Beta for Alpha: Neural Engagement in Financial Trading*

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Abstract

The emergence of wearable electroencephalogram (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 a standard 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 15 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 EI moderates canonical behavioral biases in trading, including the round number heuristic and the disposition effect.

Keywords: Engagement; Stock Trading; Electroencephalography; Neurofinance; Round Number Heuristic; Disposition Effect

JEL Codes: C80, C89, D91, G11, G41, J24

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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, Loewenstein, and Prelec, 2005; Kuhnen and Knutson, 2005; Coates and Herbert, 2008; Frydman and Camerer, 2016).

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 confined to laboratory environments with simplified tasks and non-professional subjects, often in hypothetical settings.

The main objective of this paper is to test the feasibility of using newly available wearable EEG technology to study financial decision-making in a real trading context. 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 we use, from a leading manufacturer, takes the form of an ordinary headset and retails for a fraction of the cost of clinical equipment.

Our paper reports clinical experimental data collected with wearable EEG devices from a group of professional day traders as they engage in real-world stock trading under high stakes and rapid decision 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 arise solely 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 clinical 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 repeats another five days of recording. 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 design allows 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 period and eight traders in

weeks 2, 4, and 6) so that our analysis is less influenced by temporal or market seasonality. This experiment renders a substantial dataset: we observe complete EEG signals over more than 9,000 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 15 seconds leading up to execution (by roughly 0.13 standard deviations), peaks at the trade moment, and returns quickly to baseline. When we separate entry trades from exit trades, the pre-trade spike in EI is similar, but post-trade dynamics differ: Following an entry trade, EI declines gradually back to baseline. With an exit trade, EI drops much more sharply, in fact, overshooting the pre-trade increase before slowly returning to baseline. These patterns offer an encouraging sign that the EI we build can indeed capture cognitive engagement, as it is natural for engagement to rise as traders monitor conditions and commit to a trade decision, and to fall 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 the EI also support its validity as an engagement measure. First, the 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 the EI levels recorded while traders actively performed this rigorous task were comparable in magnitude to those observed during live trading sessions, and traders who are careless on d2 test have a significantly lower EI. This alignment between a validated neuropsychological benchmark and our trading-derived metrics further provides support that the high EI values during trading reflect a genuine state of heightened cognitive focus, rather than mere physiological arousal or noise. Third, we find intuitive correlations between higher EI, both in overall levels and in pre-trade execution spikes, and trader demographics and lifestyle characteristics, such as age, gym activity, tobacco use, and sleep quality.

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 minutes before or after trade execution do not predict performance; if anything, higher background EI is associated with smaller pre-trade spikes and worse trade outcomes. Similarly, when relating daily performance to daily EI patterns, we find no positive association and, in some specifications, a negative one. The consistent pattern indicates that it is the surge in engagement immediately before a decision, not the baseline 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

significantly lower returns than those at precise, non-round prices. Linking this to EEG-measured engagement, we find that higher EI immediately prior to execution is significantly associated with less reliance on the heuristic. Correspondingly, 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 canonical behavioral bias present in our data: traders hold losing positions approximately 10.2% longer than winning ones. Merging trade behavior with moment-by-moment EI patterns, we find that higher engagement significantly mitigates the disposition effect. A one-standard-deviation increase in engagement reduces the holding duration of loss trades by 9.1 seconds, which represents a 14.5% decrease in holding duration. Engaged traders are therefore more likely to cut losses promptly, which may help reduce losses associated with the disposition bias.

Importantly, due to our repeated sampling strategy described earlier, in all of our regression analyses, we can control for individual trader fixed effects as well as granular temporal controls such as date-by-hour fixed effects. This means that the results come from within individual variation (e.g., for the same trader, a larger EI spike prior to a trade is associated with better performance) and are unlikely to be driven by common shocks affecting all traders at any given moment in time.

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. We cannot rule out this possibility given our observational design. 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.

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 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., 2011; Kandasamy et al., 2016). This literature also emphasizes persistent individual differences. 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 round number heuristic (e.g., Harris, 1991; Kuo, Lin, and Zhao, 2015) and disposition effect (e.g., Shiv et al., 2005; Cesarini et al., 2009; Grinblatt and Keloharju, 2009; De Martino, Camerer, and Adolphs, 2010; Jung et al., 2018; Max and Liêu, 2022).

Our contribution to this literature is both methodological and substantive. Methodologically, this 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 many 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.

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).

The rest of the paper is organized as follows. Section 2 provides background on EEG and related psychophysiological research. Section 3 describes the experimental 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 from the flow of ionic currents within 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 (Buzsaki 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 (Buzsaki 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 (7–13 Hz) are prominent in relaxed wakefulness, especially when the eyes are closed, and the mind is unfocused. Alpha rhythm is essentially 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) correspond to heightened vigilance and information processing demands, whereas the slower waves (alpha, theta, and delta) correspond to 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; Buzsaki and Draguhn, 2004).

2.2 Wearable EEG

We measure our traders' neural activity using a portable single-channel EEG headset produced by NeuroSky.[1] 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

[1] https://neurosky.com/

primary sensor rests on the trader's forehead at the left frontopolar position, and a reference electrode clips onto the ear lobe.[2] 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 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

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

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 demonstrate 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, 2013; Helfrich et al., 2014; Chaouachi et al., 2010; Attar, 2022), yet have received little attention among economic and finance scholars.

3. Experimental 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 facilitates 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). 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 Experimental Setup

In all descriptions below, we use the term "experiment" to refer to our field study, although it is understood that our study does not involve a treatment-versus-control intervention in the sense typically implied by "experimental studies" in economics.

Recruitment. As our study is conducted in partnership with the trading firm and received approval from the management board, all traders at the firm are involved in the experiment. 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 experiment. 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.

Experimental Schedules. Our experiment spanned 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 experiment 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 experiment. 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 used a weekly crossover design in which each subject trader participates in the experiment 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 experiment, 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 experimental window, while also reducing the traders' experimental fatigue. Appendix Figure 3 illustrates the experimental 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 administered 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 completed the survey and provided

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 experiment. 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 86.58% of traders 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.

3.4 Experimental 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:

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

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 report results using (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 60 seconds prior to trade execution and the distribution observed outside that window. 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 experiment, 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.

In Appendix Figure 6, we also 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.

Trading Outcomes. Table 2 reports summary statistics for the stock trading data. Panel A presents statistics at the trade-order level. Over the experimental period, we observe a total of 9,742 trades, and we report average statistics on trading amount, trading volume, and associated transaction costs, including commissions and taxes.

Panel B reports 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 261,301 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 2.96, 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.

Panel C reports statistics at the trader-day level, aggregating trading activities for each trader at the daily level. In our sample, the average trader executes 17.67 batches and 52.75 distinct transactions per day. This corresponds to an average daily trading volume of approximately 9.36 million CNY (≈1.34 million USD). In terms of performance, the average daily net profit stands at 4,698 CNY (≈670 USD). Given that traders typically receive a substantial portion of this profit as a performance bonus (i.e., 50%), this represents a significantly high income 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.[3]

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 15 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. In Appendix Figure 7, we report results with alternative specifications of EI, and the findings are qualitatively the same.

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

[3] We employ 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 (≈ 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 find the results to be qualitatively unchanged.

risk and must maintain continued vigilance and monitoring. In contrast, executing an exit trade resolves uncertainty and releases cognitive load.

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' trading 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 role of EI in mitigating the 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:

$$1(\text{Trade}_{i,t}) = \sum_{\tau} \beta^{\tau} \cdot \overline{\text{EI}}_{i,t\in\tau} + \alpha_i + \alpha_{\text{date-hour}} + \varepsilon_{i,t} \qquad (2)$$

The explanatory variables of interest $\overline{\text{EI}}_{i,t\in\tau}$ are lagged values of EI averaged over non-overlapping time windows τ ranging from 1 to 45 seconds before t. We control for trader fixed effects (α_i) and date-hour fixed effects ($\alpha_{\text{date-hour}}$) to pin down the within-trader temporal variation and to control for common shocks within each hour across trading days in the sample. Standard errors are also clustered at both trader and date-hour levels to account for potential serial correlations within traders and market conditions.

Table 3 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 at the 1% or 5% level. The magnitude of the coefficients is largest in the 5–10 second window and remains statistically significant up to the final second before execution. As we move further back in time, to 30–45 seconds prior to the trade, the coefficients lose statistical significance and, in some cases, become negative.

Columns (2) through (5) of Table 3 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 EI pattern right before a trade predict the trading performance, or is it a trader's average EI level in a trading day associated with the daily trading performance? We revisit the analysis in Panel A of 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 $t = -15$, 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.

Table 4 presents a more formal regression analysis linking Profit trades to traders' EI patterns. Column (1) tests the predictive power of EI measured during the baseline period, defined as the average EI over the 0–15 second window prior to order execution. Columns (2) through (6) examine changes in EI relative to the baseline. These variables are constructed as the difference between the baseline EI and a set of earlier reference windows, such as 15–150 seconds prior to execution (e.g., this difference is calculated as $\overline{EI}_{i,t=-15\to 0} - \overline{EI}_{i,t=-150\to 15}$).[4] All regressions control for trade price, trade volume, trader fixed effects, and date-hour fixed effects. Standard errors are also clustered at both trader and date-hour levels.

$$1(\text{ProfitTrade}_{i,t}) = \beta \cdot (\overline{EI}_{i,t=-15\to 0} - \overline{EI}_{i,t=-\tau 1\to \tau 2}) + \alpha_i + \alpha_{\text{date-hour}} + \varepsilon_{i,t} \qquad (3)$$

In Column (1), the coefficient on the absolute baseline level of EI is statistically insignificant. In contrast, Column (2) shows that a sharp increase in engagement relative to the broad 15–150 second window is associated with a significantly higher likelihood of a winning trade. Similar positive and statistically significant coefficients are observed when comparing the execution window to the 100–150 second window in Column (3) and to the 30–60 second window in Column (5). In the last two columns, we use the mean EI in the pre-trade 150-15s window and the post-trade 0-150s window as independent variables,

[4] Note that we run separate regressions because including both baseline level and change relative to the baseline will incur mechanical correlation between the covariates.

and the results are all negative. Overall, these results are consistent with the patterns shown in Figure 2, indicating that trade performance is only related to changes in EI right before a trade than to baseline levels of EI.

The lack of explanatory power of baseline 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 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-hour fixed effects, and clustering robust standard errors on these levels as well.

$$\%\text{ProfitTrade}_{i,d} = \beta_1 \text{DailyMean}_{i,d} + \beta_2 \text{Dailystd}_{i,d} + \beta_3 \text{DailyHi}_{i,d} + \beta_4 \text{DailyMean}_{i,d-1} + \beta_5 \text{HistoricalMean}_i + \alpha_i + \alpha_{date} + \varepsilon_{i,t} \quad (4)$$

Table 5 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 trading date d. Column (1) shows that a higher average level of EI over the day is negatively associated with performance on that day $\text{DailyMean}_{i,d}$. Column (2) shows that the standard deviation of EI $\text{Dailystd}_{i,d}$ is not significantly correlated with performance. Column (3) shows that the daily 95th percentile of EI $\text{DailyHi}_{i,d}$ is also negatively associated with performance. Column (4) shows that the mean EI on the prior day $\text{DailyMean}_{i,d-1}$ is negatively associated with today's performance, although the coefficient is not statistically significant. Column (5) shows that the historical average EI levels HistoricalMean_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, none of the measures capturing overall daily EI patterns significantly 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, if anything, 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 canonical 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 3 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) Common Round trades, executed at other multiples of 10 such as .10 or .20, excluding .00 and .50; and (3) Non-Round trades, all remaining prices. Panel B of Figure 3 reports average batch profit by category. Profitability declines with roundedness. Strong Round trades generate the lowest average returns, whereas Non-Round trades generate the highest. This gap 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.

We next examine whether EEG-measured engagement predicts reliance on round numbers. Table 6 reports regressions in which the dependent variable is an indicator for round-number pricing. Panel A focuses on Strong Round prices (.00 or .50). Panel B uses Other Round prices. Columns (1)–(3) measure EI in the immediate pre-trade window (0–15 seconds) and in the resting window (15–60 seconds). Column (4) aggregates engagement to the daily level using the daily mean, variance, and 95th percentile. All specifications control for execution price and trade volume. Trader fixed effects and date-hour fixed effects are included where appropriate, and standard errors are two-way clustered at the trader and date-hour levels.

Panel A shows that higher engagement in the decision window is negatively and significantly associated with Strong Round pricing. Traders are less likely to default to .00 or .50 when engagement is high immediately before execution. Baseline engagement has no significant effect. At the daily level, higher average engagement reduces strong rounding, while extremely high daily peaks are associated with greater reliance on round numbers. Panel B shows no systematic relationship between engagement and Other Round pricing. So, the effect is specific to the most salient anchors, .00 and .50.

We then examine how engagement interacts with roundedness in shaping performance. Figure 4 partitions trades by price category (Strong Round versus Others) and by engagement level in the 0–15 second pre-trade window, split at the trader's mean. The figure reports average profit with 95% confidence intervals. The results show a clear

asymmetry. For Non-Round trades, profitability does not differ meaningfully between high- and low-engagement states. For Strong Round trades, low engagement is associated with sharply lower profits. High-engagement trades at round prices perform substantially better than low-engagement trades at the same prices. The cost of rounding is concentrated in low-engagement states. Round numbers are most damaging when they reflect inattention rather than deliberate choice.

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 5 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 only and uses a scatter plot to examine the sensitivity of holding duration to the magnitude of the loss. Both axes in Panel B are plotted on a logarithmic scale to accommodate the skewness of the data.

The results of Panel A show that the average holding duration for losing trades is approximately 62.7 seconds, which is longer than the 56.9 seconds observed for profitable trades. This difference is statistically significant (p-value = 0.025). 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 further suggests that this reluctance is related to the severity of the loss. The scatter plot shows a positive linear relationship between the absolute magnitude of the realized loss and the holding duration. The upward-sloping regression line suggests that as losses deepen, traders hold positions for progressively longer periods.

We then test whether higher EI helps mitigate the behavioral bias of holding onto losses. Table 7 presents batch-level regression results examining the relationship between trading outcomes, brainwave activity, and holding duration. The sample is restricted to standard round-trip trades, defined as trades per batch equal to two, to ensure precise measurement of holding duration. The dependent variable is Holding Duration in

seconds. The primary independent variable is the Loss Trade Dummy, which equals one if the trade resulted in a realized loss. To capture the moderating role of cognitive engagement, Column (3) introduces the standardized EI measure and its interaction with the loss trade indicator. All specifications include trader fixed effects and date-hour fixed effects to account for individual heterogeneity and time-specific shocks, and standard errors are two-way clustered at the trader and date-hour levels.

In Columns (1) and (2), the coefficient on the Loss Trade Dummy is positive but statistically insignificant, with a point estimate of 3.05, consistent with the baseline disposition effect in which traders hold losing positions longer than winning ones. Column (3) shows that EI moderates this relationship. The coefficient on the interaction term between EI and the loss trade indicator is negative and statistically significant at −9.1, with a *t*-statistic of −2.4. This means that a one-standard-deviation increase in engagement level reduces the duration by 9.1 seconds for loss trades, which represents a 14.5% decrease in holding duration. This result suggests that when traders exhibit higher levels of EI, they are better able to overcome the psychological discomfort associated with losses (e.g., Barberis and Xiong, 2012) and execute decisions to cut losses more promptly, thereby attenuating the disposition effect.

4.4 EI Correlates

Our analysis so far suggests that EI may act as a phychophysiological mediator in trading behavior. Here we examine whether there are indeed cross-sectional correlations between EI and trader's demographic and self-reported physiological and lifestyle characteristics.

Table 8 reports regressions of EI on trader characteristics. These include age (years), trading experience (years), left-handedness (indicator), whether the trader engages almost daily in gym activity, caffeine consumption, smoking, or alcohol use (indicators), average daily sleep hours, and self-rated sleep quality on a 1–5 scale, where 1 denotes

poor and 5 denotes excellent. We estimate multivariate specifications with date-hour fixed effects and cluster standard errors at the trader level.

In Column 1, the dependent variable is EI measured during the 15 seconds prior to trade execution. EI is negatively associated with trader age and left-handedness, and positively associated with regular gym activity. In Column 2, the dependent variable is the change in EI, defined as the difference between the 0–15 second pre-trade window and the 15–150 second baseline window. This captures spike magnitude rather than level. Age remains negatively associated with EI, and regular gym activity remains positive. Handedness no longer predicts spike magnitude. Instead, smoking and both sleep duration and sleep quality are positively and significantly associated with larger EI spikes.

Appendix Table 2 further relates pre-trade EI to trading activity prior to execution. We examine cumulative trade count and cumulative trade value, which may reflect capital pressure or decision fatigue; an indicator for whether the immediately preceding trade resulted in a loss; and the time elapsed since the previous trade, which may reflect cognitive recovery. A prior loss is strongly and positively associated with the current EI spike, consistent with heightened alertness following negative feedback. Trade frequency and rest intervals exhibit weaker associations, though with the expected signs.

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 behaviors 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 less degree of behavioral biases. We document two sources distortions in our sample: the tendency to cluster trades at round numbers and the disposition effect. On round number heuristic, we find that traders are significantly less likely to rely on coarse integers (e.g., .00 or .50) when their cognitive engagement is high. 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 10% 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.

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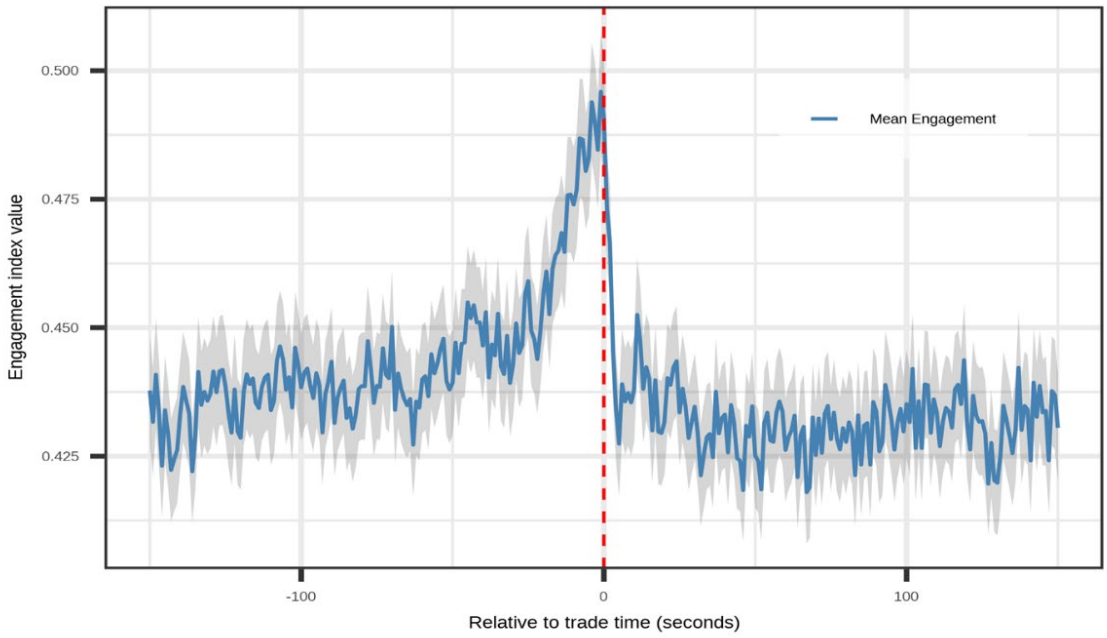
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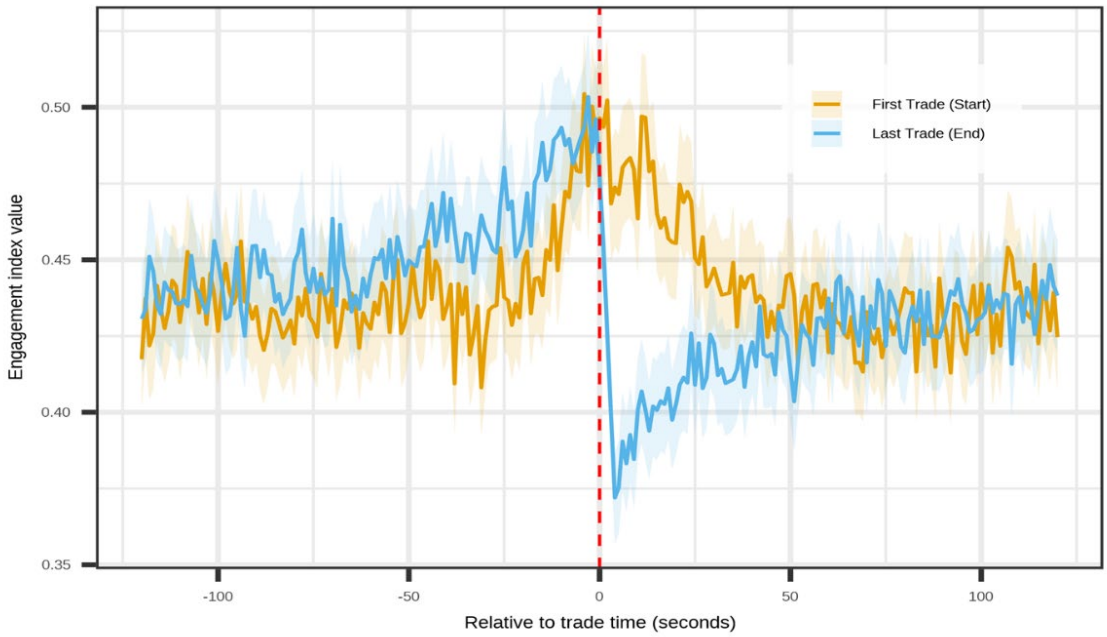
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A. Engagement Index around Trade Execution



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 red dashed line represents the exact second of trade execution (t=0). Panel B decomposes the sample to compare the cognitive patterns associated with the first trade (orange line) and the last trade (blue line) of a trading batch. For both panels, the underlying engagement data is 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.

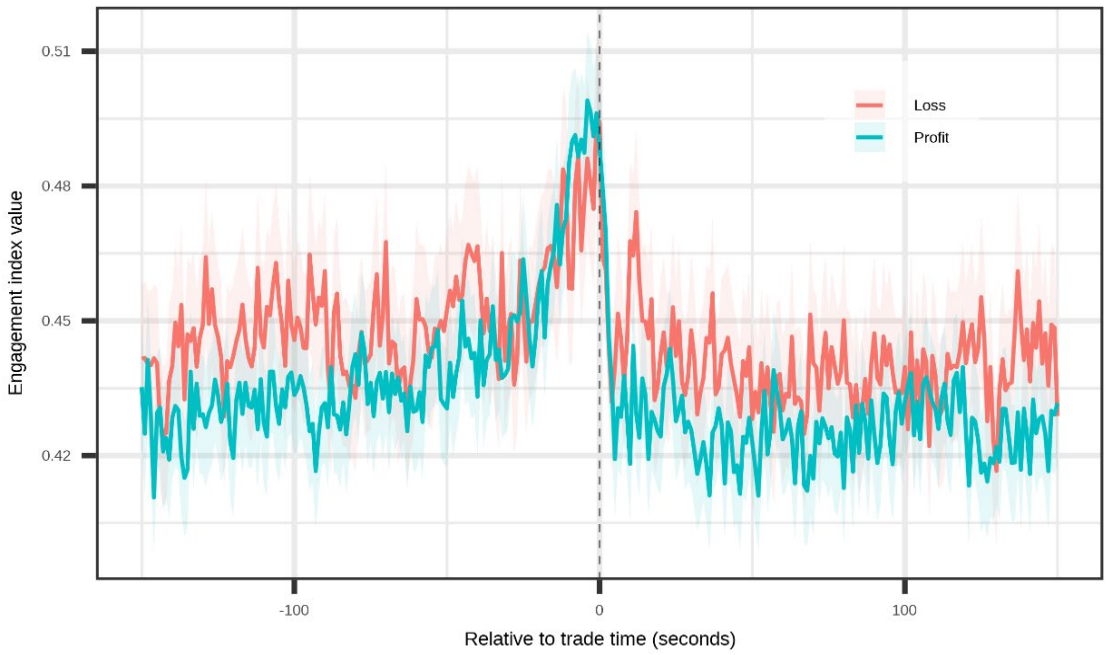
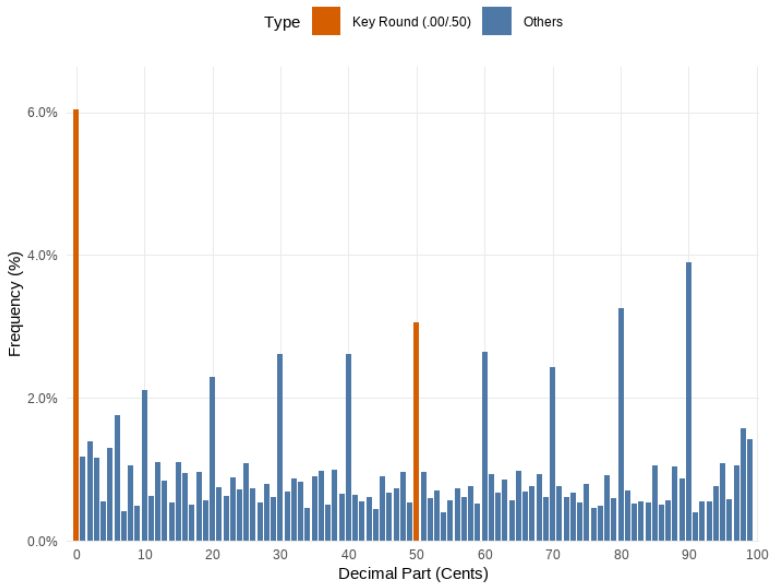
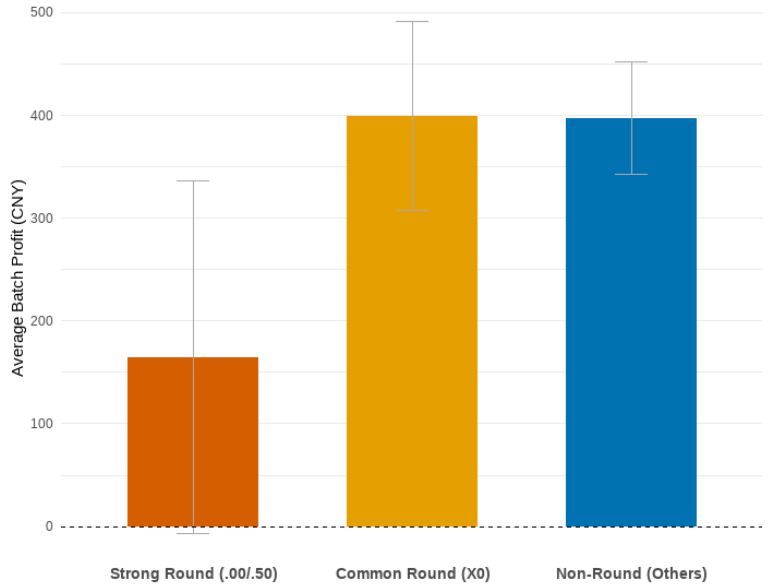


Figure 2. Engagement Index around Profit versus Loss Trades. This figure examines the heterogeneity in cognitive engagement patterns based on the performance of trading batches. The sample is split into trades associated with a realized profit (labeled "Profit," green line) and those associated with a realized loss (labeled "Loss," red line). The vertical dashed line at t=0 marks the time of trade execution. Panel A 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. Price clustering



B. Price clustering and trading performance

Figure 3 Price Clustering and Trading Performance. This figure analyzes the clustering in transaction prices and its relationship with 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. The bars highlighted in orange correspond to numbers round at .00 or .50, while the blue bars represent all other decimals. 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, orange bars), (2) "Common Round" (ending in other multiples of 10, e.g., .10, .20, excluding .00/.50, yellow bars), and (3) "Non-Round" (all other decimals, blue bars). 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.

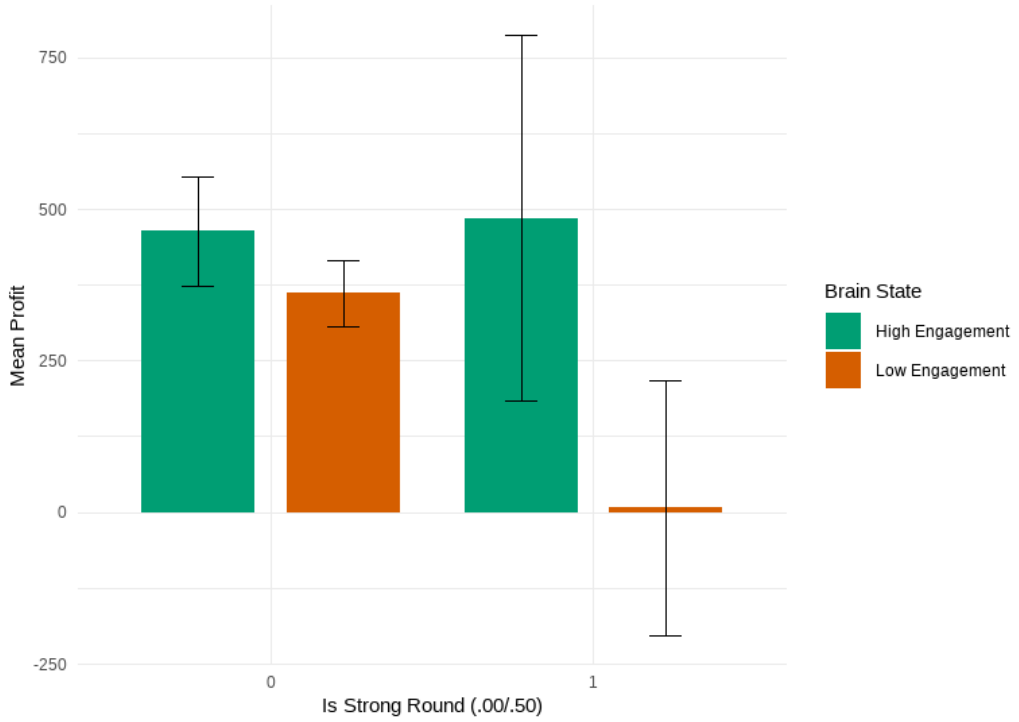


Figure 4 Cognitive Engagement, round number orders, and trading performance. This figure illustrates the heterogeneity in trading performance across price clustering categories, conditional on the trader's engagement levels. The sample is divided along two dimensions. First, transactions are classified based on their execution price: "Strong Round" (x-axis, right group) indicates prices ending in .00 or .50, while "Others" (x-axis, left group) includes all other price points. Second, within each price category, trades are split into "High Engagement" and "Low Engagement" subgroups. "High Engagement" is defined as trades where the standardized Engagement Index during the decision window (0–15 seconds pre-trade) is above the average engagement level, and "Low Engagement" otherwise. The y-axis reports the average trading profit. The vertical error bars represent the 95% confidence intervals for the mean.

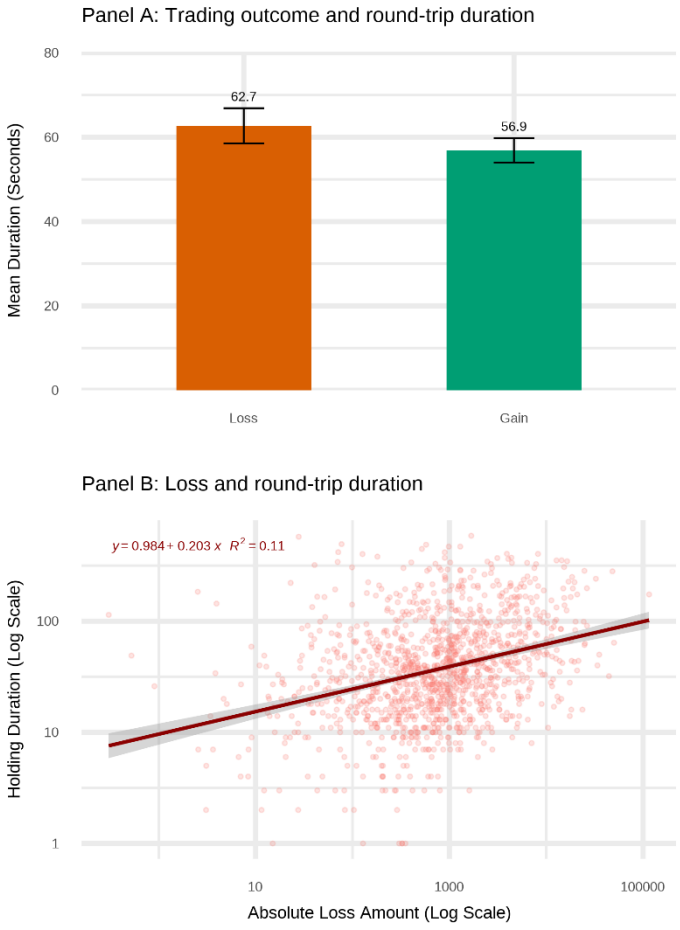


Figure 5. Disposition Effect. This figure illustrates the asymmetry in holding periods and the sensitivity of duration to trading losses. Panel A compares the average round-trip holding duration (in seconds) for profitable trades versus losing trades. The height of the bars represents the mean duration, and the error bars indicate the 95% confidence intervals. A significantly longer duration for losing trades is consistent with the Disposition Effect, where traders tend to hold onto losing positions longer than winning ones. Panel B restricts the sample to losing trades. It presents a scatter plot with a linear fit line showing the relationship between the absolute magnitude of the realized loss (x-axis) and the holding duration (y-axis). Both axes are plotted on a logarithmic scale.

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 values represent the sum of readings from the left and right hemispheres. 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 the trades investors make. We report investor transactions at two levels. First, at the order level, we detail the trading amount, volumes, average price, commission fees, and taxes for each trade. Second, we report results at the batch level, which represents round-trip trading cycles. We identify a 'batch' based on the high-frequency dynamics of an investor's daily inventory. A batch is rigorously defined as a complete round-trip trading cycle. Specifically, for a given investor and stock within a single trading day, we track the cumulative net position (inventory) transaction by transaction. A new batch is initiated when an investor opens a position (either long or short) and is considered closed or completed at the exact timestamp when the cumulative inventory returns to zero. For each batch, we report the batch profit, return rate, total investment, the number of trades included in the cycle, and the holding period (in seconds) for each trading batch. Third, we report results at the trader-day level, where we aggregate trading activities for each trader daily. At this level, we measure daily trading intensity by reporting the total number of completed batches and individual trades executed per day. Furthermore, we summarize the daily trading scale and performance by reporting the total daily trading volume, which is calculated as the sum of the absolute value of all transactions, and the accumulated daily net profit.

Variable	Unit	N	Mean	Std	Min	Q25	Median	Q75	Max
TradingAmnt	CNY	9,742	175,635.98	111,778.66	11,310.82	93,929.56	147,836.01	258,065.28	567,639.07
TradingVol	Share	9,742	2,307.70	4,365.73	100.00	300.00	800.00	2,500.00	30,000.00
AveragePrice	CNY	9,742	357.05	446.05	5.57	49.65	177.26	428.60	1,494.18
CommssnFee	CNY	9,742	95.04	82.01	4.59	36.00	70.44	124.51	415.74
Tax	CNY	9,742	43.58	59.91	0.00	0.00	0.00	74.06	262.08
BatchProfit	CNY	3,222	240.09	1163.91	–3475.39	–212.02	85.29	525.98	5,297.29
BatchRet	%	3,222	0.11	0.42	–0.96	–0.12	0.06	0.26	1.76
BatchInvestAmnt	CNY	3,222	261,301.60	208,166.85	21,634.48	116,017.66	209,937.55	323,121.85	1,174,559.67
TradesPerBatch	CNY	3,222	2.96	1.54	2	2	2	4	9
HoldingDuration	Second	3,222	58.44	65.52	3	18	37	71	370
DailyBatches	#	182	17.67	10.20	2	10	17	23	46.19
DailyTradesCnt	#	182	52.75	33.49	5	28	44	72	146
DailyTradeVol	CNY	182	9,358,623.11	6,697,023.09	765,437.03	4,700,871.53	7,871,631.79	12,629,370.04	30,744,820.42
DailyProfit	CNY	182	4,697.79	7,410.86	–8,095.72	–105.18	3,102.94	7,255.98	29,497.51

Table 3. Engagement Index and the Propensity to Trade. This table presents the results of event study regression estimating the likelihood of trade execution based on prior cognitive states. The dependent variable is a binary indicator equal to one if a transaction occurs at time *t* and zero otherwise. Columns (1) through (5) report results for five distinct trading scenarios: the full sample of all trades, market entry trades (the first trade of a batch), market 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 specific non-overlapping time windows preceding time *t* (ranging from *t*–1 second back to *t*–45 seconds). All specifications include trader fixed effects to control for time-invariant individual characteristics and date-hour fixed effects to absorb common intraday market shocks. 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.

			1(Trade)		
Engagement t=	All	First trade	Last Trade	Buy	Sell
0-1s	0.0013***	0.0005**	0.0004*	0.0005**	0.0008***
	(3.16)	(2.53)	(1.98)	(2.52)	(3.01)
1-3s	0.0012***	0.0006**	0.0004*	0.0008***	0.0004
	(3.11)	(2.91)	(1.96)	(4.22)	(1.59)
3-5s	0.0014***	0.0007***	0.0004**	0.0009**	0.0005**
	(3.80)	(3.04)	(2.64)	(2.36)	(2.58)
5-10s	0.0019***	0.0008***	0.0006*	0.0007**	0.0012*
	(3.05)	(3.65)	(2.03)	(2.58)	(2.12)
10-15s	0.0015**	–0.0001	0.0009***	0.0004	0.0012***
	(2.94)	(–0.45)	(3.26)	(1.49)	(3.62)
15-20s	–0.0001	0.0000	–0.0001	–0.0001	–0.0001
	(–0.23)	(–0.14)	(–0.26)	(–0.12)	(–0.29)
20-30s	–0.0010*	–0.0007*	–0.0001	–0.0002	–0.0008*
	(–1.79)	(–2.10)	(–0.38)	(–0.33)	(–2.09)
30-45s	–0.0009	–0.0007	–0.0001	–0.0006	–0.0003
	(–1.32)	(–1.75)	(–0.43)	(–0.99)	(–1.53)
Trader FE	√	√	√	√	√
DateHour FE	√	√	√	√	√
Num.Obs.	953,732	953,732	953,732	953,732	953,732

Table 4. Cognitive Engagement and Trading Performance. This table presents the relation between an increase in cognitive activation level and trading outcomes. The dependent variable is a binary indicator equal to one if the trading batch yields a positive realized profit and zero otherwise. Column (1) tests the predictive power of the Absolute Engagement Level, measured as the mean Engagement Index in the 15 seconds immediately preceding trade execution. Columns (2) and (3) test the predictive power of Relative Engagement Changes, calculated as the difference between the immediate pre-trade window (0-15s) and earlier reference windows (15-30s and 30-60s, respectively). These variables capture the cognitive "ramp-up" or acceleration prior to a decision. Columns (4) to (6) uses similar variables but with different time intervals. The last two columns uses the mean EI in the pre-trade 150-15s window and the post-trade 0-150s window. All specifications control for transaction characteristics, including the natural logarithm of trade volume and the execution price. In addition, the models include Trader Fixed Effects and 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.

	1 (Profit Trade)							
Baseline level	0.0678							
	(0.53)							
vs 15-150 chg		0.2939***						
		(2.64)						
vs 100-150 chg			0.2334**					
			(2.52)					
vs 60-100 chg				0.2185*				
				(1.87)				
vs 30-60 chg					0.2447**			
					(2.48)			
vs 15-30 chg						0.0618		
						(0.76)		
pre 150-15 level							-0.2970	
							(-1.34)	
post 0-150 level								-0.4430*
								(-1.91)
Price	0.0094	0.0086	0.0085	0.0091	0.0091	0.0087	0.0073	0.0061
	(0.29)	(0.25)	(0.24)	(0.26)	(0.26)	(0.25)	(0.21)	(0.18)
Vol	-0.0229	-0.0220	-0.0215	-0.0234	-0.0221	-0.0225	-0.0248	-0.0272
	(-0.49)	(-0.45)	(-0.44)	(-0.48)	(-0.45)	(-0.45)	(-0.51)	(-0.55)
Trader FE	√	√	√	√	√	√	√	√
DateHour FE	√	√	√	√	√	√	√	√
Num.Obs.	9290	9290	9290	9290	9290	9290	9290	9290

Table 5. Daily Engagement and Trading Performance. This table presents the regression results focusing on the relationship between aggregated cognitive metrics and trading performance at the half-day (AM/PM) level. The unit of observation is the trader-half-day. The dependent variable is the Win Rate, defined as the proportion of trades yielding a positive realized profit within each half-day session. Column (1) examines the predictive power of the Average Engagement Level, measured as the mean of the Engagement Index throughout the session. Column (2) tests the impact of Cognitive Variability, calculated as the standard deviation of the Engagement Index. This variable captures the stability (or volatility) of the trader's mental state. Column (3) investigates the role of Peak Cognitive Performance, proxied by the 95th percentile of the Engagement Index, to test whether moments of extreme focus drive overall performance. All specifications include Trader Fixed Effects to control for time-invariant individual characteristics and Date-by-AM/PM Fixed Effects to absorb time-specific market shocks and intraday seasonality. Standard errors are two-way clustered at the trader and date-half-day levels. Continuous variables are winsorized to mitigate the influence of outliers.

Panel A: Daily-level results					
Engagement index	% Profit Trade				
DailyMean	–0.1604*				
	(–2.01)				
DailyStd		–0.0770			
		(–1.05)			
DailyP95			–0.0496**		
			(–2.16)		
LastDayMean				–0.1776	
				(–1.64)	
HistoricAverage					–0.0390
					(–0.20)
Trader FE	√	√	√	√	√
DateHour FE	√	√	√	√	√
Num.Obs.	182	182	182	166	182
Panel B: Transaction-level results					
Engagement index	1 (Profit Trade)				
DailyMean	–0.1428				
	(–1.47)				
DailyStd		–0.0885			
		(–1.26)			
DailyP95			–0.0459		
			(–1.75)		
LastDayMean				–0.1536*	
				(–1.84)	
HistoricAverage					0.0664
					(0.38)
Trader FE	√	√	√	√	√
DateHour FE	√	√	√	√	√
Num.Obs.	9,742	9,742	9,742	8,588	9,742

Table 6. Engagement Index and Round Number Heuristic. This table examines the relationship between engagement levels and the propensity to execute trades at round price. Panel A reports results for strong round pricing, where the dependent variable is a binary indicator equal to one if the transaction price ends in .00 or .50 cents. Panel B reports results for other round pricing, where the dependent variable equals one for prices ending in other decimals divisible by 10 (e.g., .10, .20). In each column of every panel, columns (1) through (3) focus on the immediate micro-cognitive context. Column (1) tests the effect of the standardized Engagement Index during the Decision Window (0–15 seconds pre-trade). Column (2) examines the Baseline Window (15–60 seconds pre-trade). Column (3) includes both time windows simultaneously to disentangle the effect of immediate cognitive recruitment from the background attention level. Column (4) shifts to the macro-daily level, testing how the trader's overall cognitive state for the day affects rounding behavior using three daily metrics: the daily mean (general engagement), daily variance (cognitive stability), and the 95th percentile (peak cognitive stress). All specifications control for transaction characteristics, including the natural logarithm of execution price and trade volume. Models (1) through (3) include Trader Fixed Effects and Date-by-Hour Fixed Effects to absorb time-invariant individual traits and high-frequency market shocks, with standard errors two-way clustered at the trader and date-hour levels. Model (4), which utilizes daily-level explanatory variables, includes Trader Fixed Effects with standard errors clustered at the trader level. Continuous variables are winsorized at the 1st and 99th percentiles.

	Panel A: Strong round				Panel B: Other round			
	1(Round at '00 or '50)				1(Other round at 'X0)			
Baseline	-0.0039*		-0.0067*		0.0127		0.0069	
	(-1.99)		(-1.88)		(1.44)		(1.14)	
EI pre 15-60		0.0002	0.0044			0.0137	0.0093	
		(0.06)	(0.93)			(1.52)	(1.42)	
DailyMean				-0.0228**				0.0024
				(-2.54)				(0.12)
DailyStd				-0.0103				0.0046
				(-1.58)				(0.39)
DailyP95				0.0295**				0.0020
				(2.28)				(0.11)
Price	0.0388***	0.0385***	0.0387***	0.0445***	0.0907***	0.0907***	0.0905***	0.0864***
	(5.08)	(5.13)	(5.09)	(5.12)	(4.88)	(4.85)	(4.87)	(4.54)
Vol	0.0161**	0.0159**	0.0160**	0.0191**	0.0141	0.0140	0.0139	0.0121
	(2.33)	(2.34)	(2.33)	(2.37)	(1.46)	(1.44)	(1.43)	(1.15)
Trader FE	√	√	√	√	√	√	√	√
DateHour FE	√	√	√		√	√	√	
Num.Obs.	9452	9452	9452	9452	9452	9452	9452	9452

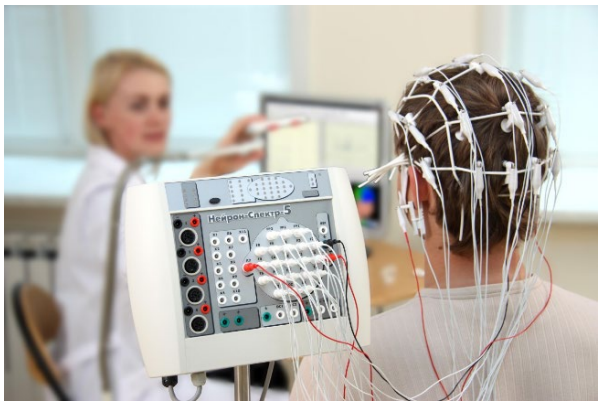
Table 7. Engagement Index and Disposition Effect. This table investigates the moderating role of cognitive engagement on the Disposition Effect. The sample is strictly restricted to standard round-trip trades (consisting of exactly one opening and one closing execution). Outliers for duration, engagement, and trading volume are trimmed at the 1st and 99th percentiles. The dependent variable is the Holding Duration in seconds. The key independent variable is the Loser Dummy that is equal to one if the trade resulted in a realized loss, and zero otherwise. Column (1) establishes the baseline disposition effect, testing whether losing trades are held significantly longer than winning trades. Column (2) includes the Average Engagement during the holding period as a covariate. Column (3) introduces the interaction term. All specifications employ a high-dimensional fixed effects structure, including Trader Fixed Effects and Date-by-Hour Fixed Effects. Standard errors are two-way clustered at the trader and date-hour levels.

	Duration		
IsLoss	3.0489	3.0451	7.5168
	(0.88)	(0.87)	(1.73)
Engagement		0.2438	4.1588*
		(0.08)	(1.76)
IsLoss × Engagement			–9.0651**
			(–2.43)
Trader FE	√	√	√
DateHour FE	√	√	√
Num.Obs.	3,636	3,636	3,636

Table 8. Engagement Index and Trader Characteristics. This table examines the cross-sectional determinants of traders' cognitive states with demographics, physiological traits, and lifestyle habits. The sample consists of all executed traders. In Column (1), the dependent variable is Engagement Level, defined as the standardized mean engagement index during the Decision Window (0–15 seconds pre-trade). In Column (2), the dependent variable is Engagement Reaction, defined as the difference in mean engagement between the Decision Window and the Baseline Window (15–150 seconds pre-trade). The explanatory variables are derived from a post-experiment survey. Age and Experience are measured in years. Left-handed is a binary indicator equal to one if the trader is left-handed. Lifestyle variables (Gym Habit, Caffeine, Smoking, Alcohol) are binary indicators equal to one if the trader reports having the respective habit. Sleep Duration is the self-reported average daily sleep in hours, and Sleep Quality is a self-assessed score ranging from 1 (poor) to 5 (excellent). We control for Date-by-Hour Fixed Effects. Standard errors are clustered at the trader level. Continuous EEG and financial variables are winsorized at the 1st and 99th percentiles to mitigate the influence of outliers.

	Baseline	Baseline vs 15-150
Age	-0.0323**	-0.0109**
	(-2.57)	(-2.51)
TradExperience	0.0190	0.0069
	(1.17)	(1.11)
LeftHand	-0.2179***	0.0142
	(-3.64)	(0.56)
Gym	0.1330***	0.0718***
	(4.92)	(7.88)
Caffeine	-0.1151	0.0060
	(-1.51)	(0.32)
Smoke	-0.0013	0.0796***
	(-0.03)	(5.14)
Alcohol	0.0654	-0.0372
	(0.91)	(-1.21)
SleepHr	-0.0116	0.0507**
	(-0.26)	(2.55)
SleepQuality	-0.0041	0.0196**
	(-0.12)	(2.30)
DateHour FE	√	√
Num.Obs.	7923	7923

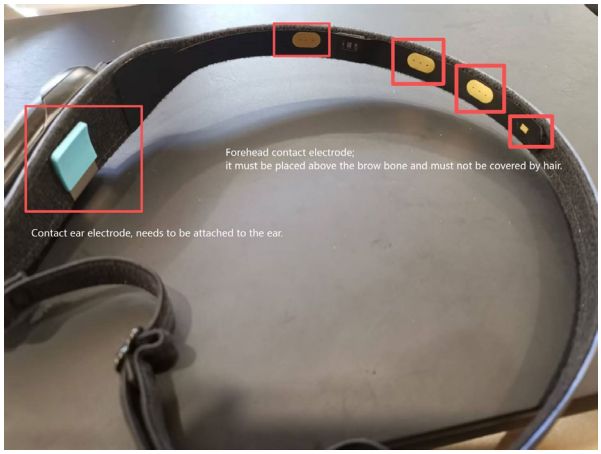
Appendix A. Additional Figures and Tables.



A. Clinical ("Wet") EEG device

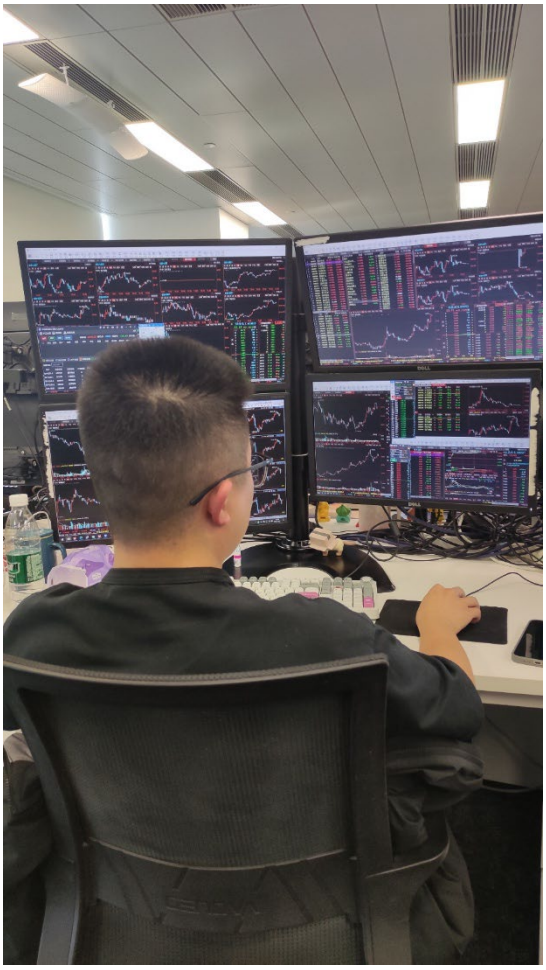


B. Wearable ("Dry") EEG device

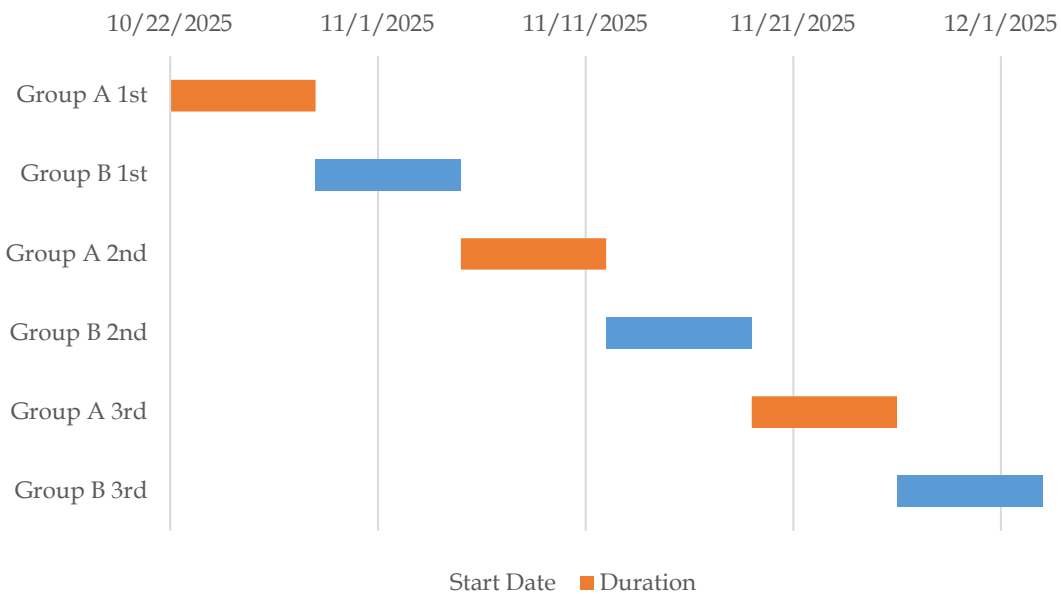


C. Wearable EEG sensors

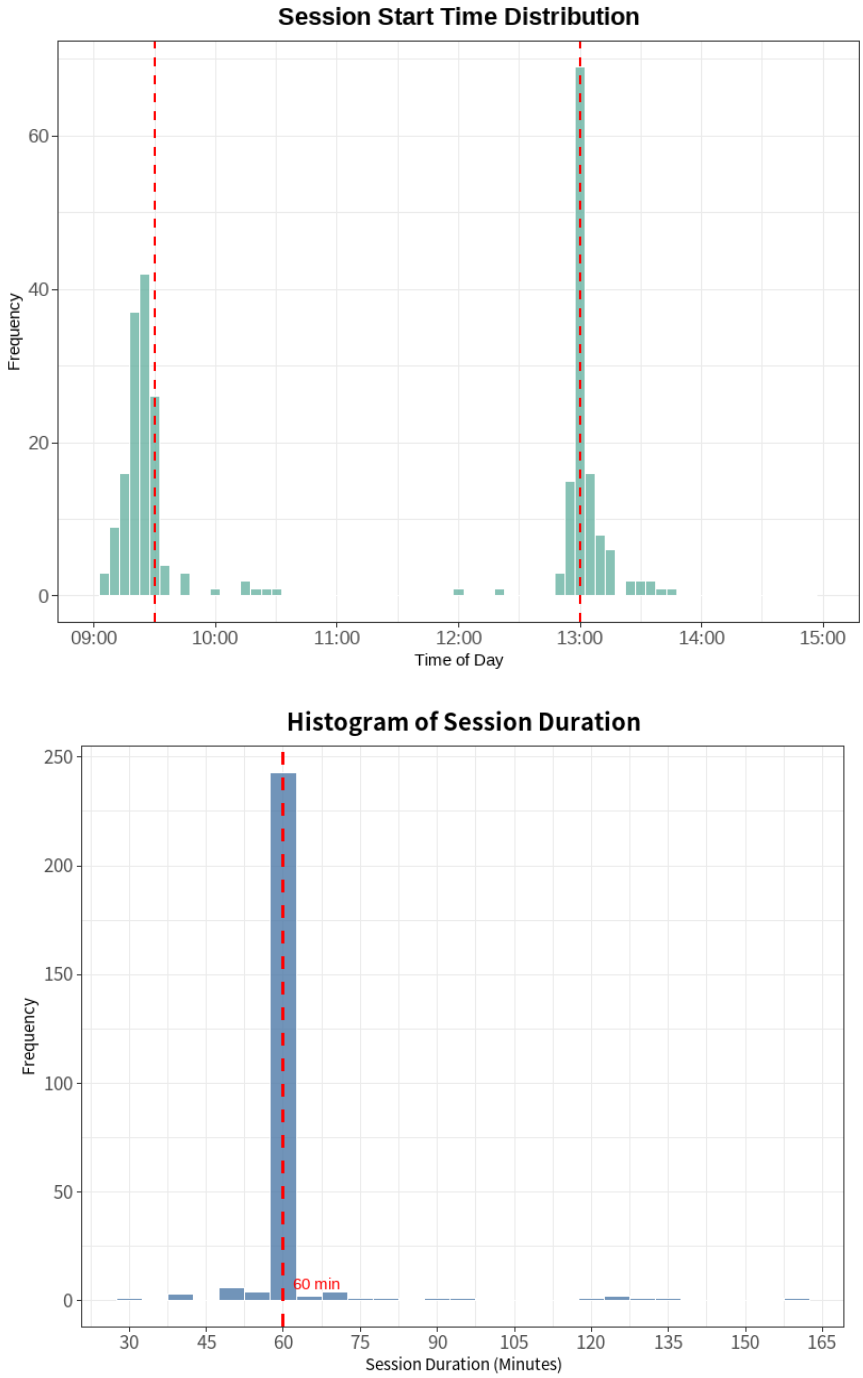
Appendix Figure 1. EEG devices comparison. Panel A illustrates clinical EEG devices (Image source: Wikimedia Commons). Panels B and C illustrate the wearable EEG device developed by NeuroSky.



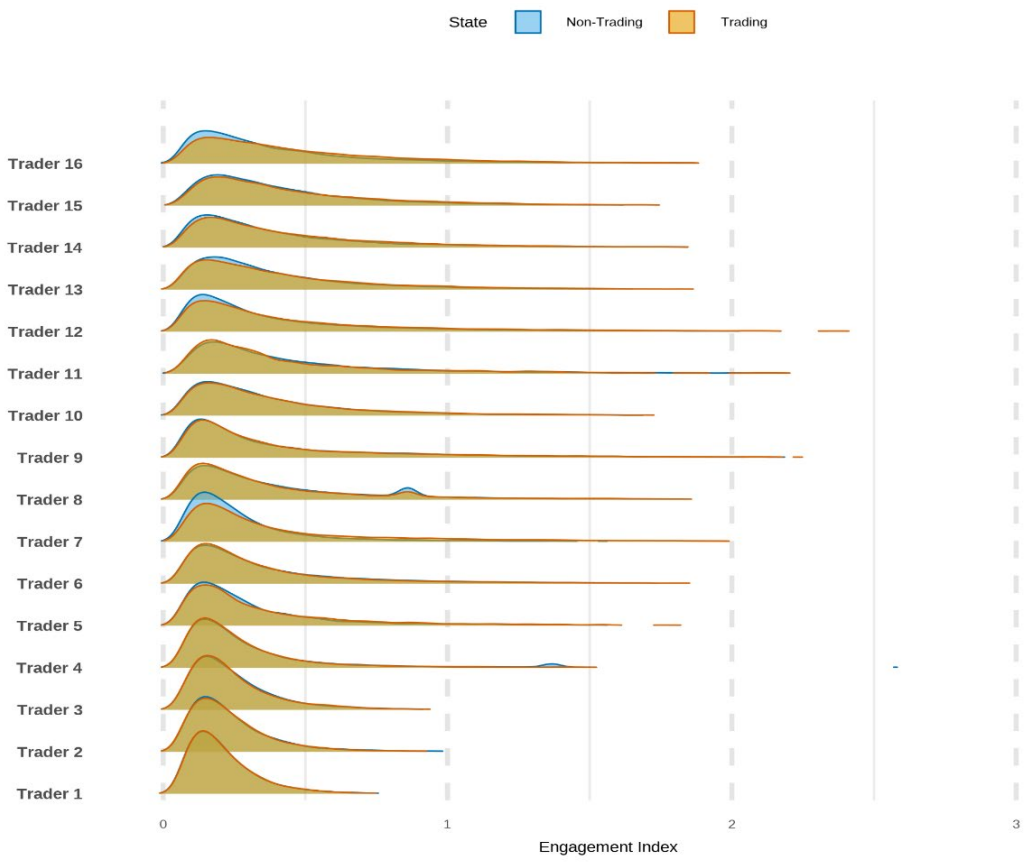
Appendix Figure 2. Trading environment. This figure shows an example of the workspace of the traders. Each trader operates a workstation equipped with four monitors. The top-left screen displays broad market indices, and the top-right screen tracks sector-level price trends. The bottom-left monitor shows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



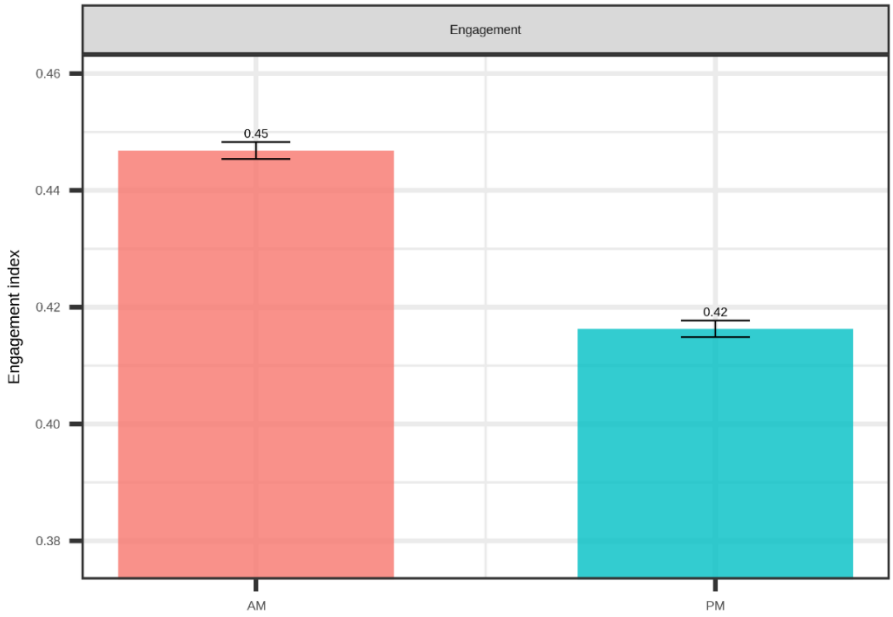
Appendix Figure 3. Experimental sequence. Our experiment spanned a six-week period between October 22nd and December 2nd, 2025. In practice, we randomly divided the 16 subject traders into two groups. Eight traders participated in the 1st, 3rd, and 5th weeks of the experiment, while the other eight participated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



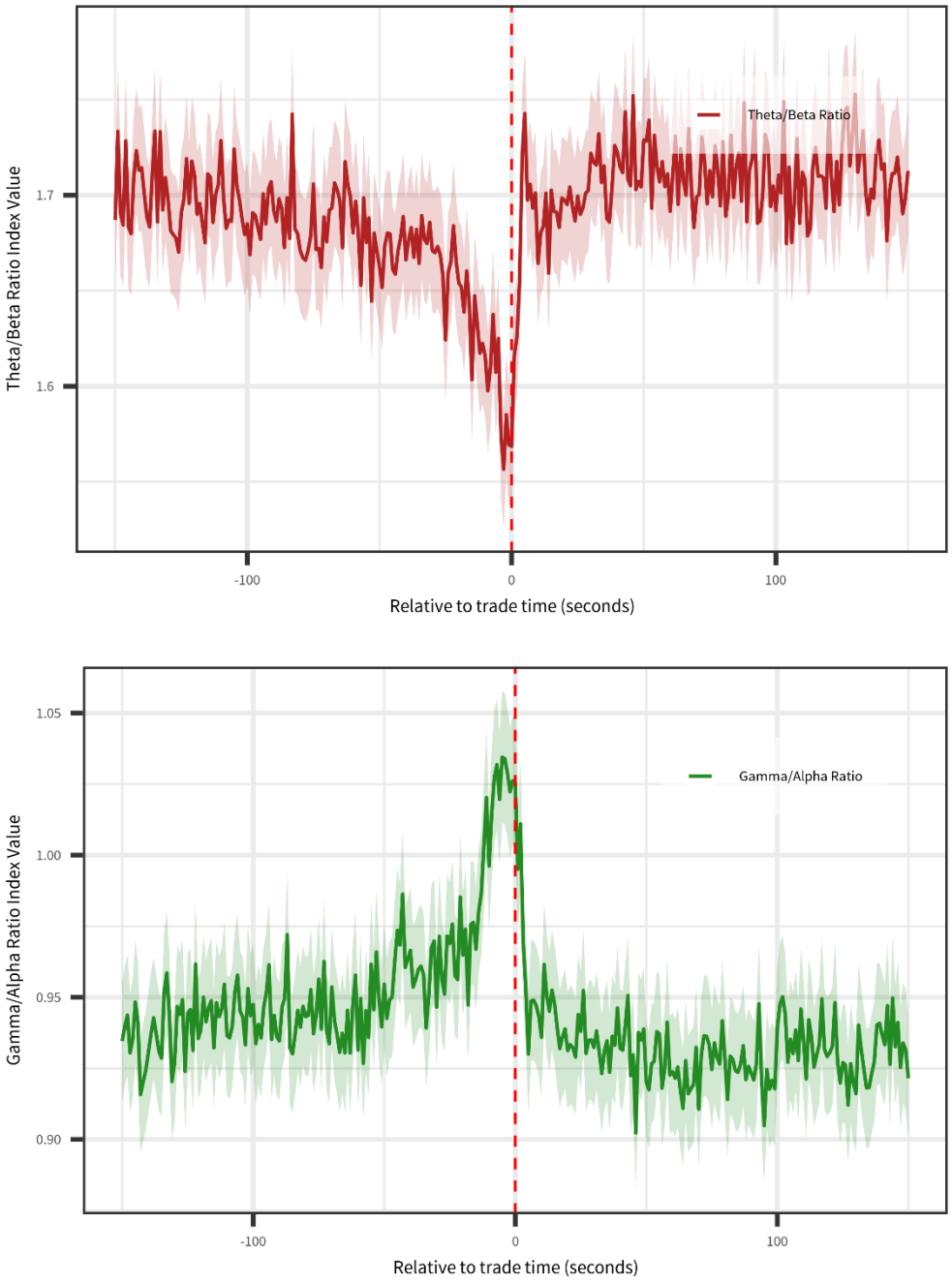
Appendix Figure 4. Compliance Statistics. This figure reports compliance statistics for EEG recording sessions. Panel A plots the distribution of session start times, defined as the first EEG recording time in the morning and afternoon for each trader-day. Vertical dashed lines mark the official market 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. This figure displays ridgeline plots comparing the probability density of the Engagement Index for each trader across two distinct states, where the baseline represents the unconditional distribution of engagement derived from the full sample of valid EEG recordings and the trading window represents the conditional distribution of engagement captured specifically at the timestamps of trade execution. To mitigate the impact of outliers, the engagement data is winsorized at the 1st and 99th percentiles. Traders are ordered vertically based on their median engagement levels during the trading window.



Appendix Figure 6. Engagement index in the morning and afternoon. This figure 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 is 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.



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 is 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 Table 1. Comparison with attentional benchmarks. This table presents the summary of the engagement index during trading windows and a cognitive attention task d2, which is a standardized neuropsychological assessment requiring participants to identify target symbols under time pressure. The unit of observation is the individual trader. Traders are ranked in descending order based on their mean trade Engagement. The trade engagement (150s) column reports the mean EEG-derived EI measured during a 150-second window centered on trade execution events. The d2 test engagement column captures the mean EI during a designated post-market resting period (after 15:00). To rigorously test the difference between the active trading state and the resting state, we report *t*-statistics and *p*-values from Welch's *t*-tests, which account for unequal variances and sample sizes between the two conditions. The final column, d2 Test Correct, reports the number of correct answers this trader gives from the d2 Test of Attention. The total correct answer is 100 (max). This behavioral metric serves as an external validation benchmark, aiming to corroborate the link between the neural patterns observed during trading and the cognitive profiles associated with sustained selective attention. For each engagement metric, the top row presents the mean value, while the bottom row (in parentheses) reports the standard deviation. The cognitive assessment was administered following the conclusion of the trading session and the subsequent resting period; consequently, data for one trader is unavailable due to absence.

	Engagement levels				
Trader	Trade window	d2 test	*t*-stat	*p*-value	d2 Test Correct
Trader 15	0.517	1.343	-2.969	0.004	99
	(0.565)	(2.865)			
Trader 14	0.302	0.318	-1.252	0.211	95
	(0.498)	(0.244)			
Trader 13	0.292	0.627	-8.125	0.000	94
	(0.434)	(0.602)			
Trader 12	0.462	0.518	-1.703	0.090	93
	(0.874)	(0.501)			
Trader 11	0.211	0.225	-2.109	0.036	92
	(0.132)	(0.130)			
Trader 10	0.519	0.468	1.968	0.050	92
	(0.693)	(0.440)			
Trader 09	0.642	0.832	-3.828	0.000	89
	(0.931)	(0.724)			
Trader 08	0.466	0.452	0.829	0.408	88
	(0.643)	(0.270)			
Trader 07	0.503	0.380	9.022	0.000	85
	(0.686)	(0.262)			
Trader 06	0.587	0.477	7.428	0.000	80
	(0.896)	(0.284)			
Trader 05	0.525	0.330	19.333	0.000	76
	(0.604)	(0.203)			
Trader 04	0.563	0.225	27.610	0.000	73
	(0.744)	(0.235)			
Trader 03	0.447	0.287	14.878	0.000	71
	(0.599)	(0.157)			
Trader 02	0.531	0.292	15.510	0.000	71
	(0.640)	(0.197)			
Trader 01	0.556	0.292	25.080	0.000	66
	(0.568)	(0.179)			

Appendix Table 2. Determinants of Engagement Index at Market Entry Trade. This table examines the determinants of Cognitive Activation. The sample is restricted to market entry trades, defined as the first trade of each batch. The dependent variable is the cognitive activation, calculated as the difference between the mean Engagement Index during the decision window (0–15 seconds pre-trade) and the baseline window (15–150 seconds pre-trade). A higher value indicates a stronger recruitment of cognitive resources relative to the trader's resting state. Column (1) tests the effect of intraday fatigue, measured by the natural logarithm of the cumulative number of trades executed by the trader on the same day prior to the current transaction. Column (2) examines the impact of capital pressure, measured by the natural logarithm of the cumulative trading volume processed up to that point. Column (3) captures the psychological shock of immediate negative feedback using a binary indicator equal to one if the immediately preceding trade resulted in a loss. Column (4) analyzes the effect of rest duration, defined as the natural logarithm of the time elapsed (in seconds) between the current transaction and the immediately preceding transaction. All specifications control for transaction characteristics (the natural logarithm of price and transaction volume), and include Trader Fixed Effects to control for time-invariant individual traits and Date Fixed Effects plus Hour Fixed Effects to absorb high-frequency market shocks. Standard errors are two-way clustered at the trader and date-hour levels. Continuous variables are winsorized at the 1st and 99th percentiles.

	Baseline vs 15-150			
Sample	First trade of every batch			
CumTradCnt	-0.0076			
	(-1.26)			
CumTradAmnt		-0.0084*		
		(-1.98)		
LastTradLoss			0.0148**	
			(2.68)	
RestTime				0.0054*
				(1.99)
Price	0.0038	0.0039	0.0038	0.0038
	(0.76)	(0.78)	(0.75)	(0.76)
Vol	-0.0023	-0.0016	-0.0023	-0.0019
	(-0.25)	(-0.17)	(-0.26)	(-0.22)
Trader FE	√	√	√	√
Date FE	√	√	√	√
Hour FE	√	√	√	√
Num.Obs.	2989	2989	2989	2989

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⁗

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