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Electroencephalographic (EEG) Brain Wave Patterns as Descriptors of Financial Risk-Taking Behavior

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Abstract: This study was designed to evaluate brain wave (i.e., alpha, beta, and gamma) patterns as descriptors of financial risk-taking behavior using quantitative EEG. Specifically, ten healthy adults were asked to answer a series of financial risk-tolerance, risk aversion, risk-taking, and personal characteristic questions using a computerized survey and to engage in a financial risk-taking game of chance. Using the Dual-Process Theory as a conceptual framework, findings indicate that brain wave activation was not directly associated with the choice to engage in the financial risk-taking task. Brain wave activation was found to be more directly related to a study participant's level of financial knowledge, financial experience, and willingness to take risks rather than the act of taking a financial risk. These factors may act in a way that primes someone to take risks. The use of EEG methodologies as clinical and research tools, as exemplified by this study, shows great promise in providing insights into the way individuals conceptualize risk and act when faced with financial choices that entail the possibility of uncertain gains and losses.

Keywords: Electroencephalography (EEG), Dual-Process Theory, Risk-Taking Behavior, Risk Tolerance.

Introduction

Imagine two people walk into an investment advisor's office. In nearly all respects, these two individuals share common demographic and socioeconomic characteristics—both are of similar age and are well-educated. Now assume both individuals enter the financial advisor's office with a monetary endowment. This might be in the form of savings, an inheritance, or a gift from a relative. What happens when each person is presented with an opportunity to make a financial choice in which the outcome is uncertain and potentially negative, which is a hallmark of nearly all investment products? Three possibilities exist. First, both could choose to participate in the risky activity. Second, both could opt out of the decision scenario, or third, one could elect to take the risk while the other chooses not to participate.

The choice to participate in what is, as with this example, essentially a gamble has been extensively evaluated in the literature (Charness et al., 2013). Explanations of why two otherwise similar individuals might make different choices that entail risk have traditionally been explained using either an economic or a psychological lens. Someone trained as an economist would likely view the scenario as a simple risk-taking choice and then conclude that each person's choice to participate is tied to their risk preference (Mata et al., 2018). In this sense, risk preference describes the degree of variance in returns someone is willing to accept. From an economic perspective, the decision choice is associated with each person's effort to maximize utility in the context of financial constraints. Someone with psychological training would be more likely to view the scenario from a cognitive and behavioral perspective. Instead of assuming that each person's choice is linked to the goal of maximizing utility, a psychologist might argue that cognitive, attitudinal, and trait-like factors (e.g., extraversion, openness, etc.) are the primary determinants underlying the choice (Cunningham et al., 2014; Yi & Kanetkar, 2010). In this regard, the choice to engage in a risk-taking behavior is only remotely associated with the decision-maker's financial capacity to engage in the behavior. Of course, elements from each argument, in all likelihood, help describe differences in choice decisions (Kahneman & Tversky, 1979). For example, certain behavioral biases and cognitions may be at play when a decision is made (e.g., the endowment effect (Note 1)).

A third complementary explanation that some researchers use to describe decisions involving financial risk is essentially a neural one (Chen & Wallraven, 2017; Mata et al., 2018; Studer et al., 2013). As Rudorf et al. (2012) noted, risk preferences may reflect neural correlates of risk. Although not extensive, the extant literature shows risk preferences and risk choices appear to be associated with brain activation responses, with those willing to take risks exhibiting different prefrontal, temporal, and parietal brain patterns compared to those who present risk aversion tendencies (Gianotti et al., 2009). Rudorf and associates (2012) noted that anticipation of risk is also associated with changes in specific brain regions. Specifically, those who are risk averse—unwilling to take a risk—show strong ventral striatum and anterior insula (both of which are located deep in the brain) responses compared to risk seekers. Based on an analysis of neuroimaging scans, Rudorf et al. noted that neural activation associated with increased anticipation reflects risk aversion. In other words, risk-averse people exhibit different brain patterns than risk seekers.

Much of the research that has explored the relationship between brain activation and risk-taking behavior has used neuroimaging technologies, primarily event-related functional magnetic resonance imaging (fMRI). While neuroimaging techniques are quite effective in (a) identifying brain activation, (b) mapping brain functioning, and (c) acquiring data about a person's executive, cognitive, and emotional functions (Blume & Paavola, 2011), this approach does suffer from disadvantages, most of which are logistical. fMRI procedures require a study participant to sit or lay still in a relatively small tube. Nusslock et al. (2015) suggested that laying in a size-constrained tube causes brain activation related to claustrophobia and associated stressors. Additionally, fMRI techniques can generate skewed data if a subject exhibits a significant muscle-related episode. Additionally, data collection tends to be lagged, particularly concerning hemodynamic responses. A simpler, more cost-effective technique—quantitative electroencephalography (EEG)—exists. EEG assessment techniques are widely used in clinical situations when a researcher or clinician is resource-constrained or when a study participant may be asked to engage in movement or muscle-related behavior. Additionally, EEG techniques are non-invasive and fast. Compared to fMRI, EEG allows data to be collected more efficiently and at a quicker rate (e.g., in milliseconds versus seconds [Nusslock et al., 2015]). A limitation associated with EEG is that the technique does not offer a high-quality spatial resolution.

This study was designed to evaluate brain wave patterns as descriptors of financial risk-taking behavior using quantitative EEG. The study was set up as a quasi-experimental study to compare groups that were asked to make choices on a risk-taking task. The study did not utilize a randomized controlled trial methodology (Maciejewski, 2020). Specifically, this study was conceived as a way to assess brain wave patterns among healthy adults who were asked to (a) answer a series of financial risk-tolerance, risk aversion, risk-taking, and personal characteristic questions using a computerized survey and (b) engage in a financial risk-taking game of chance. This study aimed to obtain exploratory data to provide insights as to whether engagement in a risk-taking choice scenario and risk-taking task is associated with alpha, beta, and gamma brain wave activation. The focus on alpha, beta, and gamma waves was due to their association with distinct states of consciousness, cognitive processes, and activities, respectively.

Literature Review and Research Questions

1. Technical Background

Risk-taking is a common feature of human behavior. Risk-taking involves a complex cognitive process of evaluating options and making choices based on available information (Kohler, 1996; Zack, 2006). According to cognitive control theory, brain activity plays a key role in cerebral control and behavioral outcomes (Braver & Barch, 2002; Gonzalez-Prendes & Resko, 2012; Hammond & Summers, 1972; Zelazo & Anderson, 2013).

The relationship between neural mechanisms and risk-taking behaviors has been studied extensively in neuroscience, psychophysiology, and across a variety of biobehavioral sciences (Gratton et al., 2017). A number of researchers (e.g., Christopoulos et al., 2009; Fecteau et al., 2007; Krawczyk, 2002) have reported that individuals with high (low) levels of alpha (gamma) activity are more likely to engage in risk-taking behaviors. Cavanagh et al. (2010) noted that individuals who exhibit high alpha waves are more likely to make risky decisions in a gambling task. Numerous studies also show that risk-taking behaviors are associated with certain brain lobes. Kuhnen and Knutson (2005), for example, claimed that the frontal cortex is less active when individuals engage in more risky behaviors. In contrast, Moser and associates (2008) observed that brain activity, measured as EEG waves, is particularly strong in the frontal and temporal regions of the brain when taking risky behaviors.

EEG recordings have been used to capture brain wave activities in clinical settings since 1924 (Roohi-Azizi et al., 2017). EEG methodologies rely on scalp-recorded electroencephalographic oscillations, which are generated by the summation of inhibitory and excitatory postsynaptic potentials across thousands of cortical pyramidal neurons (Nusslock et al., 2015). Electrodes placed on the scalp, with each electrode corresponding to a specific brain lobe, have been shown to measure these potentials effectively. Figure 1 illustrates the primary location of brain lobes. Table 1 shows the relationship between each brain lobe and specific tasks and functions.

Figure 1. Location of Brain Lobes (Illustration Adapted from Heo, 2019)

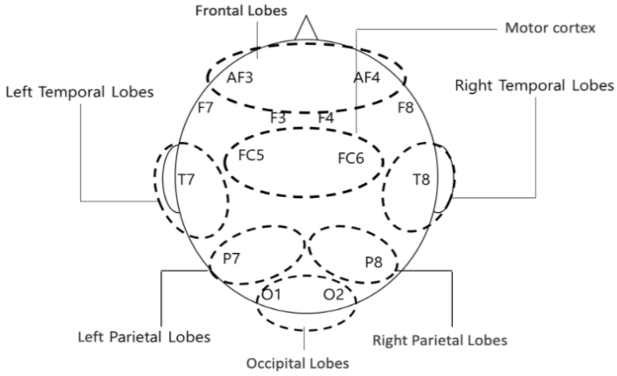


Table 1. Brain Lobe Locations and Functions

Lobe Location	Function
Frontal Lobes	Thinking, planning, memory, social awareness, and mood control.
Motor Cortex	Volitional movement.
Left Temporal Lobes	Verbal memory, word recognition, reading, and emotion.
Right Temporal Lobes	Facial recognition, social cues, and object recognition.
Left/Right Parietal Lobes	Sensation and perception.
Occipital Lobes	Visual perception.

Based on spectral analyses, EEG data is typically converted into frequency bands, which are measured as the number of pulses per second or Hertz (Roohi-Azizi et al., 2017). These bands are sometimes referred to as brain waves. Within the neuro- and psychophysiological research community, five brain waves are typically assessed and evaluated: alpha, beta (low- and high-beta), theta, gamma, and delta. Independently and mutually, these brain waves have been found to help describe human behavior in relation to specific tasks. Table 2 summarizes the characteristics of the five frequency bands (see Aminoff, 2012; Kropotov, 2009; Neumann et al., 2016; Nusslock et al., 2015; Rowan & Tolunsky, 2003). A key element associated with the frequency bands shown in Table 2 is the frequency range associated with each type of wave. For example, alpha waves are generally observed within a tight frequency range of 8 Hz to 13 Hz, whereas gamma waves are observed in a wider frequency range, extending beyond 30 Hz.

Table 2. EEG Frequency Bands

Frequency	Band	Frequency Range	Related Activity
Low-Frequency Waves	Delta	0.5 Hz – 4 Hz	Associated with dreamless sleep, most often observed in infants and young children; sometimes associated with unconscious body functions.
	Theta	4 Hz – 8 Hz	Associated with deep meditation.
	Alpha	8 Hz – 13 Hz	Related to feelings of relaxation, alpha waves are most pronounced when someone is transitioning from conscious thinking to a state of unconsciousness.
High-Frequency Waves	Low Beta	13 Hz – 16 Hz	Generally observed during periods of concentration and when someone is engaged in mild performing tasks.
	High Beta	16 Hz – 30 Hz	Associated with feelings of stress and anxiety; observed when someone is engaged in high-energy performance tasks.
	Gamma	Greater than 30Hz	Related to conscious perception and cognitive tasks.

Although each band is present and can be measured at all times across brain lobes, different bands dominate prior to and during specific tasks (Demos, 2005; Thatcher, 2016; Van Cott & Brenner, 1998). As illustrated in Table 2, brain waves can be classified as either low or high frequency. Low-frequency bands (i.e., alpha, theta, and delta) are most pronounced during rest, meditation, and sleep. High-frequency bands (i.e., beta and gamma) are activated during periods of energy use, concentration, and mental processing (Balaz et al., 2006; Başar-Eroglu et al., 1996; Bertrand & Tallon-Baudry, 2000; Pulvermüller et al., 1997; Steriade, 2006; Thatcher, 2016; Vanderwolf, 2000). When evaluating brainwave activity, greater EEG values suggest increased brainwave activation.

The placement of scalp electrodes generally follows the International 10-20 system (Bastos et al., 2016; Roohi-Azizi et al., 2017). Under the International 10-20 system, odd-numbered electrodes refer to the left-brain regions, whereas even-numbered electrodes represent right-brain regions. It is possible to isolate brain wave activity by the millisecond using spectral analyses and high-pass, low-pass, and notch filters (Bastos et al., 2016). In this study, brain wave data were transformed to power spectral densities (PSD) that were calculated using the following functions (see Jebelli et al., 2018):

$$S = [\, S_i(0), S_i(t=1), S_i(t=2), \ldots, S_j(i=T-1)],\ i = 1, \ldots, N \qquad (1)$$

where T is number of data set instants with ith epoch (i.e., time-locked with respect a specific event). A covariance matrix of the vectorized form of the ith epoch [s_j = vec (S_j)] is

$$R_i(\tau) = \mathrm{E}\,[(s_i - \mu_i)(s_i - \mu_i)^T],\ i = 1, ..., N \text{ and } = 0, ..., T\text{-}1 \quad (2)$$

where μ_i is the mean value of the ith epoch. The power spectral density matrix $p_i(\omega)$ of the ith epoch signal at any frequency ω as the autocorrelation function is

$$P_i\,(\omega) = \sum_\tau e^{-j\omega\tau}\, R_i(\tau),\ i = 1, ..., N \quad (3)$$

The resulting dimension was μV^2 for the power and $\mu V^2/Hz$ for the power spectral density. Brain wave power is measured by the product of 10 and the log of the micro-voltage (μV^2) squared divided by voltage fluctuations (Hz).

$$\text{Log Power Spectral Density (PSD)} = 10*\log\,(\mu V^2/Hz) \quad (4)$$

In this study, frequency data were measured as Hz elicited in the frontal, parietal, and temporal lobes. The μV^2 were then divided by frequencies to estimate PSD in a format normalized with the log (E Rawls et al., 2021; Jebelli et al., 2016, 2018; Vecchio, 2021). When measured this way, PSD indicates the strength of brain wave variation as a function of frequency. These transformed data are referred to as power bands in this study.

2. Theoretical Background

2.1. Dual-Process Theory in Decision-Making Behavior

Dual-Process Theory (DPT) is a widely used framework for understanding human decision-making and information processing (Evans & Stanovich, 2013). The theory explains two distinct systems, System 1 and System 2, that influence decision-making behavior. System 1 is characterized by intuitive, fast, emotional, and automatic processing, whereas System 2 involves analytical, cognitive, slow, and deliberative thinking. The foundations of DPT were first introduced as an aspect of Prospect Theory (Kahneman & Tversky, 1979) and later expanded to a cognitive science perspective by Stanovich (2011). This theoretical framework has been widely applied in financial decision-making and risk-taking studies, particularly within the cognitive and behavioral sciences (Grayot, 2020).

DPT can be used to explain how personal traits and neural activation influence financial risk-taking behavior. The theory provides a comprehensive way to view behavior that integrates behavioral tendencies (System 1) and cognitive control (System 2). DPT connects behavioral and neurobiological perspectives on financial decision-making by considering these two factors. The framework describes how individual traits and neural mechanisms shape financial risk-taking behavior (Gronchi & Glovannelli, 2018; Petracca, 2020). DPT's alignment with psychological and neurobiological perspectives makes it a robust theoretical foundation for understanding financial decision-making at various levels and supports the design of this study.

2.2. System 1: Personal Characteristics and Financial Risk-Taking Behavior

The relationship between personal characteristics and engagement in financial risk-taking behaviors has been widely explored over the past two decades. Some evidence suggests that individuals who exhibit positive affective states (e.g., emotions, willingness to gamble, financial satisfaction, etc.) are more likely to engage in financial risk-taking behaviors (Juergensen et. al., 2018; Winarta & Pamungkas, 2020). Other studies, however, suggest the opposite, with individuals who report a positive affective state noting a reduced need to take financial risks (Efimov et al., 2021; Mahto & Khanin, 2014; Marini, 2023).

Regarding financial satisfaction, knowledge, and experience, nearly all studies indicate that a positive association exists between these factors and financial risk-taking behavior. Individuals with more financial knowledge tend to report greater engagement in risk-taking behavior (Bianchi, 2018; Sobaih & Elshaer, 2023; Song et. al., 2022). There are counter-reports as well. Some researchers argue that financial knowledge does not provide a robust direct path to risk-taking behavior. Instead, the thought is that knowledge may influence risk perceptions and decision-making strategies, resulting in only a limited direct effect on financial risk-taking behavior (Shahzad, 2024; Shaikh & Ullah Khan, 2024). Similarly, financial experience has been linked to financial risk-taking behavior, with some studies showing that individuals with more extensive financial experience take more significant financial risks (Bayar et al., 2020; Ismiyanti & Mahadwartha, 2020; Sindhu & Kumar, 2014). Those who have experienced more negative outcomes are likewise less likely to engage in risk-taking behavior (Mei et al., 2021). When interpreting the literature, it is important to note that different financial experiences can shape risk-taking behavior in distinct ways. For example, Mei et al. (2021) found that past financial setbacks generally lead to more conservative investment decisions. This highlights how adverse financial experiences reinforce risk aversion rather than encourage risk-taking.

In relation to risk preferences and attitudes (e.g., risk tolerance and risk aversion), much of the existing literature supports the notion that holding a favorable preference or attitude is associated with an increased likelihood of engaging in risk-taking behavior (Ainia & Lutfi, 2019; Baruah & Parikh, 2018; Hemrajani & Dhiman, 2024; Oliya &

Sabunchi, 2019). While some studies suggest indirect relationships through other personality traits, the positive relationship between financial risk preference and financial risk-taking behavior remains well-documented.

2.3. System 2: Neural Mechanisms and Financial Risk-Taking Behavior

Financial risk-taking behavior has traditionally been studied using an economic and psychological lens. However, recent advances in neuroscience and neuroeconomics have expanded the way in which researchers conceptualize and study risk-taking. Neuroscience and neuroeconomics provide a way to gain a deep insight into the neurobiological mechanisms underlying financial decision-making. Although research in this field is emerging, several studies have explored the neural correlates of financial risk-taking behavior. For instance, there is evidence to suggest that brain activity is associated with financial risk-taking behavior (Tisdall et al., 2020; Vieito et al., 2014; Wu, 2014). Vieito et al. (2014) found that men who engage in more risk-taking behaviors show higher alpha and beta power than women. In contrast, women exhibit higher theta power. This may explain why women tend to take fewer financial risks. Using EEG methodologies, Eyvazpout et al. (2023) found that individuals with higher alpha and theta wave activity are more likely to engage in risk-taking behaviors. In contrast, beta waves appear to have weak predictive power, and gamma and delta waves have no descriptive power. Similarly, Lebedkin et al. (2023) reported that higher beta and gamma wave activities are often observed in the context of riskier decision-making behaviors. However, some researchers have reported contrasting findings. Yu et al. (2018) noted that lower alpha values are associated with increased risk-taking, while higher theta values are related to less risky decisions. Even though inconsistencies have been reported in the literature, including observations that lower or higher alpha values predict higher risk-taking, the predictive role of neurobiological mechanisms in financial risk-taking is well-supported across multiple studies. Building on the existing literature that examines the relationship between affective factors (System 1), neurological factors (System 2), and financial risk-taking behavior, this study was designed to answer, using an EEG measurement technique as a direct estimation of brain response (i.e., an event-related potential [ERP]), the following research questions:

> RQ_1. Do measures of self-assessed financial risk-tolerance/aversion and other personal characteristics correlate with engagement in risk-taking behavior?
>
> RQ_2. Can alpha, beta, and gamma waves be used to describe who is more or less likely to engage in a financial risk-taking activity?

Methods

1. Sample and Procedure

Prior to beginning the study, approval for the methodology was received from the University of Georgia Institutional Review Board (Ethics Ref: PROJECT00001110). Ten individuals (five female and five male) voluntarily participated in the study. The participants were recruited from the university community. Although the number of participants was relatively small, the data collected was extensive. Data were collected by the millisecond (i.e., 60,000 data points in one minute) over approximately 20 minutes per participant. This resulted in approximately 12 million data points for use in the analyses.

The mean age of study participants was 31 years (*SD* = 8.59 years). The demographic profile of participants is shown in Table 3. Those who participated in the study were relatively young and well educated, but in other respects, diverse in sex, race/ethnicity, relationship status, employment status, housing situation, and income (i.e., household income was measured on a six-point scale ranging from 1 = less than $20,001 to 6 = Above $100,000).

Table 3. Demographic Profile of Study Participants

Variable	Percentage	*M* (*SD*)
Sex		
Male	50	
Female	50	
Age		31.00 (8.59)
Race/Ethnicity		
Caucasian/White	20	
African American/Black	20	
Asian	50	
Multi-racial	10	
Relationship status		
Living with significant other	30	
Single	70	
Employment status		
Part-Time	40	
Full-Time	20	
Not employed	20	
Student	20	
Housing situation		
Own home	20	
Rent	70	
Live with relative	10	
Household income		
Less than $20,001	40	
20,001 to $30,000	10	

30,001 to $40,000	10
$40,001 to $50,000	10
$50,001 to $60,000	10
$70,001 to $80,000	20
Above $100,000	
Education	
Some college/Trade/Vocational training	20
Bachelor’s degree	10
Graduate/Professional degree	70

As shown in Figure 2, the study was conducted in three stages. As an initial step, participants were welcomed to the research lab. Each participant was fitted with an EEG measurement device (described below). The assessment process began after baseline EEG data were obtained.

Figure 2. The Three Procedural Stages of the Study

In the first stage, participants completed an online survey that included questions eliciting each person's willingness to take financial risks and other participant characteristics. The survey process took approximately 15 minutes. Once the survey was finished, the participant was compensated with a $25 gift card.

At the next stage, participants were asked to discuss a choice dilemma while holding the gift card. This involved engaging in a brief conversation about risk-taking and wagering. The discussion occurred in full sight of a Las Vegas-style gaming table (Note 2).

In the third stage, participants were invited to make a wager to double their $25 gift card endowment. The scenario was set up by reading the following statement:

> “At this point, you may leave the study, or you may wager your $25 and possibly leave with a total of $50 ... If you do decide to make the wager, you may lose the $25.”

The wager involved engaging in a dice game where, in order to win, the participant was required to roll two dice (similar to a real craps game). To double their $25 endowment, a participant was informed that they must roll a 5, 6, 8, or 9. The participant was also told that if they rolled any other number, they would lose their wager amount. The following statement was read to those who chose to make the wager:

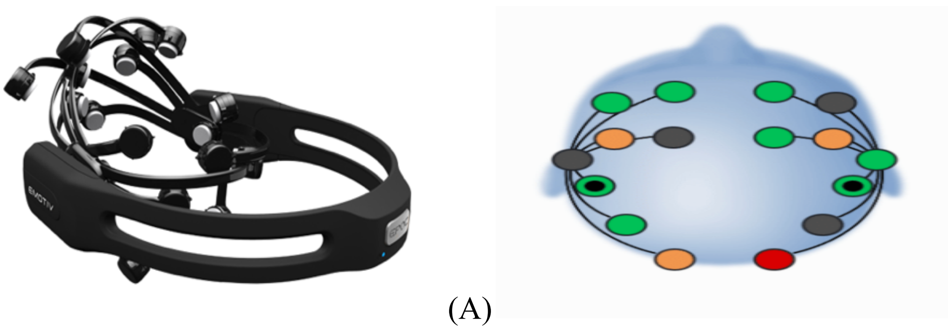
> “Before you roll, I would like to share the actual or true odds with you. The odds of rolling a 5, 6, 8, or 9 is 50% or 1 out of 2.

Now that you know the true odds, would you like to change your wager?"

Those who opted to make the wager and rolled a winning number received another $25 gift card. They were then asked to sign a receipt, at which time participation in the study was concluded. If a participant lost the wager (i.e., they rolled a non-winning number), they were given an opportunity to draw a colored ball from an opaque jar. The participant was told that the jar consisted of balls of two different colors (blue and white). The participant was also informed that if they selected a "blue" ball, they would win back their original wager plus an additional $25. The game was manipulated so that each participant was guaranteed to select a winning ball. The same ball choice game was offered to those who elected not to participate in the risk-taking game. Although participants did not know it at the time of the study, they were guaranteed to receive $50 regardless of their risk-taking choice. EEG data were collected from each participant throughout the study process.

2. Equipment

An Emotiv EPOC+® EEG commercial-grade gaming device (Figure 3) was used to gather brain wave data. This wireless EEG system is an effective tool in the measurement of ERPs, offering researchers a valid and reliable way to estimate brain wave data (Badcock et al., 2013). The headset measures alpha, beta, gamma, delta, and theta brain waves using a 16-point monopolar montage. The Emotiv EPOC+® EEG device provides a non-intrusive way to gather EEG signals. The device measures a person's brain waves via voltage fluctuations (i.e., Hz; Sanei & Chambers, 2013). The device uses 16 electrodes, with 14 that measure frequencies of voltage fluctuations from 14 locations on the scalp and two reference nodes (See Figure 1 and Figure 3; Note 3).



(A) (B)

Figure 3. (A) EEG Headset, Emotiv EPOC+, (B) EEG Headset Placement on Scalp (Illustration adapted from Emotiv, 2025 (`https://www.emotiv.com`); in the public domain).

Similar to Heo (2019), in this study, brain waves from the following head regions were measured and analyzed: (a) left- and right-temporal, (b) left- and right parietal, and (c) left- and right frontal lobes. Brain waves in the parietal lobes were measured at P7 and P8. Waves in the left temporal lobes were measured at T7, whereas those in the right temporal lobes were measured at T8. Frontal lobe brain waves were measured at FC5 and FC6.

3. Survey

The online survey was comprised of questions designed to reveal unique participant characteristics. Mood was assessed by asking, "How would you describe your current mood?" A 10-point scale was used with 1 = *bad mood* and 10 = *good mood*. Willingness to gamble and willingness to bet were measured by adapting the following questions from Blais and Weber (2006): "How likely is it that you would bet a day's income at a casino?" and "How likely is it that you would bet a day's income at the horse races?" Both questions used a 10-point scale ranging from 1 = *extremely unlikely* to 10 = *extremely likely* to measure participant responses. Financial satisfaction was measured by asking, "How satisfied are you with your present overall financial situation?" A 10-level response choice was offered with 1 = *lowest* and 10 = *highest levels.* Subjective financial knowledge was assessed by asking, "How knowledgeable are you about personal finance issues?" A 10-point scale, with 1 = *not knowledgeable at all* and 10 = *extremely knowledgeable*, was used to record each participant's level of perceived knowledge. Knowledge about casino games was used on the same 10-point scale with the following question: "How knowledgeable are you about casino games?" Financial experience was measured by asking, "How much experience do you have making financial decisions?" A 10-level response scale was used with 1 = *none at all* and 10 = *a great deal.*

Participants were also asked to answer a variety of risk-related questions. Self-assessed willingness to take risks was evaluated by asking each participant to "Rate yourself as a financial risk-taker" on a 10-step scale with 1 = *much lower* and 10 = *much higher*. The stated risk preference of each participant was measured with the following single-item question that was adapted from the Survey of Consumer Finances (SCF):

> "Which of the following statements comes closest to the amount of financial risk that you are willing to take when you save or make investments?"

Four answer choices were provided: (a) Take substantial financial risk expecting to earn substantial returns (coded 4); (b) Take above-average financial risks expecting to earn above-average returns (coded 3); (c) Take average financial risks expecting to earn average returns (coded 2); and (d) not willing to take any financial risks (coded 1). Financial risk tolerance was measured with the 13-item Grable and Lytton (1999) propensity measure. Scores on the scale can range from 13 to 47, with lower scores indicating *lower tolerance for risk* and higher scores indicating *greater tolerance for risk*. This measure of risk tolerance has been shown in other studies to offer valid and reliable estimates of a person's willingness to take the financial risk (Grable et al., 2014; Kuzniak et al., 2015; Rabbani et al., 2017). Constant relative risk aversion (CRRA) was assessed using the following item, which was adapted from Grable et al. (2020). The dollar amount choices linked to the question are the certainty equivalent amounts associated with the dollar tradeoffs in the question. A higher dollar amount indicates a lower degree of risk aversion.

> "Suppose you are considering making an investment. You have a chance to make an investment that will return either \$50,000 or \$100,000. Your financial advisor estimates that the probability of receiving \$50,000 is 50% and the probability of receiving \$100,000 is also 50%. You also learn from your financial advisor that shares in this investment are limited and difficult to obtain. Therefore, the less you are willing to invest, the lower the chance that you will be able to participate in the investment. Based on this information, what is the largest amount of money you would be willing to pay to participate in this investment, assuming you had the money? (1) \$70,711, (2) \$66,667, (3) \$63,246, (4) \$60,571, (5) \$58,566, (6) \$57,083, (7) \$55,978, (8) \$55, 143, (9) \$54,499, and (10) \$53,991."

Finally, each participant's revealed risk preference was assessed using a question adapted from Barsky et al. (1997). The question first asked:

> "Suppose you are the only income earner in the family, but that your current job is ending. You have to choose between two new jobs. The first job would guarantee your current family income for life. The second job is also guaranteed for life and possibly better paying, but the income is less certain. There is a 50-50 chance that the second job will double your current family income for life and a 50-50 chance that it will cut your current family income by a third for life. Which would you take?"

This was followed by one of two questions based on each participant's original choice:

(a) "Now suppose the chances were 50-50 that the second job would double your current family income and 50-50 that it would cut it in half. Would take the job?" or

(b) "Now suppose that chances were 50-50 that the second job would double your current family income and 50-50 that it would only cut it by 20 percent. Would you take the job?"

An ordinal score ranging from 1 = *low-risk tolerance* (high-risk aversion) to 4 = *high-risk tolerance* (low-risk aversion) was estimated based on answers to these questions.

4. Data Analysis Methods

EEG data were processed offline using EEGLAB version 2019.1 through MATLAB (Delorme & Makeig, 2004). Before analyzing participant data, measurement artifacts were identified and removed. Cleaning of data is important because EEG signals are susceptible to bodily changes (e.g., sudden movements and physiological disturbances such as eye movements, eye blinking, and muscular activity). These artifacts must be removed to ensure the EEG signals are not contaminated (Roy et al., 2021). In this regard, EEG signals contain two categories of artifacts (i.e., extrinsic and intrinsic) (Kotte & Dabbakuti, 2020). Extrinsic artifacts mainly arise from external factors (e.g., environmental noise and body movements) or movements in the EEG device, whereas intrinsic artifacts come from bodily physiological activities (Uriguen & Garcia-Zapirain, 2015). To remove extrinsic artifact signals, the data in each channel was bandpass filtered from 0.5 to 65 Hz (Christiano & Fitzgerald, 2003). Intrinsic artifacts were removed using the Independent Component Analysis (ICA) method embedded in EEGLAB. ICA is widely used in EEG research to remove artifacts in EEG data by decomposing mixed-signal sources. Specifically, the Extended Infomax ICA algorithm, as discussed below, was used in this study because of its reliability (Delorme et al., 2007; Jebelli et al., 2018; Lee et al., 1999; Viola et al., 2010).

Extended Infomax ICA algorithm. The following discussion highlights the procedure used to remove intrinsic artifacts. The process assumes there is an M-dimensional zero-mean vector $s(t) = [s_1(t), \dots, s_M(t)]^T$, such that the components $s_i(t)$ are mutually independent. The vector $s(t)$ corresponds to M independent scalar-valued source signals $s_i(t)$. The multivariate probability density function of the vector as the product of marginal independent distribution is:

$$p(\mathrm{s}) = \prod_{i=1}^{M} p_i(s_i) \tag{5}$$

A data vector $x(t) = [x_1(\mathrm{t}), \dots, x_N(\mathrm{t})]^T$ is observed at each time point t, such that

$$x(t) = \mathrm{As(t)} \tag{6}$$

$$\mathrm{u}(t) = \mathrm{W}x(t) = \mathrm{WAs}(t) \tag{7}$$

where u is the unmixed signals at each time point t, W is the linear mapping of a data vector $x(t)$, A is a full-rank N x M scalar matrix, and s is the sources from the mixed signals.

After removing artifacts, data were linked with the three elements of the study by participants: (a) the survey, (b) the choice dilemma, and (c) the risk-taking task. EEG features in the frequency domain were then extracted for each element. Alpha, beta, and gamma EEG waves were compared between those who elected to engage in the risk-taking task and those who did not engage in the task.

Results

Table 4 shows the results from the tests designed to address the first research question, which asked: Do measures of self-assessed financial risk-tolerance/aversion and other personal characteristics correlate with engagement in risk-taking behavior? Given the size of the sample, median, Median Absolute Deviation (*MAD*), and Mann-Whitney U tests were used to evaluate this question. Four variables were found to be associated with risk-taking. Participants who reported higher levels of subjective financial knowledge and experience were likelier to make the wager. These results align with existing literature, suggesting that financial knowledge and experience positively correlate with risk-taking behavior. It is possible that given the complexity of estimating odds associated with the risk-taking task, those with greater financial knowledge and experience were able to conceptualize the activity in a way that reduced the stress associated with the choice dilemma. Answers to the SCF risk-assessment item and the measure of CRRA were also found to be associated with engagement in the risk-taking task. Those who indicated a greater willingness to take risk (i.e., they were less risk averse) were observed to be more likely to engage in the wager. These results are consistent with previous studies discussed in the literature review.

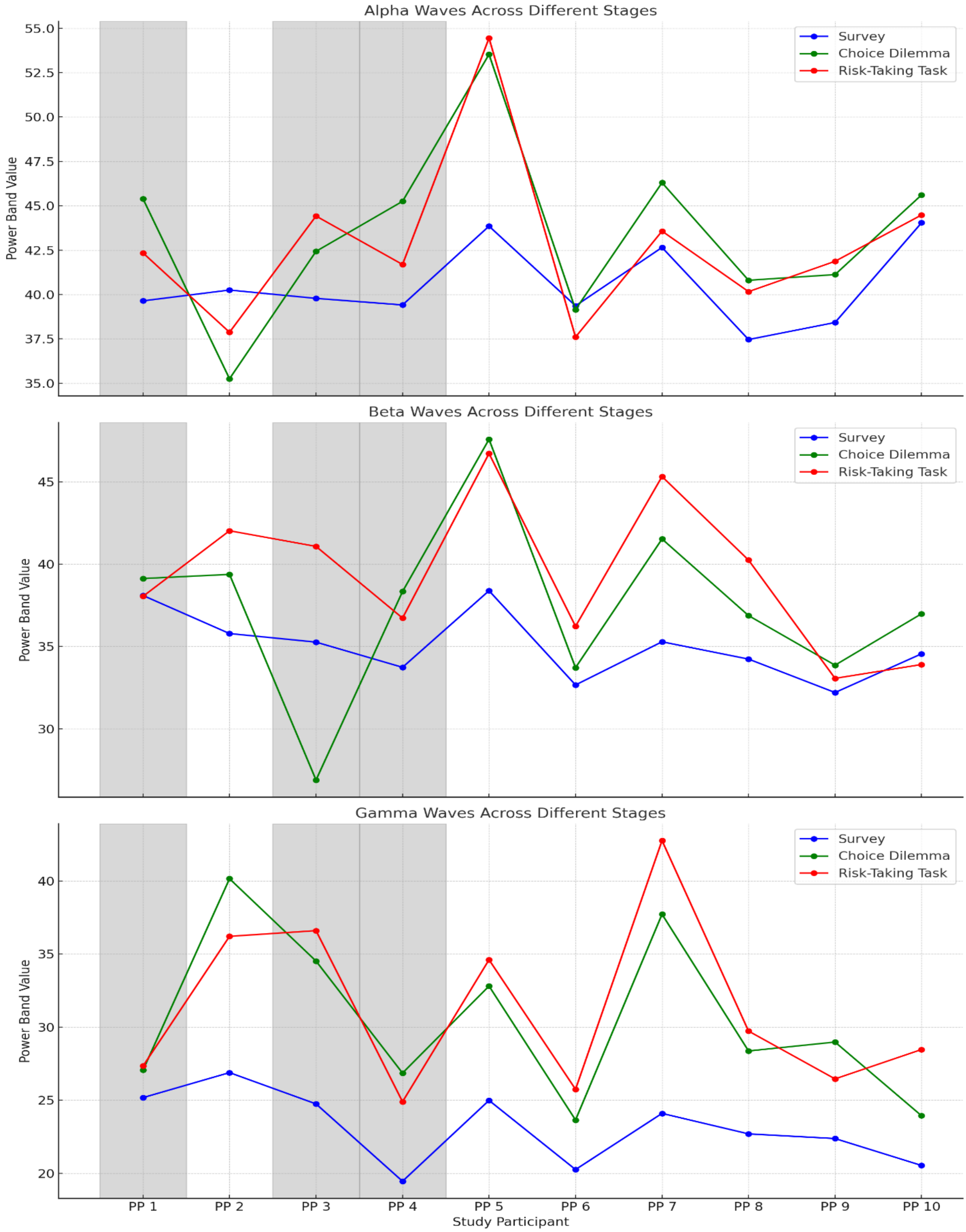
Table 4. Risk Tolerance and Personal Characteristics Associated with Engaging in a Risk-Taking Task

Variable	*Mdn*	*MAD*	RTT: No *Mdn* (*MAD*)	RTT: Yes *Mdn* (*MAD*)	*p* [a]
Mood	8.00	1.35	8.86 (1.22)	7.33 (1.16)	n.s.
Willingness to Gamble	2.00	0.92	2.14 (1.07)	2.33 (0.58)	n.s.
Willingness to Bet	1.00	1.06	1.57 (1.13)	2.00 (1.00)	n.s.
Financial Satisfaction	5.50	1.65	5.14 (1.58)	6.00 (2.00)	n.s.
Financial Knowledge	6.00	2.04	5.29 (1.60)	8.33 (1.16)	< .05
Knowledge of Games	2.50	2.31	3.71 (2.69)	2.33 (0.58)	n.s.
Financial Experience	7.00	2.30	5.86 (2.04)	9.00 (1.00)	< .05
Self-Assessed Risk Tolerance	4.50	2.22	4.00 (2.31)	5.33 (2.08)	n.s.
SCF Risk Measure	2.00	0.79	1.86 (0.69)	3.00 (0.00)	< .05
Financial Risk Tolerance	23.00	3.69	22.00 (3.06)	26.67 (3.22)	n.s.
Constant Relative Risk Aversion	6.50	3.31	7.57 (2.15)	2.00 (1.73)	< .05
Revealed Risk Preference	2.00	1.07	2.57 (1.13)	2.67 (1.16)	n.s.

Note. n.s. = not significant; [a]Mann-Whitney U Test; RTT = Risk-Taking Task.

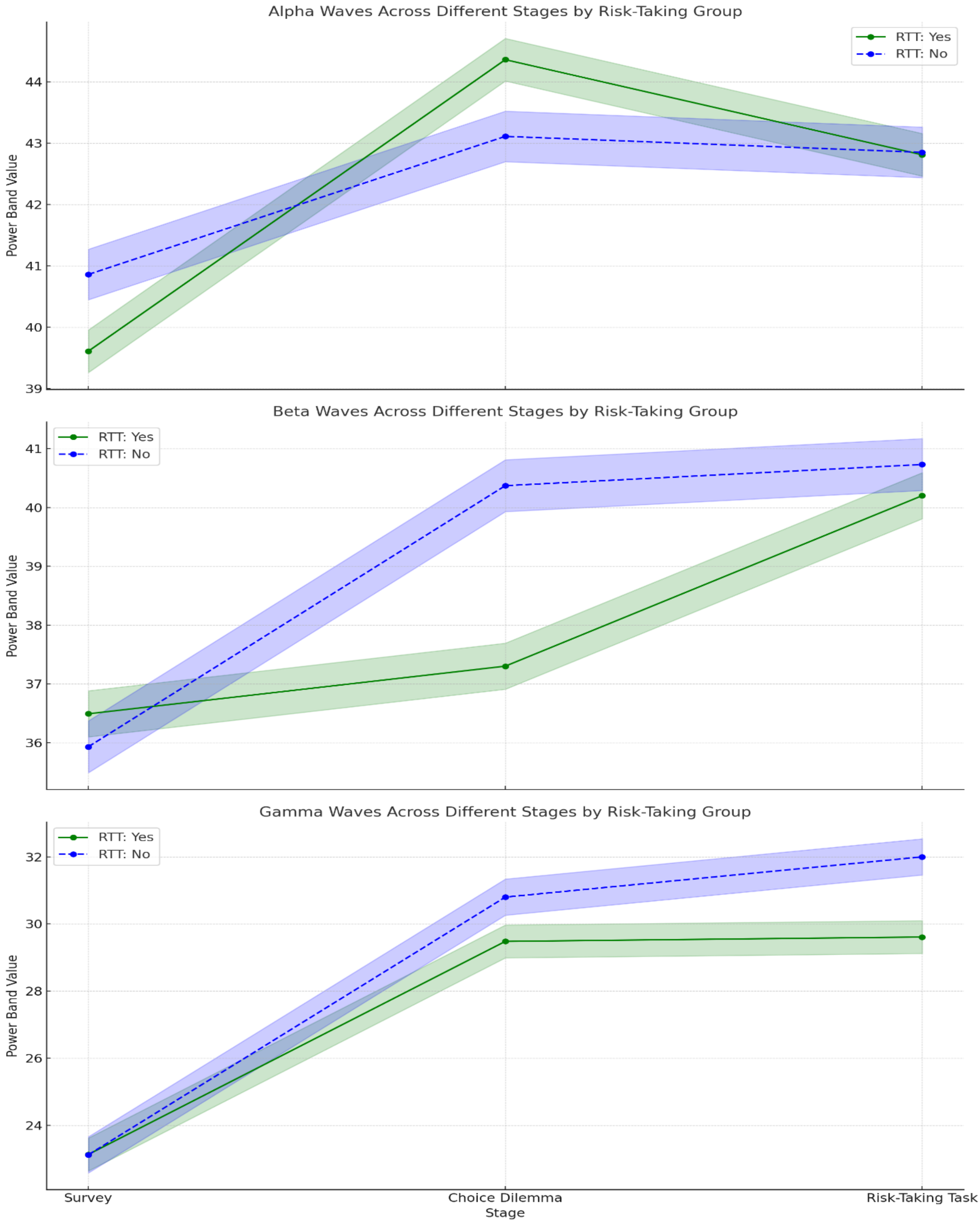
Figure 4 shows the mean power band scores by study participants across the three brain waves by each element of the study (i.e., survey, choice dilemma, and risk-taking task). The fifth, eighth, and eleventh columns show the average power band wave size by participant. The comparison tests used these data to answer the question, "Can alpha, beta, and gamma waves be used to describe who is more or less likely to engage in a financial risk-taking activity?" Figure 5 shows the same data by group (i.e., those who engaged in the risk-taking task and those who did not).

Figure 4. Mean Power Band Alpha, Beta, and Gamma Brain Wave Values by Node



Note: PP = Participant. The shaded areas indicate participants who engaged in the Risk-Taking Task.

Figure 5. Mean Power Band Alpha, Beta, and Gamma Brain Wave Values by Group and Node



Note. RTT = Risk-Taking Task. The shaded regions around each line indicate the 95% confidence intervals (CIs).

Whereas data in Figures 4 and 5 show power band data by study participant and node, Table 5 shows average alpha, beta, and gamma brain wave data across the three elements of the study. Differences between those who engaged in the risk-taking task and those who did not were assessed with *t*-tests. Only one significant difference was observed: Those who engaged in the risk-taking task exhibited lower beta wave activation during the choice dilemma phase of the study. These findings contrast with other studies that have reported higher beta wave activity in risk-takers (e.g., Lebedkin et al., 2023; Vieito et al., 2014). The results do, however, align with research by Yu et al. (2018). Although the risk takers almost uniformly exhibited less brain activation, none of the other comparisons were statistically significant.

Table 5. Statistical Significance in Power Band Wave Values

	Alpha			Beta			Gamma		
Risk-Taking Task Group	Survey	Choice Dilemma	Risk-Taking Task	Survey	Choice Dilemma	Risk-Taking Task	Survey	Choice Dilemma	Risk-Taking Task
No	40.86	43.11	42.85	35.93	40.37	40.73	23.12	30.80	32.00
Yes	39.61	44.36	42.81	36.49	37.30	40.20	23.13	29.48	29.61
p	.104	.406	.959	.100	< .001	.449	.996	.431	.140
Number of Observations		50			170			340	

Note. The number of observations was estimated as the total number of values within the frequency range of each wave (i.e., Alpha: 8Hz – 13Hz, Beta:13 Hz – 30Hz, and Gamma: greater than 30Hz) for each participant.

When viewed holistically, the results from Figures 4, 5, and Table 5 offer tantalizing insights into the risk-taking decision-making process. Recall from Table 4 that greater financial knowledge, more financial experience, elevated risk tolerance, and a lower aversion to risk were associated with engagement in the risk-taking task. The results present the possibility that rather than being a neural activity, risk-taking may be primarily a trait or trait-like factor. According to this line of thinking, knowledge, experience, and risk tolerance create a personal framework in which someone is predisposed to engage in a risk-taking activity. It follows then that any brain activation observed in relation to risk-taking tasks is something that is associated with other trait-like personal characteristics. If true, differences in alpha, beta, and gamma brain waves should be observed between those with low and high degrees of financial knowledge, experience, and risk tolerance/aversion. Tests were undertaken to examine this possibility. Participant data were segmented into financial knowledge, financial experience, risk tolerance (i.e., the SCF risk measure), and risk aversion (i.e., CRRA) categories based on a variable median split. Alpha, beta, and gamma waves across the three elements of the study (i.e., survey, choice dilemma, and risk-taking task) were examined with *t*-tests.

Table 6 shows the test results. Significant differences existed in more than half of the comparisons. Those with high self-assessed financial knowledge exhibited lower alpha wave activation during the survey and risk-taking task, lower beta wave activation during the choice dilemma, and lower gamma wave activation during the choice dilemma and risk-taking task. Those with more financial experience were observed to have lower alpha wave activation during the survey and lower beta wave and gamma wave activation during the choice dilemma and risk-taking task. A similar pattern of brain activation was observed in relation to risk tolerance. Differences based on risk aversion were also observed. Those with low-risk aversion had lower alpha wave activation during the survey, choice dilemma, and risk-taking task. Those with low-risk aversion also exhibited lower beta wave activation during the choice dilemma.

Table 6. Power Band Alpha, Beta, and Gamma Brain Wave Values by Knowledge, Experience, Risk Tolerance, and Risk Aversion

	Financial Knowledge			Financial Experience			Risk Tolerance			Risk Aversion		
Stage	Low	High	*p*	Low	High	*p*	Low	High	*p*	Low	High	*p*
Alpha												
Survey	41.84	39.13	.001	41.11	39.55	.028	41.11	39.55	.028	39.31	41.66	.001
Choice Dilemma	44.35	42.61	.204	43.76	43.06	.618	43.76	43.06	.618	41.83	45.14	.014
Risk-Taking Task	44.43	41.30	.015	43.72	41.58	.111	43.72	41.58	.111	41.29	44.44	.015
Beta												
Survey	36.21	35.99	.481	36.30	35.81	.124	36.30	35.81	.124	36.37	35.84	.091
Choice Dilemma	41.58	37.29	.001	41.23	36.75	.001	41.23	36.75	.001	38.33	40.54	.001
Risk-Taking Task	41.16	39.98	.068	41.34	39.41	.003	41.34	39.41	.003	40.83	40.31	.413
Gamma												
Survey	23.78	22.47	.321	23.60	22.41	.378	23.60	22.41	.378	23.80	22.45	.309
Choice Dilemma	32.65	28.05	.001	31.94	27.97	.007	31.94	27.97	.007	31.39	29.31	.149
Risk-Taking Task	33.70	28.86	.001	33.04	28.65	.004	33.04	28.65	.004	30.96	31.61	.660

The new insights gained from this study suggest that engagement in risk-taking tasks is not primarily associated with alpha, beta, or gamma brain wave activation. Brain wave activation and the resulting engagement in a risk-taking task appear to be associated most directly with levels of financial knowledge, financial experience, risk tolerance, and risk aversion. These factors may act in a way that primes someone to take risks. It is noteworthy, however, that those who engaged in the risk-taking task exhibited lower alpha, beta, and gamma brain wave activation.

Discussion

The following questions were asked at the outset of this study: (a) Do measures of self-assessed financial risk-tolerance and other personal characteristics correlate with the engagement in risk-taking behavior and (b) Can alpha, beta, and gamma waves be used to describe who is more or less likely to engage in a financial risk-taking activity? In relation to the first question, results indicated that, among those in the sample, subjectively assessed financial knowledge, financial experience, and risk tolerance/aversion were associated with engaging in the risk-taking task. Those with more knowledge and experience were more likely to take the risk offered. As expected, those with a higher risk tolerance (less risk aversion) were also more likely to engage in the risk-taking task. These findings support what has generally been reported in the risk-tolerance and risk-taking literature (Blais & Weber, 2006; Fisher & Yao, 2017; Grable et al., 2020).

Findings from this study add to the financial risk-taking literature by integrating neuroscientific insights with perspectives from behavioral finance. The DPT framework provides a model to evaluate this study's results. Overall, the findings suggest that both affective (emotional) and cognitive (analytical) processes influence financial risk-taking behaviors. The results emphasize the importance of personal characteristics (associated with System 1) and neural mechanisms (related to System 2) in understanding how people make decisions involving uncertain outcomes. Instead of being driven solely by neural activation, the decision to take risks appears to be influenced primarily by financial knowledge, experience, and risk tolerance. This insight indicates that stable trait-like factors can shape decision-making tendencies even before a risk-taking opportunity presents itself. This insight adds to the expanding body of neuroeconomics literature by illustrating the complex interplay between cognitive control, emotional states, and financial decision-making.

Findings from this study are also noteworthy in expanding the risk-tolerance and risk-taking literature beyond the use of personal characteristics and attitudinal factors in describing risk-taking behavior. Risk takers, at least in the context of the type of wager used in this study, appear to be less engaged, focused, and thoughtful compared to those who are more risk averse. Risk takers also appear to be more relaxed during periods leading up to a risk-taking opportunity. Rather than being triggered by the activation of brain waves, the choice to take a risk or not take a risk appears to be described more completely by someone's financial knowledge, experience, and willingness to take the risk. These factors appear to make someone predisposed to taking a risk. This does not mean, however, that a risk-taker is not psychophysiologically aroused before or during a risk-taking activity. Instead, this means, in response to the second research question, that risk-taking is not reliant on the activation of alpha, beta, or gamma waves.

Additionally, findings support the idea that a person's risk tolerance—their willingness to engage in a financial behavior in which the outcome is both uncertain and potentially negative—is the key descriptor of risk-taking activity. The difference between a risk seeker and a risk avoider appears to be their degree of willingness to take risks, which is influenced by their knowledge and experience. It is this willingness to take risks that primes a person to be more likely to engage in a risk-taking activity. Risk seekers appear to react with less cognitive effort. Data from this study suggest that a risk seeker does not necessarily need to be cognitively engaged in the risk-taking decision process. Risk avoidance appears to be associated with elevated levels of brain activation, particularly among those with lower levels of financial knowledge, financial experience, and risk tolerance. In order to prompt a risk avoider to take a risk, it may be necessary to reduce stimuli and moderate the brain response. This could be achieved by providing mindfulness mediation practices or managing distractions during the decision-making process.

Results have implications for financial education, investment advisory practices, and risk assessment methodologies. To begin with, traditional approaches to measuring and predicting financial risk-taking behavior have largely emphasized personal characteristics and attitudinal factors. This study underscores the importance of moving beyond these factors and integrating cognitive and physiological dimensions into financial decision-making models.

From a policy perspective, findings highlight the need for tailored financial education programs that enhance individuals' financial knowledge and experience, thereby equipping them with the cognitive tools necessary to make informed risk-taking choices. Financial advisors and policymakers should consider developing educational interventions that account for varying cognitive engagement levels between risk seekers and risk avoiders. For instance, risk-averse individuals who exhibit heightened brain activation and cognitive effort when faced with financial decisions may benefit from structured decision-support tools, mindfulness training, or simplified investment frameworks that reduce cognitive overload and encourage rational engagement with financial risks.

Findings from this study also have implications for consumer protection policy. Given that financial knowledge and experience are known to be associated with risk-taking behavior, policymakers should consider mandating a multi-layered approach to financial education that moves beyond simply using a series of quantitative assessments leading to risk profiles. This study highlights the need for a more comprehensive evaluation framework that incorporates qualitative insights such as an individual's financial experience, cognitive decision-making processes, and risk perceptions to better capture how people assess and respond to financial risks. Even when external conditions (e.g., income, wealth, and age) appear similar, internal cognitive and emotional factors can lead individuals to make different financial decisions. Financial education programs should, therefore, integrate behavioral and experiential components, ensuring that individuals are aware of the financial risks associated with different courses of action and equipped with the critical thinking skills necessary to evaluate them effectively. A structured, multi-dimensional risk-assessment approach that acknowledges objective financial factors and subjective cognitive and affective influences is essential for guiding individuals toward safe, personalized, and achievable financial plans that align with their long-term goals.

Furthermore, financial institutions and regulatory bodies could refine risk assessment instruments to incorporate not only self-reported risk tolerance but also behavioral and physiological indicators of decision-making tendencies. By integrating neuroscientific insights into risk profiling, policymakers can design more effective investor protection measures and enhance the accuracy of financial suitability assessments. Ultimately, recognizing the interplay between cognitive processing, financial literacy, and risk behavior can inform the development of policies that promote responsible and confident financial decision-making across diverse investor populations.

The findings from this study also have direct implications for those in the financial services and gaming industries. Consider again the scenario presented in the introduction to this paper. Two otherwise similar people were described as walking into an investment advisor's office. The two individuals, like the participants in this study, share common demographic and socioeconomic characteristics. Both enter the financial advisor's office with a monetary endowment. Knowing nothing else about them, who should be more likely to make a risky investment or savings choice or to engage in a wager in which the outcome is uncertain and potentially negative? It turns out that the person with more financial knowledge, more financial experience, and a higher tolerance for risk is more apt to engage in these types of risky behavior. Results from this study also suggest that the risk taker will likely be the one who is less cognitively engaged and less emotionally focused on the choice dilemma. It is important to note that rather than presenting anxiety, fear, or stress, the risk takers in this study initially exhibited relaxation and calmness, even when the situation was potentially stressful (i.e., wearing a scalp assessment device while taking a survey). This indicates a strategy when presenting risky choices to individuals: Make the risk-taking choice environment as enjoyable and relaxing as possible.

Conclusion

The results from this study, while providing unique insights into the way brain activation is associated with financial risk-taking, have generated as many or more questions than the questions answered. For example, using larger samples, future studies are needed to determine if the way a risk-taking question is framed may trigger different alpha, beta, and gamma brain wave responses. In this study, the risk-taking task was framed neutrally. As described in prospect theory (Kahneman, 2011; Kahneman & Tversky, 1979; Tversky & Kahneman, 1992), it is possible that framing the risk-taking task either positively or negatively might activate different alpha, beta, and gamma responses. Additionally, the dollar amount at risk may be related to the choice to engage in a risk-taking behavior. It is possible that the $25 endowment used in this study was not enough to warrant someone's time to engage in the last step of the study. It is also possible that the endowment was considered too valuable to lose. Future studies using different dollar endowments are needed to explore this issue. In addition, the activity itself may trigger different brain activation. It may be that a gambling scenario activates different brain regions compared to investment or saving scenarios. Finally, although prescreening and a general comparison of brain waves were conducted across the participants, differences in cognitive ability (i.e., Attention-Deficit/Hyperactivity Disorder, etc.) were not evaluated before, during, or after the experiment. The potentiality that medically diagnosed cognitive conditions could be related to brain wave activity in the context of risk-taking behavior is worthy of future study.

Additionally, while this study presents analyses based on individual respondents and group-level comparisons, an alternative approach would be to use pooled data across participants and apply a mix-effects modeling framework. A mixed-effect analysis would include both fixed and random effects, providing a more nuanced understanding of financial risk-taking behavior. Future research could extend this study by implementing mixed-effect models to examine within-subject variations in EEG activity across different phases of financial risk-taking behaviors, offering more profound insights into the relationship between these factors and decision-making dynamics.

When viewed holistically, the results from this study are noteworthy in showing that brain wave activation is not directly associated with the choice to engage in a financial risk-taking task. Brain wave activation in relation to financial risk-taking is more directly related to someone's level of financial knowledge, financial experience, and willingness to take risks. As a clinical and research tool, the use of EEG methodologies, as exemplified by this study, shows great promise in providing more insights into how individuals conceptualize and act when faced with financial choices that entail the possibility of uncertain gains and losses.

Note 1: The endowment effect is the observation that people attach additional value to things they own compared to what they do not own (Kahneman et al., 1990; Knetsch, 1989; Thaler, 1980).

Note 2: This element of the study was introduced as a way to make the decision-making process as realistic as possible.

Note 3: In concordance with Badcock et al. (2013), one mastoid sensor was used as a ground reference point for comparison. The other mastoid was used as a feed-forward reference that reduces external electrical interference. As outlined by Badcock (p. 3), "The signals from the other 14 scalp sites (channels) were high-pass filtered with a 0.16 Hz cut-off, pre-amplified and low-pass filtered at an 83 Hz cut-off. The analog signals were then digitized [sic] at 2048 Hz. The digitized [sic] signal was filtered using a 5th-order since notch filter (50—60 Hz), low-pass filtered, and down-sampled to 128 Hz … The effective bandwidth was 0.16—43 Hz."

Ethics approval

The University of Georgia Ethics Review Committee for Human Research approved the project, "Electroencephalographic Brain Wave Patterns as Descriptors of Financial Risk-Taking Behavior," on September 17, 2019 (PROJECT 00001110).

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Relative Contributions

All authors conceived of the study. EK conducted the analyses and wrote the draft of the paper. JG revised the draft. All authors approved the final version.

Competing interests

None.

Research Promotion

This study explores how EEG brain wave patterns relate to financial risk-taking behavior. The purpose was to identify neurological indicators of risk preferences, offering an objective approach to understanding investor behavior. Findings suggest that specific EEG signals are significantly associated with varying levels of financial risk tolerance.

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