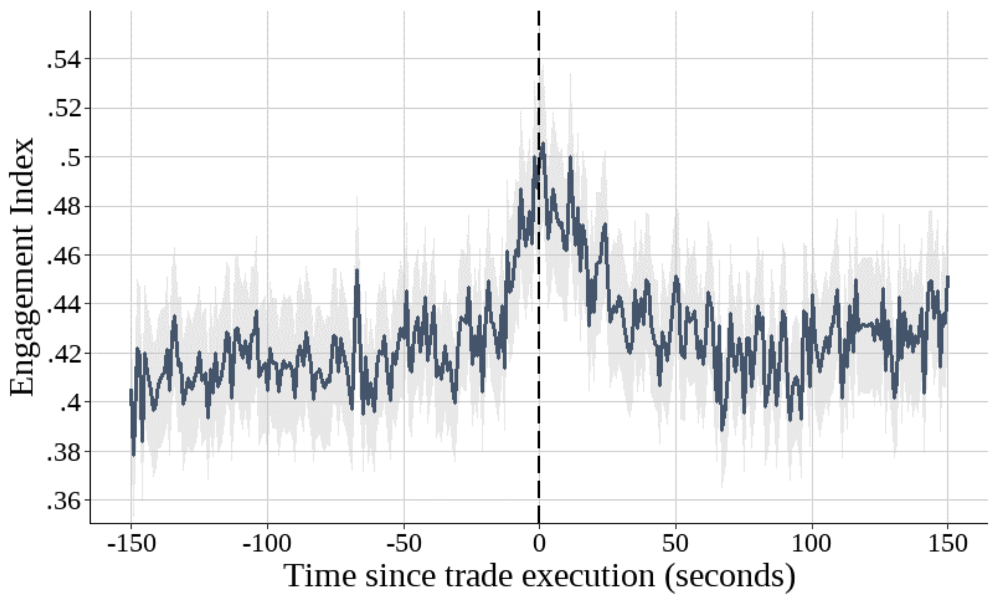


A. Mind Wandering Index

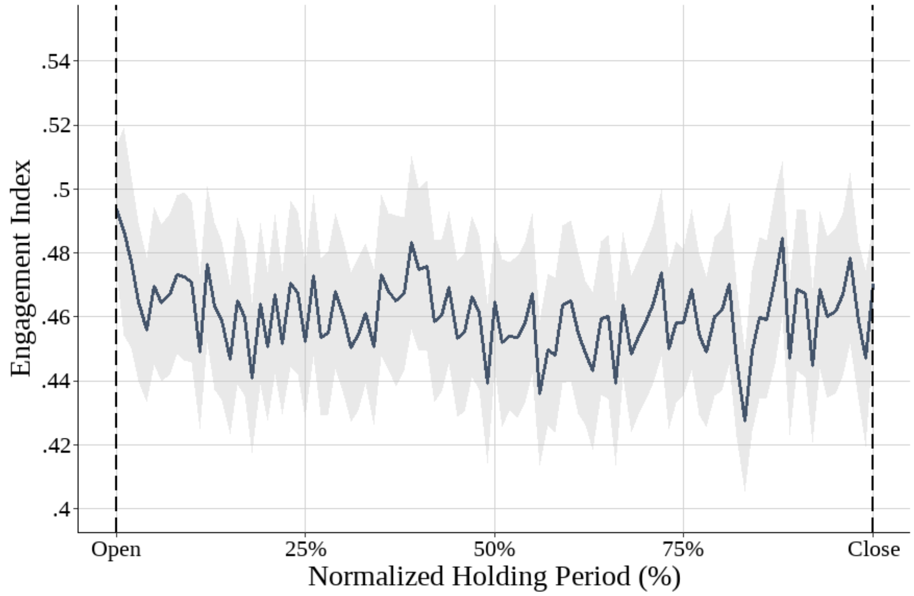


B. Arousal Index

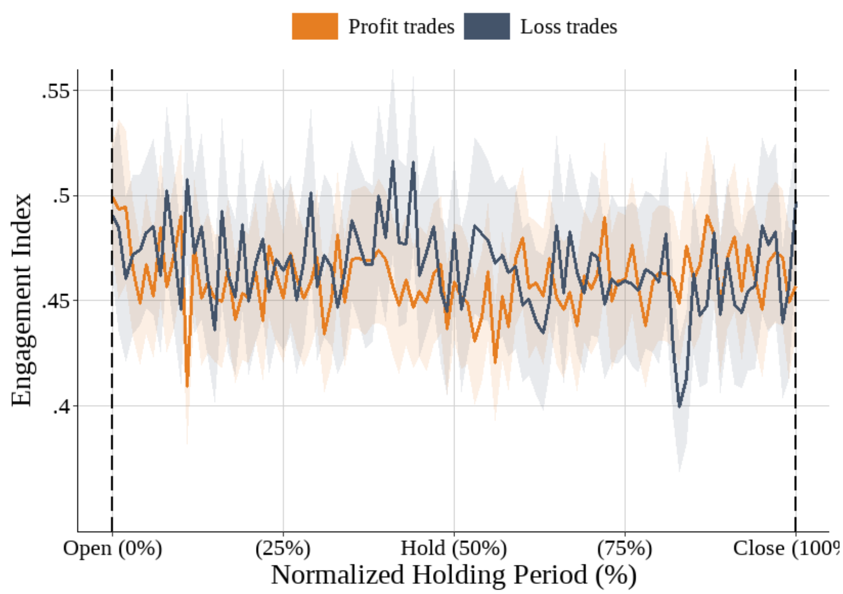
Appendix Figure 7. Other specifications of the engagement index. This figure reports the results of an event study analyzing the evolution of the Engagement Index within ±150 seconds surrounding trade execution with different specifications. Panel A calculates the ratio of theta/beta that represents mind wandering and reduced attentional control, used in Putman et al. (2010) and van Son et al. (2019). Panel B calculates the ratio of gamma/alpha that represents cognitive engagement and focused information processing. For both panels, the underlying engagement data are winsorized at the 1st and 99th percentiles to limit the impact of outliers, and standard errors are calculated based on the number of observations in each relative time bin.



Appendix Figure 8. Engagement Index around Isolated Trade Execution. This figure reports the results of an event study examining the evolution of the Engagement Index within a ±150-second window surrounding isolated trade executions. The sample is restricted to trades for which the same trader did not execute any other trade during the preceding 150 seconds. The solid line plots the sample mean of the Engagement Index at each relative-time bin, and the shaded area denotes the 95% confidence interval. The vertical dashed line marks the exact second of trade execution (t = 0). The underlying engagement data are winsorized at the 1% and 99% levels to mitigate the influence of outliers, and standard errors are computed based on the number of observations in each relative-time bin.

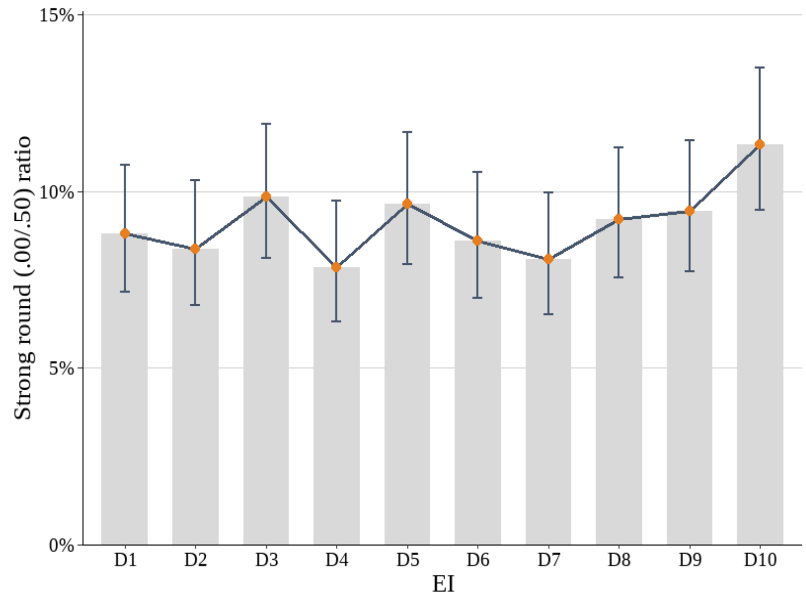


A. All trades

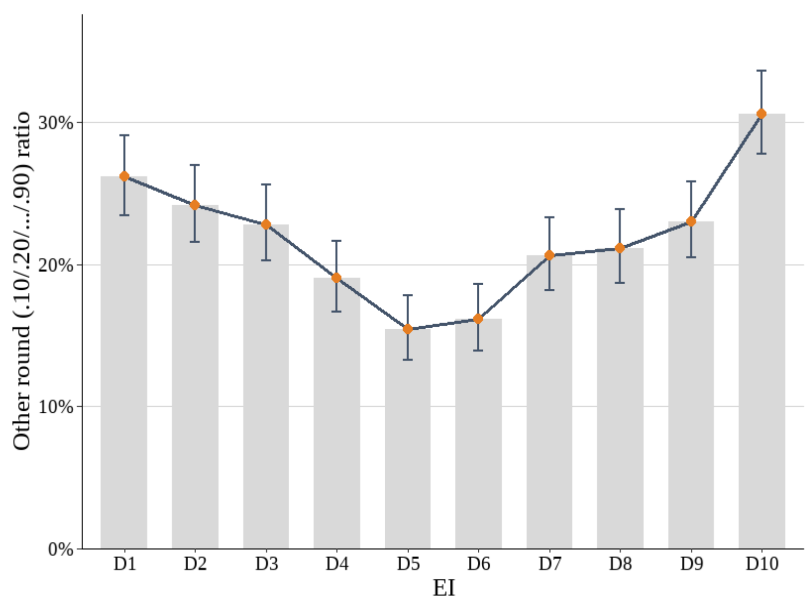


B. Subsample analysis

Appendix Figure 9. Engagement Index over the Normalized Holding Period. This figure reports the evolution of the Engagement Index over the normalized holding period of round-trip trading batches. For each batch, the holding interval is defined as the time between the first trade that opens the position and the last trade that closes it. Because holding durations vary across batches, each batch is linearly rescaled to a common 0–100% timeline, where 0% denotes position opening, 50% denotes the midpoint of the holding period, and 100% denotes position closing. The solid lines plot the sample mean of the Engagement Index at each normalized-time bin for profit and loss batches, and the shaded areas denote the corresponding 95% confidence intervals. The vertical dashed lines mark the beginning and the end of the holding period. To reduce the influence of outliers, the underlying Engagement Index series is winsorized at the 1st and 99th percentiles. The sample excludes batches with holding durations longer than 600 seconds. Standard errors are computed based on the number of observations in each normalized-time bin. Panel A reports EI for the whole sample, and Panel B reports separately for profit and loss batches.



A. Strong Round Trades (.00 / .50)



B. Other Round Trades (.10–.90, excluding .00 and .50)

Appendix Figure 10. Pre-Trade Engagement and Round-Number Trading. This figure examines the relation between traders' pre-trade Engagement Index (EI) and their propensity to trade at round-number prices. For each trade, we construct the sorting variable as the average EI over the 150-second window prior to trade execution. Trades are then sorted into deciles based on this measure, ranging from D1 (lowest pre-trade EI) to D10 (highest pre-trade EI). For each decile, the bars report the fraction of trades executed at round-number prices, and the connected points trace the same decile-level ratios. Vertical error bars represent 95% confidence intervals, constructed using the Wilson score interval for binomial proportions. Panel A reports the fraction of Strong Round trades, defined as trades executed at prices ending in .00 or .50. Panel B reports the fraction of Other Round trades, defined as trades executed at prices ending in .10, .20, ..., or .90, excluding .00 and .50. The sample includes all trades with non-missing pre-trade EI measures.

Appendix Table 1. Test of the Hawthorne Effect. This table examines whether traders change their trading behavior when wearing the EEG device (the Hawthorne effect). The unit of observation is at the batch level. The sample is restricted to batches classified as either profitable or loss-making and with holding durations shorter than ten minutes. The key explanatory variable is EEG Monitoring, an indicator equal to one if the batch start time falls within the interval during which the trader was wearing the EEG device on that day, and zero otherwise. EEG monitoring windows are identified from the earliest and latest EEG timestamps recorded for each trader on each trading day. The dependent variables capture different aspects of trading behavior and performance. Column (1) examines holding duration, measured as the time difference in seconds between the first and last trade within a batch. Column (2) analyzes batch profit, defined as the net monetary profit of the round-trip batch. Column (3) studies batch return rate, calculated as the percentage return of the batch. Column (4) examines win probability, a binary variable equal to one if the batch yields a positive profit. Column (5) analyzes trade splitting intensity, measured as the number of individual transactions contained within a batch. All specifications include Trader × Date-Hour fixed effects and control for log average transaction price, log batch transaction amount, and log batch transaction quantity. Standard errors are two-way clustered by trader and date-hour. Batch durations are restricted to less than 600 seconds, and the continuous control variables are winsorized at the 1st and 99th percentiles. T-statistics are reported in parentheses.

	BatchDuration	BatchProfit	BatchRet	1 (Profit Trade)	Trades PerBatch
	(1)	(2)	(3)	(4)	(5)
IsHeadsetOn	1.0592	8.8156	0.0178	-0.0065	0.1446
	(0.16)	(0.11)	(0.66)	(-0.27)	(1.07)
Controls	√	√	√	√	√
Trader × DateHr FE	√	√	√	√	√
Num.Obs.	4194	4194	4194	4194	4194

Appendix Table 2. d2 test-period neural measures and attentional performance. This table validates the Engagement Index using the d2 Test of Attention. The d2 Test of Attention is a standardized neuropsychological task that requires participants to identify target symbols under time pressure. Panel A reports trader-level descriptive statistics during the d2 testing period. Traders are anonymized and ranked in descending order based on their d2 test correctness score. The column D2-period Engagement reports the mean EEG-derived Engagement Index measured during the post-15:00 d2 testing interval, and the number in parentheses reports the corresponding standard deviation. The column D2 Test Correct reports the number of correct answers in the d2 test, with 100 being the maximum possible score. One trader is missing because the cognitive assessment was not completed. Panel B reports regressions relating d2 test correctness to engagement measured during the d2 testing period. Columns (1) and (2) use second-level EEG observations, with EI measured at the second level. Column (1) clusters standard errors at the trader level. Column (2) adds elapsed-minute fixed effects within the d2 task and applies equal trader weights, so that traders with more EEG observations do not receive disproportionate weight. Column (3) aggregates the data to the trader level and regresses standardized d2 test correctness on standardized average d2-period EI. T-statistics are reported in parentheses.

	Panel A: d2 Test overview	
Trader	d2 Engagement levels	D2 Test Correct
	(1)	(2)
Trader 15	1.343	99
	(2.865)	
Trader 14	0.318	95
	(0.244)	
Trader 13	0.627	94
	(0.602)	
Trader 12	0.518	93
	(0.501)	
Trader 11	0.225	92
	(0.130)	
Trader 10	0.468	92
	(0.440)	
Trader 09	0.832	89
	(0.724)	
Trader 08	0.452	88
	(0.270)	
Trader 07	0.380	85
	(0.262)	
Trader 06	0.477	80
	(0.284)	
Trader 05	0.330	76
	(0.203)	
Trader 04	0.225	73
	(0.235)	
Trader 03	0.287	71
	(0.157)	
Trader 02	0.292	71
	(0.197)	
Trader 01	0.292	66
	(0.179)	

	Panel B: Evaluation		
Dep. Var.	d2 Correctness		
	(1)	(2)	(3)
EI	2.6397**	2.0136**	
	(2.33)	(2.18)	
Avg EI			0.5758***
			(3.58)
Constant	√		√
Test-Minute FE		√	
Num.Obs.	4346	4346	15

Appendix Table 3. Determinants of the Engagement Index: Entry. This table repeats the analysis in Table 3 after restricting the sample to entry trades, defined as the first execution within each round-trip batch. All other specifications remain the same.

	Panel A: Trading history			Panel B: Technical Indicators							Panel C: Personal traits	
Dep. Var.	EI level	EI chg		EI level	EI chg	EI level	EI chg	EI level	EI chg		EI level	EI chg
			Time horizon	30s		60s		180s				
	(1)	(2)		(3)	(4)	(5)	(6)	(7)	(8)		(9)	(10)
CumBatch Cnt	0.0116	0.0395	MOM	-1.1226	-0.8358	-0.6500	1.5997	0.1204	0.2139	Age	-0.0356**	-0.0108***
	(0.19)	(1.44)		(-0.55)	(-0.33)	(-0.52)	(0.73)	(0.13)	(0.28)		(-2.76)	(-3.52)
CumBatch Loss	0.0151	-0.0225	Realized Volatility	-0.2789	0.9650*	-0.6724	0.0999	-0.6129	-0.0116	TradExp	0.0283*	0.0119***
	(0.24)	(-0.54)		(-0.44)	(1.83)	(-1.19)	(0.28)	(-1.69)	(-0.05)		(1.81)	(3.37)
CumTrad Cnt	-0.0166	-0.0260	#Trades	-0.0209	0.0054	-0.0347	-0.0047	-0.0409	-0.0061	LeftHand	-0.2568***	0.0090
	(-0.38)	(-1.35)		(-0.77)	(0.41)	(-1.13)	(-0.28)	(-1.27)	(-0.33)		(-4.93)	(0.78)
CumTrad Amnt	-0.0007	-0.0048*	Trade Vol	-0.0017	-0.0093	0.0020	-0.0046	0.0011	-0.0043	Gym	0.0779**	0.0616***
	(-0.19)	(-1.99)		(-0.12)	(-1.17)	(0.13)	(-0.64)	(0.08)	(-0.68)		(2.88)	(14.53)
CumProfit Amnt	-0.0009	-0.0015	#Order	0.0395*	0.0138	0.0528*	0.0198	0.0574*	0.0151	Caffeine	-0.1275	0.0166
	(-0.50)	(-1.03)		(1.78)	(0.96)	(2.04)	(1.10)	(1.95)	(0.73)		(-1.62)	(1.17)
LastTrad Loss	0.0116	0.0079	Efficiency Ratio	0.1625	0.2098**	0.2544	0.2063*	0.1529	0.1834	Smoke	-0.0386	0.0797***
	(0.75)	(0.88)		(1.66)	(2.34)	(1.70)	(1.91)	(0.58)	(0.94)		(-0.57)	(7.55)
LastTime Gap	-0.0036	0.0033	DistanceTo High	4.0554	5.0423	0.1830	-1.4002	-2.2215**	-0.9195	Alcohol	0.0429	-0.0728***
	(-1.01)	(1.64)		(1.20)	(1.47)	(0.09)	(-0.58)	(-2.61)	(-0.85)		(0.61)	(-9.25)
Price	0.0032	0.0021	DistanceTo Low	-0.3963	-1.6851	1.0814	-2.0917	0.9763	-0.0562	SleepHr	-0.0574	0.0176***
	(0.50)	(0.43)		(-0.15)	(-0.45)	(0.77)	(-1.03)	(0.63)	(-0.04)		(-1.29)	(3.76)
Vol	0.0096	-0.0009	Relative Price	-0.0088	0.0018	-0.0037	0.0193	0.0242	0.0229	Sleep Quality	-0.0168	0.0240***
	(0.96)	(-0.09)		(-0.70)	(0.11)	(-0.44)	(1.56)	(1.46)	(1.57)		(-0.57)	(4.05)
Trader ×DateHr FE	√	√		√	√	√	√	√	√			
DateHr FE											√	√
Num.Obs.	3202	3189		3189	3176	3190	3177	3190	3177		2637	2629

Appendix Table 4. Determinants of the Engagement Index: Exit. This table repeats the analysis in Table 3 after restricting the sample to exit trades, defined as the last execution within each round-trip batch. All other specifications remain the same.

	Panel A: Trading history			Panel B: Technical Indicators							Panel C: Personal traits	
Dep. Var.	EI level	EI chg		EI level	EI chg	EI level	EI chg	EI level	EI chg		EI level	EI chg
			Time horizon	30s		60s		180s				
	(1)	(2)		(3)	(4)	(5)	(6)	(7)	(8)		(9)	(10)
CumBatch Cnt	-0.0165	-0.0169	MOM	0.0697	0.6398	-0.7637	-0.3283	0.7191	0.0597	Age	-0.0463***	-0.0163***
	(-0.24)	(-0.36)		(0.03)	(0.24)	(-0.49)	(-0.20)	(1.41)	(0.11)		(-3.11)	(-4.56)
CumBatch Loss	0.0170	0.0017	Realized Volatility	-0.7056	0.1207	-0.8160	0.0253	-0.5016	0.0389	TradExp	0.0319*	0.0116***
	(0.37)	(0.06)		(-0.82)	(0.14)	(-1.44)	(0.04)	(-1.52)	(0.12)		(1.85)	(3.34)
CumTrad Cnt	-0.0024	0.0085	#Trades	-0.0086	-0.0044	-0.0071	0.0006	-0.0175	-0.0180	LeftHand	-0.2845***	-0.0183
	(-0.06)	(0.52)		(-0.29)	(-0.17)	(-0.23)	(0.02)	(-0.63)	(-0.63)		(-5.50)	(-1.65)
CumTrad Amnt	0.0002	-0.0069	Trade Vol	-0.0136	-0.0064	-0.0146	-0.0083	-0.0146	-0.0037	Gym	0.0825**	0.0572***
	(0.02)	(-0.29)		(-1.24)	(-0.83)	(-1.24)	(-1.18)	(-1.47)	(-0.41)		(2.44)	(7.82)
CumProfit Amnt	-0.0018	-0.0016	#Order	0.0354	0.0154	0.0390	0.0155	0.0483	0.0265	Caffeine	-0.1026	0.0380***
	(-0.95)	(-1.27)		(1.42)	(0.63)	(1.36)	(0.59)	(1.70)	(0.98)		(-1.24)	(3.53)
LastTrad Loss	0.0225**	0.0148**	Efficiency Ratio	-0.0553	0.0255	0.0164	0.1178	0.0163	0.1107	Smoke	-0.0279	0.0735***
	(2.28)	(2.34)		(-0.80)	(0.47)	(0.16)	(1.32)	(0.17)	(0.49)		(-0.42)	(12.37)
LastTime Gap	0.0003	-0.0011	DistanceTo High	-4.2591	-3.0821	-3.4634	-1.7492	-3.1945**	-0.5978	Alcohol	-0.0211	-0.1257***
	(0.06)	(-0.47)		(-0.96)	(-0.79)	(-1.36)	(-0.74)	(-2.89)	(-0.60)		(-0.27)	(-11.25)
Price	0.0036	0.0037	DistanceTo Low	-0.2382	0.1857	0.7398	0.4900	-0.2445	0.1332	SleepHr	-0.0745	-0.0085
	(1.03)	(0.82)		(-0.06)	(0.05)	(0.44)	(0.23)	(-0.19)	(0.09)		(-1.72)	(-0.80)
Vol	0.0299**	0.0108	Relative Price	0.0350	0.0107	0.0347	0.0019	0.0299	-0.0196	Sleep Quality	-0.0134	0.0284***
	(2.73)	(1.36)		(1.31)	(0.45)	(1.63)	(0.06)	(1.15)	(-0.63)		(-0.40)	(4.75)
Trader ×DateHr FE	√	√		√	√	√	√	√	√			
DateHr FE											√	√
Num.Obs.	3157	3150		3141	3134	3144	3137	3146	3139		2598	2591

Appendix B. d2 Test of Attention

【Instructions】

Please identify and cross out the target symbols in every row of the letter sequence as quickly and accurately as possible.

1. The Target Symbol: The letter d accompanied by two short dashes (the dashes may appear above the letter).
2. Distractors: All other symbols (the letter p, or the letter d with 1, 2, 3, or 4 dashes) are distractors; do not cross them out.
3. Procedure: Upon hearing the "Start" command, begin with the first row and proceed sequentially until you have completed the entire test. Please ensure your marks are precise.

【Experiment Protocols】

The participant must wear the brain-sensing headband. Select a fellow trader to act as a partner to record the timing.

1. Timing: Accurately record the Start Time and End Time (precise to the second, e.g., December 2, 2025, 15:10:15).
2. Analysis: After the experiment concludes, the experiment team will compile and analyze the results.

【Data Collection Fields】

- ✓ Participant Name:
- ✓ Start Time:
- ✓ End Time:
- ✓ Recorder Name:

(Answer Key: The estimated duration of the test is approximately 6 minutes. This answer page should not be printed for the traders; it is intended solely for operations staff to use when grading.)

p′	p‴	d″	d″	p′	d⁗	p⁗	p‴	p″	p′	d″	d″	d′	p⁗	d‴	p⁗	d⁗	d′	d″	d′	d′	p⁗	d″	p″	p⁗	d⁗	p‴	d‴	p⁗	p″	p‴	p‴	d″	p⁗
p‴	d‴	d⁗	d″	p‴	p‴	d⁗	d‴	p″	d″	p″	d‴	p′	p″	d″	p⁗	p′	d′	p″	d⁗	d″	p″	d⁗	p⁗	d⁗	d″	p″	d‴	d⁗	d⁗	p′	p′	p′	d‴
p″	d″	d‴	d⁗	p″	d‴	p‴	d⁗	d′	p″	p⁗	d′	p⁗	d‴	d⁗	p⁗	p‴	d′	d′	p′	p′	p⁗	p‴	p‴	d‴	p‴	d′	d‴	p″	p‴	p″	d⁗	p″	d‴
d‴	d′	d⁗	p′	p‴	p‴	d′	d′	p⁗	p‴	d′	d⁗	p″	d‴	p‴	d′	d″	p′	d″	d″	d″	d″	d‴	p⁗	d′	p‴	d‴	p‴	d″	d′	p′	p′	p⁗	d‴
d′	p″	d″	p″	p″	d′	p′	d⁗	p′	p⁗	p″	d′	d⁗	d′	p″	p′	p⁗	p⁗	d″	p‴	d′	p″	d‴	d⁗	d′	p⁗	d″	p″	d″	p⁗	d′	d‴	p⁗	d⁗
d⁗	d″	d′	p′	d‴	d″	d⁗	d′	d″	p⁗	p‴	p′	p″	d‴	p‴	p‴	d″	p⁗	d‴	p′	p⁗	p′	d″	p‴	d′	p‴	p″	d′	p‴	p′	p‴	d‴	d″	p‴
p′	p‴	p′	p′	p′	p‴	p″	d′	d‴	d⁗	p⁗	d‴	p″	d⁗	p‴	d″	d⁗	p′	d″	d⁗	p″	p‴	p‴	p⁗	d″	p″	d″	d″	d′	p⁗	p⁗	p⁗	p′	p‴
d″	d′	p‴	p‴	p″	p⁗	d″	d″	p‴	p″	d′	p‴	p′	d‴	p‴	d⁗	p⁗	d‴	p″	d‴	p⁗	d‴	d″	p″	d″	d″	d″	p⁗	d″	p⁗	d‴	p‴	d″	p⁗
p⁗	p″	d″	d′	p″	p″	p⁗	d″	p⁗	p′	p′	d‴	p‴	p‴	p″	p⁗	p‴	d⁗	d′	p⁗	d′	p‴	p″	p‴	d‴	d⁗	d‴	d′	d⁗	d⁗	d′	p‴	d′	d⁗
d″	d″	d″	d′	d″	d′	d″	d‴	d⁗	d⁗	p′	d⁗	d″	d⁗	p‴	p″	d′	p′	d‴	d″	d‴	d‴	p⁗	d′	d⁗	p‴	p⁗	p′	d⁗	d⁗	p‴	p′	d′	d′
d⁗	d′	p⁗	p‴	p⁗	p″	p⁗	p‴	p⁗	p′	d′	d′	d′	p⁗	d‴	p⁗	d‴	p″	d″	p‴	d″	d⁗	d⁗	p″	d′	p‴	d‴	d‴	d‴	d′	d″	d‴	d⁗	p″
d⁗	d‴	d″	d″	p⁗	p⁗	d⁗	p″	p′	p′	p″	p‴	p′	d″	d⁗	d⁗	d⁗	d″	d″	p′	p′	p″	p‴	p″	d″	d′	p′	p′	d′	d″	d″	d⁗	p‴	d″
d″	p‴	d″	p‴	p⁗	p″	p⁗	d″	p″	p″	d‴	d′	p″	d‴	d⁗	d″	p⁗	d″	d‴	d″	d⁗	p′	d⁗	p″	p″	p″	d″	p″	d″	p″	d⁗	d″	d′	p⁗
d⁗	p‴	d′	d′	p⁗	p′	d″	d⁗	p′	d‴	d⁗	d⁗	p′	d′	d′	d⁗	p′	p⁗	d⁗	d″	p‴	p′	d‴	d⁗	d″	p⁗	d⁗	p⁗	p″	p‴	p″	p′	d′	d′
d″	d⁗	d′	p′	d″	p⁗	p′	d″	d‴	d‴	d″	p″	d⁗	p′	d‴	p″	d⁗	p⁗	p⁗	p⁗	p′	p⁗	p‴	p⁗	d′	d″	d″	d″	p⁗	d⁗	p‴	p″	d′	d⁗
p″	d‴	d⁗	d″	d‴	p‴	d″	p″	p″	d⁗	p⁗	p⁗	p‴	p‴	p″	d‴	d″	p‴	d″	d‴	p′	d′	p‴	p‴	p⁗	d″	d⁗	p⁗	p‴	p″	d‴	d⁗	d‴	d⁗
d‴	p‴	p′	d⁗	p‴	p′	p⁗	d′	d′	p⁗	p″	p″	p′	d‴	p‴	p‴	d⁗	p⁗	d″	d‴	p‴	d‴	p⁗	p⁗	p‴	p″	d‴	d′	d⁗	d‴	p″	p‴	p‴	d″
p″	p″	d‴	d‴	d‴	d′	p⁗	d⁗	p′	d‴	p″	d″	p″	d‴	p⁗	d⁗	p′	p⁗	d‴	d″	p⁗	p⁗	p⁗	p′	d″	d′	d′	d″	p′	p⁗	d″	p″	d″	p⁗
d⁗	p‴	d′	p‴	p‴	d⁗	d⁗	p″	p′	d′	d‴	d⁗	p′	d′	p⁗	d′	d‴	p′	p′	p⁗	d⁗	p′	p‴	p⁗	d″	p⁗	d⁗	d‴	d′	p′	p⁗	d‴	p⁗	p′
p‴	p″	p′	p″	d′	d‴	p‴	p⁗	p⁗	p‴	d‴	d⁗	d⁗	p′	d‴	p″	p‴	p‴	d″	d‴	p⁗	d′	d″	d‴	d′	p″	d″	p‴	p⁗	p′	p″	d′	p‴	p″