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Heart–Brain Dynamics in Analytical and Non-Analytical Intuition: A Study of HRV and EEG Correlates

Şahin, İsmet[1] https://orcid.org/0000-0002-2268-9289

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Abstract

This study examined the physiological correlates of intuitive processes by exploring the relationships between heart rate variability (HRV), electroencephalogram (EEG) activity, and two perceptual modes: analytical (AP) and non-analytical (NAP). A total of 110 healthy university students completed AP and NAP tasks under resting and testing conditions while HRV and EEG data were recorded. Correlational analyses indicated that higher AP scores were positively related to HRV indices (RMSSD, PNN50, HF power, HRV mean) during rest, reflecting a link between analytical intuition and parasympathetic stability. In contrast, NAP scores were negatively correlated with HRV indices during testing but positively related to mean heart rate, suggesting elevated arousal and reduced autonomic flexibility. EEG results showed no significant correlates for AP, while NAP performance was associated with greater high beta activity and alpha peak frequency variability, indicating increased cortical arousal. Group comparisons revealed physiological differences between high and low performers, particularly in HRV during testing and EEG at rest. Stepwise regression identified HRV mean, LF peak, broad beta mean, and SMR variability as significant predictors of NAP, explaining 17.3% of its variance. Findings suggest that AP and NAP rely on distinct physiological states, supporting a dual-process model of intuition.

INTRODUCTION

Intuition is a multifaceted construct situated at the intersection of philosophy and psychology. Philosophically, it has been described as a direct, non-inferential grasp of truth, consciousness, or inner reality (Gündoğan, 2024; Bibika, 2024; Soyaslan, 2024). Psychologically, intuition is understood as a rapid, unconscious, emotionally charged process grounded in holistic associations and distinct from analytical reasoning (Hammond, 1996; Pretz et al., 2014). Dual-process theories classify it as implicit, automatic, and evolutionarily adaptive (Gore & Saddler-Smith, 2011; Cai Shi & Lucietto, 2022).

Recent literature emphasizes that intuition is not a unitary phenomenon but varies according to context, function, and underlying cognitive processes (Cai Shi & Lucietto, 2021; Pretz et al., 2014). While traditional philosophical accounts frame intuition as a singular mental faculty (Nado, 2014; Patton, 2003), empirical classifications differentiate forms such as problem-solving, moral, emotional, creative, relational, inferential, and somatic intuitions (Glöckner & Witteman, 2010; McCraty, 2015). These distinctions reflect the increasing recognition that intuitive processes may shift depending on familiarity, complexity, and time pressure in decision-making environments.

Based on these typologies, intuition can be conceptualized in three interrelated forms. The first is an explicit, experience-based comprehension operating in familiar contexts and relying on accumulated schemas and reasoning (Evans & Stanovich, 2013; Pretz et al., 2014). The second reflects an implicit, unconscious sensitivity to environmental cues in unfamiliar situations, shaped by past learning and heuristics (Gigerenzer, 2007; Gore & Saddler-Smith, 2011). The third describes an affective, immediate form of knowing arising in emotionally salient or uncertain conditions, marked by visceral signals and somatic markers (Bechara & Damasio, 2005; McCraty, 2015; Holzer, 2022).

[1] Şahin, İsmet. Kocaeli University, Faculty of Education, İzmit, Türkiye ismetsahin@gmail.com,

Accurate responses derived through schema-based reasoning or implicit perception are widely regarded as essential functions of intelligence (Simon, 1990; Ericsson & Charness, 1994; Kahneman & Klein, 2009). However, non-analytical perception involving bodily signals and emotional resonance may offer an alternative pathway to insight, one that enhances self-awareness and instinctive decision-making.

Recent research suggests that the heart plays an active role in intuitive processing, lending physiological support to the metaphor “follow your heart” (Holzer, 2022; Damasio, 1994). Once seen primarily as a symbolic center of wisdom and emotion (Salem, 2009), the heart is now recognized as a neurophysiologically complex organ with its own intrinsic nervous system, or “heart brain,” capable of bidirectional communication with the central nervous system (Armour & Ardell, 1994; Cantin & Genest, 1986; Tiller et al., 1996; McCraty et al., 2004a). These pathways—including vagal input, electromagnetic fields, and neurochemical signals—contribute to emotion regulation, stress response, and cognitive coherence (Lacey & Lacey, 1978; Rein et al., 1995; McCraty, 2000).

McCraty et al. (2004a) found that heart rate activity decreased several seconds prior to participants viewing emotional stimuli, suggesting a non-analytical anticipatory mechanism. This idea is expanded in later studies showing that the heart may act not only as a responder but also as a transducer of intuitive signals, potentially preceding cortical activity (McCraty et al., 2004b; McCraty, 2015; Dunn et al., 2010). Palser et al. (2021), Soosalu et al. (2019), and Mulukom (2024) support this embodied view, reporting that individuals more attuned to bodily states—particularly cardiac signals—demonstrate greater intuitive accuracy.

Supporting this, McCraty and Zayas (2014) observed that coherent heart rhythms enhance emotional self-regulation and facilitate deeper intuitive access. Hodgkinson et al. (2008) highlight the dynamic interplay between affect and cognition, suggesting that cardiac signals shape conscious evaluations. Sands (2022) further proposes that the heart’s electromagnetic field may influence both intra- and interpersonal intuitive processing.

Electroencephalography (EEG) has also proven valuable in identifying neural correlates of intuition. Beyond its clinical uses, EEG studies show that intuitive individuals often exhibit increased theta and alpha activity—brainwave patterns associated with emotional integration, creativity, and holistic thinking (Azhari & Hernandez, 2016; Uyulan et al., 2022). In contrast, analytical cognition is typically marked by elevated beta wave activity, linked to focused reasoning and linear thought.

This study investigates the dynamic interplay between heart rate variability (HRV) and electroencephalographic (EEG) activity under both resting and task-oriented conditions. Participants performed two distinct tasks: one requiring **analytical perception (AP)**, which involves the interpretation of explicit cues, and another requiring **non-analytical perception (NAP)**, characterized by intuitive recognition of implicit signals. The overarching aim of the research is to identify the cardiac and neural correlates of intuition by analyzing HRV markers and EEG patterns associated with each perceptual mode. Through correlational and regression analyses, the study seeks to determine the extent to which physiological indicators can predict performance in AP and NAP contexts. The findings are expected to advance the empirical understanding of intuition as a measurable cognitive–physiological construct, offering implications for educational, clinical, and decision-making domains.

To clarify this aim, the following **subproblems** were formulated:

1. Are there significant relationships between analytical perception (AP) scores and heart rate variability (HRV) indices during resting and testing conditions?

2. Are there significant relationships between non-analytical perception (NAP) scores and HRV indices during resting and testing conditions?
3. Are there specific EEG activity patterns (e.g., in alpha, beta, or gamma frequency bands) associated with AP and NAP performance?
4. Do individuals with high and low AP/NAP performance differ significantly in HRV and EEG parameters?
5. Which physiological variables (HRV and EEG indices) significantly predict AP and NAP performance?

METHODS AND MATERIALS

The research was carried out with the endorsement of the ethics committee of Kocaeli University's Social and Human Sciences department, as well as the consent of the dean of the faculty where the research took place (Ethics Committee Decision no 20, made during the meetings 2024/06. For writing the research report, the artificial intelligence applications Quillbot.com, ChatGPT.com, and Deepseek.com were used to a limited extent, specifically for tasks such as literature review, paraphrasing, and translation.

Research Design

The research is descriptive and employs a relational methodology. The study entailed examining the correlation between heart rate variability (HRV) indicators and concurrently recorded brain waves over a duration of five minutes, during both a resting state and a testing state in which participants addressed two separate categories of enquiries: analytical perception (AP) and utilizing non-analytical perception (ANP) to derive answers purportedly linked to intuitive success. The disparities in heart rate and brain wave indices between samples with higher and lower AP and NAP scores were also examined. The correlations between heart rate and brain wave indices were analyzed in both resting and testing settings. Ultimately, the heart rate and brain wave variables that may serve as predictors of AP and NAP success were assessed using the stepwise regression method.

Population and samples of the research

The study examines the student population enrolled in the Faculty of Education at Kocaeli University. The research sample comprises 147 male and female students, predominantly in the 1st and 2nd grades, aged 19-23, from diverse disciplines. The students were informed about the research, and their agreement was obtained, indicating their voluntary involvement in the study.

The shortened general health scale, developed by Demiral et al. (2006), was administered to the samples with appropriate authorization. The scale has 8 subdimensions on 3 main dimensions as physical, social and psychological. Participants whose psychological health scores fell below the reference threshold or who were previously diagnosed with psychiatric conditions were excluded from the analysis. Analyses were conducted both with all samples 147 and with those remaining 110 healthy subjects.

Heart Rate and Brain waves Indices

The recorded indices of heart rate and brainwaves and summaries of how they are interpreted psychologically and biologically can be found in the study by Shaffer and Ginsberg (2017) and Campbell et al. (2021)

The estimated brain wave indices include delta, theta, alpha, sensorimotor rhythm (SMR), wide beta, high beta, gamma, low inhibit, reward, and high inhibit wave forms, along with their respective means and standard deviations. In addition to theta/alpha, theta/wide beta, and theta/SMR ratios were computed. Furthermore, the mean, standard deviation, and mode of the alpha peak frequency were computed.

A detailed summary of the HRV and EEG indices used in this study is available in Supplementary Tables 1 and 2 at the end of the manuscript.

Data Collection Tools

Kyto2935 HRV Sensors

The sensor used to measure heart rate variability is Kyto2935, the operation frequency is 2402–2480 MHz, the modulation type is GFSK, Bluetooth version 4.0, the bitrate of the transmitter is 1 Mbps, and it has 40 channels. Shenzhen Asia Test Technology Co., Ltd. tested the device for validity and reliability. It is found to accomplish FCC standards, part 15.247 (FCC ID: 2ALC3KYT02935). The report reveals that the level of confidence for the sensors was found to be 95%. In the literature review, many research papers on HRV were found using the Kyto2935 device, like Cheng et al. (2019) and Laurman (2023).

Elite HRV Bluetooth APP

The Elite HRV Bluetooth App calculates various HRV metrics by directly obtaining the R-R intervals, the time intervals between successive heartbeats, from compatible devices. Scholarly investigations assess the accuracy and consistency of the application. Moreover, it has been noted that it has been utilized in various research studies. Chhetri et al. (2022) and Ramon et al. (2022) determined that the Elite HRV Bluetooth application is dependable for assessing heart rate variability at rest, consistent with data from the Polar V-800 monitor. Perrotta et al. (2017) identified a robust correlation between Elite HRV and Kubios HRV 2.2, whereas Himariotis et al. (2022) reported no significant differences in lnRMSSD data between the software in seated or supine positions.

EEG Equipment; Procomp Infiniti and Biograph Infiniti

The following components to record EEG were utilized in the study: Three electrodes: Active electrode for the head, and grand electrodes for the earlobe. The Biograph Infiniti Software system (version 5.0) operates with a filtering frequency of 60 Hz, utilizing the ProComp differential amplifier (Thought Technology Ltd, Montreal, Quebec) for EEG sessions.

The ProComp Infiniti and Biograph Infiniti systems have been widely utilized in various research contexts, demonstrating their validity and effectiveness in capturing physiological data across multiple domains. Some samples are Lier et al. (2019), Groeneveld et al. (2019), Nazari et al. (2012), Schnabel (2019), Stępnik et al. (2023), Richesin et al. (2020), Morel and Hautier (2016). Warmbrodt et al. (2021), Ziaee et al. (2016) and Kingsnorth et al. (2011) are some other papers that implemented Procomp and Biograph Infiniti equipment in their research.

Test/Activity for Intuitive Performance

The literature categorizes intuition into two primary forms: analytical perception, which involves interpreting explicit or implicit cues, and non-analytical perception, which refers to insight beyond conscious reasoning. Based on this distinction, a custom task was developed to assess participants' intuitive performance.

The test consisted of two types of items. The first group required analytical interpretation through the observation of visible or inferred details in photographs. The second group included items designed to rely solely on intuition, with no visible clues or signs to guide responses.

Initially, approximately 40 items were prepared. Rather than focusing on the validity of each question's content, the aim was to examine the cognitive processes participants engaged in: whether they actively searched for clues or responded intuitively or randomly. Expert feedback was obtained from three faculty members in educational sciences, and items deemed inappropriate were excluded.

The refined items were administered to 15 students using the think-aloud technique. Their responses were observed for evidence of sign-based reasoning or intuitive guessing. Items that yielded mixed interpretations were eliminated. The final pool of items was piloted with 84 students for further validation.

For the analytical perception section, 12 items were retained, with difficulty levels ranging from 30% to 74.1% (M = 57%).

Figure 1

Some samples for AP type items

For the non-analytical section, 18 items were included, each having a predetermined "correct" answer based on researcher-defined intuitive recognition. These items ranged in difficulty from 15% to 66.7% (M = 47%).

Figure 2

Some samples for NAP type items

Point-biserial correlations were used to evaluate item-total relationships. In the analytical section, all items showed significant positive correlations (r = .168 to .376). In the non-analytical section, 13 of the 18 items demonstrated significant positive correlations (r = .180 to .378), while 5 others showed non-significant positive correlations.

Furthermore, an investigation was conducted to determine if a correlation existed between the scores of these two sections; inferring implicit and explicit signs and answering with non-analytical perception. The correlation between the scores from the two sections was r = .127 and $p > .05$ with 142 degrees of freedom. In this instance, $R^2 = .016$ ($F=2.319$, $p > .05$) which can be regarded as evidence that the two item types assess distinct performances.

Data Collection

Prior to the data collecting procedure, all samples were administered the abbreviated version of the General Health Inventory, as established by Demiral et al. (2006). All participants underwent heart rhythm and brainwave measures during both rest and a task in which participants respond to two distinct categories of enquiries: analytical (interpreting implicit signals) and employing non-analytical (insight beyond conscious reasoning) perception to uncover answers believed to correlate with intuitive success. The heart rate recordings were collected by measuring the right ear using KYTO2935 finger and ear sensors for 5 minutes in a specially prepared unoccupied room. At the same time, the brain wave recordings were also measured for 5 minutes from Cz point as to 10-20 system using Procomp Infiniti amplifier with related sensors and cables.

Participants were instructed to assume a relaxed posture, breathe effortlessly, and maintain their typical body position and breathing pattern. The measurements were primarily taken during the daytime, specifically between the hours of 11 and 17. Throughout the procedure, the measurements of each person were documented following a brief period of acclimation lasting 10-15 seconds. Throughout the procedure, no practices that could divert or draw the attention of persons were permitted or deliberated. The entire data collection process took approximately 30 minutes for each individual. The values obtained as a result of heart rate measurements were instantly recorded on the forms. The EEG data obtained were calculated for different wave forms and transferred to excel database using Biograph Infiniti software. All data collected was cross-verified by two individuals to ensure accurate data entry.

Data Analysis

Data collected using the specified tools was analyzed within the SPSS version 27 database. The analyses were conducted on healthy sample data, based on the general health inventory and its psychology related subdimensions established by Demiral et al. (2006).

The initial analysis focused on the bivariate correlations (Spearman's rho, due to non-normality) between HRV and EEG indices and AP/NAP scores under rest and test conditions. Additionally, to extract further insights, the samples were classified based on their intuitive success in the test about the presumed talents into two categories: high and low score groups as to -/+ 1 standard deviation above and below the means. Subsequently, heart rate and brainwave indices were examined between high and low score groups to determine any significant disparities in these metrics. Mann Whitney U test was implemented to analyze the differences. Furthermore, in order to see the connection between heart and brain, the Spearman correlations between heart rate and brain wave indices were analyzed in both resting and testing settings. Lastly, the heart rate and brainwave variables that may serve as predictors of AP and NAP success were assessed using the stepwise regression method. While the .05 significance level was taken into account when examining the analysis results, relationships and differences approaching significance up to .10 were also examined assuming that they would show a general trend.

RESULTS

The results are presented under four main sections: (1) correlation analyses between heart rate variability (HRV) and electroencephalogram (EEG) indices with participants' performance scores, (2) comparisons of physiological responses between high and low achieving groups, (3) interrelationships between HRV and EEG indicators under resting and task conditions, and (4) multiple regression analyses to identify predictors of success in analytical (AP- interpreting implicit and explicit signs) and non-analytical (NAP - intuitive insight beyond conscious reasoning or observable cues) tasks. All analyses were conducted on data obtained from physiologically healthy participants. Due to non-normal distributions observed in several variables, non-parametric statistical methods—Spearman's rho for correlations, Mann–Whitney U for group comparisons, and stepwise multiple regression—were employed.

Correlation Analyses

The results regarding heart rate and brainwave indices during rest and test are presented in the following sections.

Correlations between Heart Rate Indices, AP and NAP scores during Rest and Test,

Table 1

Correlations between Heart Rate Indices, AP and NAP Scores during Rest and Test

Spearman Correlation Coefficient		AP, Resting	NAP, Resting	AP, Testing	NAP, Testing
RMSSD	rho=	**.203***	-.143	.114	**-.254****
	Sig.	**.033**	.138	.236	**.008**
	N	**110**	109	110	**109**
SDNN	rho=	.126	-.176	.028	**-.241***
	Sig.	.191	.068	.771	**.011**
	N	110	109	110	**109**
LnRMSSD	rho=	**.204***	-.139	.115	**-.251****
	Sig.	**.032**	.149	.232	**.008**
	N	**110**	109	110	**109**
PNN50	rho=	**.196***	-.128	.133	**-.224***
	Sig.	**.041**	.186	.165	**.019**
	N	**110**	109	110	**109**
Mean RR Interval	rho=	.060	**-.192***	.124	**-.191***
	Sig.	.536	**.046**	.197	**.047**
	N	110	**109**	110	**109**
Total Power	rho=	.146	-.134	.029	**-.224***
	Sig.	.128	.166	.762	**.019**
	N	110	109	110	**109**
Low Frequency Power	rho=	.090	-.115	.005	**-.302****
	Sig.	.352	.236	.957	**.001**
	N	110	109	110	**109**
High Frequency Power	rho=	**.216***	-.104	.079	**-.222***
	Sig.	**.024**	.280	.414	**.020**
	N	**110**	109	110	**109**
Heart Rate Mean	rho=	-.051	**.195***	-.104	**.202***
	Sig.	.593	**.042**	.279	**.036**
	N	110	**109**	110	**109**
Heart Rate Variability Mean	rho=	**.222***	-.144	.122	**-.254****
	Sig.	**.020**	.136	.205	**.008**
	N	**110**	109	110	**109**

Statistics obtained during resting position for RMSSD, LnRMSSD, PNN50, HF Power and HRV mean indices have significant positive correlations with AP scores that can be seen in Table 1. Since increase in these indices imply calm and relax mood in heart rate indices, it means that being successful in AP is positively correlated with having more regular heart rate or being in calm and peaceful mood.

Upon examining the relationships between heart rate indexes and the number of correct answers in NAP type items, it is observed that MRRINT and HR mean have significant correlations in a resting state. MRRINT has negative but HR mean has positive correlation. Success in NAP scores is associated with decrease in MRRINT and increase in HR mean. A high resting heart rate average seems to be associated with success in NAP scoring.

In test mode, notable correlations are found between RMSSD, SDNN, LnRMSSD, PNN50, MRRINT, total power, LF power, HF power and HRV mean and the number of correct answers in NAP type items. The only positive correlation is between HR mean, all the others are negative. Explanation for this positive correlation is that a higher heart rate may indicate increased arousal or alertness, which could help improve cognitive/intuitive performance, especially in tasks requiring concentration or quick response. The negative correlations between HR indices and performance could indicate that tasks requiring high levels of focus or concentration may benefit from a lower state of physiological variability, more sympathetic activation and less parasympathetic influence.

While AP success exhibits a positive correlation with heart rhythm indices, especially at rest, NAP success mostly exhibits a negative correlation except for HR mean in the test situation.

AP scores (both resting and testing) are positively associated with HR indices except for MRRINT in testing mode, indicating higher parasympathetic activity and better autonomic flexibility. This suggests that individuals with higher AP scores may have better stress regulation and emotional resilience. Higher NAP scores are consistently associated with lower HR indices (e.g., reduced RMSSD, PNN50, HF, and LF power), reflecting decreased autonomic flexibility. This could indicate increased stress, cognitive load, or arousal associated with higher NAP during testing.

The LF/HF ratio, LF peak, and HF peak indices were excluded from the table due to their lack of substantial connection in all states.

Correlations between Brain Wave Indices, AP and NAP Scores during Rest and Test.

No significant correlation exists between AP, NAP scores and brain waves during rest and test mode. AP scores at resting manner has nearing significance negative correlation with SMR standard deviation and NAP scores has nearing significance negative correlation with high beta (high inhibit) mean and positive correlation with alpha peak frequency standard deviation.

Comparing Means of Low and High Achieving Samples

The samples were categorized into high and low score groups based on their intuitive performance (AP and NAP scores), and heart rate and brain wave indices were compared between these groups to identify significant differences. The sample was categorized into low and high groups based on scores that fell outside the range of +/-1 standard deviation. The classifications indicate that there are 35 individuals in the low group (5 points and below) and 39 individuals in the high group (8 points and above) based on the AP scores, resulting in a total of 74 individuals. The NAP scores indicate that there are 46 individuals categorized in the low group (scores of 7 and below) and 40 individuals in the high group (scores of 10 and above), resulting in a cumulative total of 86 individuals. The differences between these groups were assessed using Mann Whitney U test to determine their significance.

Analysis of the differences in Heart Rate indices during rest and test between high and low achieving groups according to AP and NAP scores.

No significant differences were observed in AP scores for heart rate indices at rest between the high and low successful groups, with the exception of HF power. The analysis of disparities in HF power indices ($\bar{x}l$= 575.5 - $\bar{x}h$= 831.2) yielded MWU=223 with $p<.05$. The effect size computed for the Mann-Whitney U test was $r = .291$, indicating a medium effect size as per Cohen's (1988) standards. Furthermore, RMSSD, LnRMSSD, and PNN50 values also suggest a difference nearing significance. The MWU values are 232, 231, and 235.5, with corresponding significance values of .051, .051, and .06.

Table 2 presents analyses of Heart Rate Indexes in both rest and test states concerning NAP scores.

Table 2

Mann Whitney U Statistics for Disparities between Low and High Achieving Groups in NAP Scores during Rest and Test

	Resting					Testing				
Disparities between NAP scores of Low and High achieving groups	N L/H	Means L/H	MWU	Sig.	Effect size for MWU r	N L/H	Means L/H	MWU	Sig.	Effect size for MWU r
RMSSD	36/28	35,01/29,05	422	0,27	-0,14	**36/28**	**36,52/26,71**	**326,5**	**0,02**	**-0,30**
SDNN	36/28	54,14/49,28	386	0,11	-0,20	*36/28*	*59,72/45,72*	*360*	*0,05*	*-0,24*
LnRMSSD	36/28	3,41/3,28	424	0,28	-0,14	**36/28**	**3,49/3,20**	**331**	**0,02**	**-0,29**
PNN50	36/28	12,75/9,54	436	0,36	-0,12	*36/28*	*14,36/36,86*	*370*	*0,07*	*-0,23*
Mean RR Interval	36/28	740,56/711,63	390	0,12	-0,19	36/28	722,62/772,55	390	0,12	-0,19
Total Power	36/28	1922,02/1409,39	402	0,17	-0,17	**36/28**	**2338,17/1514,94**	**350**	**0,04**	**-0,26**
LF/HF Ratio	36/28	2,09/2,03	489,5	0,84	-0,02	36/28	2,19/2,37	476,5	0,71	-0,05
LF Power	36/28	1211,29/842,59	406	0,19	-0,17	**36/28**	**12051,53/789,16**	**279**	**0,00**	**-0,38**
HF Power	36/28	711,05/560,36	433	0,34	-0,12	**36/28**	**6026,23/464,53**	**339**	**0,03**	**-0,28**
LF Peak	36/28	0,09/0,09	492,5	0,88	-0,02	36/28	0,10/0,11	409,5	0,20	-0,16
HF Peak	36/28	5,01/0,23	439,5	0,38	-0,11	36/28	0,20/0,21	467	0,62	-0,06
HR Mean	36/28	83,19/86,50	388,5	0,12	-0,20	*36/28*	*85,56/89,54*	*370,5*	*0,07*	*-0,23*
HRV Mean	36/28	52,44/50,46	425	0,28	-0,13	**36/28**	**53,83/49,39**	**337**	**0,02**	**-0,28**

In the resting and testing state, while nearly all indices, except for the mean heart rate, are lower in the successful group, no differences are statistically significant in the resting state. The disparities in RMSSD, LnRMSSD, total power, LF power, HF power, and HRV mean values under the test condition are significant. The effect sizes are moderate in magnitude. Nonetheless, the values of SDNN, PNN50, and mean HR exhibit differences that approach statistical significance. All indices, with the exception of the HR mean, are significantly lower in the highly successful group.

In the test mode, RMSSD, SDNN, and HRV mean values exhibited a slight increase in the low successful group, whereas a decrease was observed in the high successful group compared to rest condition. A notable alteration in the rest and test conditions is the variation detected in LF and HF power. In the test condition, these values dramatically rose in the low successful group, whereas they either remained constant or exhibited a slight decrease in the high successful group.

Analysis of the differences in brainwave indices during rest and test between high and low achieving groups according to AP and NAP scores in the healthy samples data.

No significant differences were observed between the EEG indices of the high and low successful groups during the resting state concerning the AP scores. During the testing phase, a notable disparity was observed solely in the standard deviations of the Gamma waves. In the low-score group, the mean of the gamma standard deviations is $\bar{x}= 1.572$, whereas in the high-score group, this value is $\bar{x}= 1.014$. The MWU value is 218.5, with $p < 0.05$. The effect size computed for the Mann-Whitney U test is $r = 0.166$.

Significant differences were noted in the high beta (high inhibit) mean and alpha peak frequency standard deviation values of brain wave indices recorded during the resting state between high and low successful groups in NAP scores. The effect sizes (r) were moderate. The high beta (high inhibit) values of the highly successful group were found to be lower than those of the lowly successful group. Despite the alpha peak frequency values appearing similar, the mean ranks differ. The average rank of the low successful group is 25.57, whereas that of the high successful group is 36.94. No significant differences were detected between the NAP scores of the low and high successful groups regarding brain wave indices in the healthy sample data during the test state.

Correlations between Heart Rate and Brain Wave Indices during Rest and Test

Relationships between heart rate and brain wave indices in rest state

Analysis of Table 3 reveals bidirectional clusters of correlations between heart rate variability (HRV) and brain wave indices during the resting state. From the HRV perspective, LF peak (a marker of sympathetic activity) shows significant negative correlations with theta mean (rho = –.263, p < .01), low inhibit mean (rho = –.263, p < .01), theta/wide beta ratio (rho = –.223, p < .05), theta/SMR ratio (rho = –.215, p < .05), delta standard deviation (rho = –.204, p < .05), and theta standard deviation (rho = –.244, p < .01). It also demonstrates near-significant correlations with delta mean (rho = –.170, p > .05), theta/alpha ratio (rho = –.173, p > .05), and wide beta standard deviation (rho = .162, p > .05). These findings suggest that increased sympathetic activity is associated with suppression of slower brain rhythms linked to emotional processing and memory.

HF peak, reflecting parasympathetic activation, positively correlates with wide beta mean (rho = .202, p < .05), alpha peak frequency mode (rho = .193, p < .05), and SMR standard deviation (rho = –.188, p < .05), while negatively correlating with theta/wide beta ratio (rho = –.188, p < .05) and theta/SMR ratio (rho = –.196, p < .05). Near-significant associations are also observed with SMR mean (rho = .163, p > .05), reward mean (rho = .163, p > .05), and wide beta standard deviation (rho = .181, p < .05). These results imply that parasympathetic activation may enhance cognitive readiness and attention, although excessive levels might suppress inhibitory control under low arousal conditions.

From the EEG perspective, theta/wide beta ratio and theta/SMR ratio exhibit extensive connections to HRV indices. The theta/wide beta ratio is significantly correlated with SDNN (rho = .252, p < .01), total power (rho = .193, p < .05), LF power (rho = .235, p < .05), LF peak (rho = –.223, p < .05), and HF peak (rho = –.188, p < .05). It also shows near-significant correlations with RMSSD (rho = .185, p = .05), LnRMSSD (rho = .181, p > .05), PNN50 (rho = .173, p > .05), HF power (rho = .177, p > .05), and HRV mean (rho = .179, p > .05). The theta/SMR ratio is significantly correlated with SDNN (rho = .222, p < .05), LF power (rho = .207, p < .05), LF peak (rho = .207, p < .05), and negatively with HF peak (rho = –.189, p < .05). These relationships underscore the regulatory function of autonomic flexibility in balancing attentional control and emotional regulation.

Finally, wide beta standard deviation, an indicator of cognitive stress, negatively correlates with nearly all HRV indices: RMSSD (rho = –.218, p < .05), SDNN (rho = –.252, p < .01), LnRMSSD (rho = –.220, p < .05), PNN50 (rho = –.193, p < .05), total power (rho = –.196, p < .05), LF power (rho = –.214, p < .05), HF power (rho = –.192, p < .05), and HRV mean (rho = –.215, p < .05). Additional near-significant associations are found with LF peak (rho = .162, p > .05) and HF peak (rho = .181, p < .05). These correlations indicate that increased variability in beta activity may be linked to reduced autonomic adaptability and higher stress sensitivity.

In summary, the resting-state data suggest that LF and HF peaks are central HRV indices associated with shifts in cortical activity, particularly in theta and SMR-related waveforms. Conversely, from the EEG perspective, theta-based ratios and wide beta variability appear to be the most sensitive to changes in autonomic regulation. These findings highlight a reciprocal, tightly coupled relationship between cardiac and neural systems in supporting emotional balance, attentional control, and cognitive resilience.

Table 3

All Correlations between Heart Rate and Brain Wave Indices during Rest and Test.

	RMSSD	SDNN	LnRMSSD	PNN50	MRRINT	Total Power	LF/HF ratio	LF Power	HF Power	LF Peak	HF Peak	HR Mean	HRV Mean
Delta Mean										-R◐			
Theta mean										-R◉**			
Alpha mean							T◉*		-T◐				
SMR mean					-R◉*						R◐	R●*	
Wide Beta mean		-R◐	-R◐								R◉*		
High Beta mean													
Gamma mean													
Lowinhibit Mean										-R◉**			
Reward mean					-R◉*						.R◐	.R◉*	
High Inhibit Mean													
Theta/Alpha means ratio		R◐		T◐	T◉*/R◐		-T◉*			-R◐	T◉*	-T◉*/R◐	
Theta/Wide Beta means ratio	R◐	R◉**	R◐	R◐		R◉*		R◉*	R◐	-R◉*	-R◉*		R◐
Theta/SMR means ratio		R◉*						R◉*		-R◉*	T◐/-R◉*	-T◐	
Alpha Peak Frequency mean													
Alpha Peak Freq Std. Dev.													
Alpha Peak Frequency mode	-T◐	-T◉**	-T◐	-T◐		-T◉*		-T◉*	-T◐		R◉*		
Delta Standard Deviation										-R◉*			
Theta Standard Deviation										-R◉*			
Alpha Standard Deviation					-.R◐		.T◉*		-T◐			.R◐	
SMR Standard Deviation		.R◐			-.T◐/-R◐						R◉*	.T◐/.R◐	
Wide Beta Standard Deviation	-R◉*	-R◉*	-R◉*	-R◉*		-R◉*		-R◉*	-R◉*	R◐	R◐		-R◉*
High Beta Standard Deviation													
Gamma Standard Deviation													

T: Testing State, R: Resting, -:Negative Corr., ◉: Significant (p<.05), ◐: Near Significant (p=.05-.10), *: P<.05, **:P<.01, No star: Not significant. (Highlighted bands denote regions of increased correlational density across physiological domains).

Relationships between heart rate and brain wave indices in testing state

Testing-state data reveals significant and near-significant correlations between heart rate variability (HRV) metrics and brain wave activity, particularly involving the theta/alpha ratio and the alpha peak frequency mode. These findings reflect the dynamic interplay between autonomic regulation and cortical processes related to attention, emotional control, and cognitive resilience.

From the HRV perspective, the LF/HF ratio is significantly correlated with alpha mean (rho = .223, p < .05), alpha standard deviation (rho = .219, p < .05), and the theta/alpha ratio (rho = –.220, p < .05). Additionally, HR mean negatively correlates with the theta/alpha ratio (rho = –.204, p < .05), suggesting that increased sympathetic activity or physiological arousal is linked to reduced attentional regulation.

Near-significant correlations are also found between the theta/SMR ratio (rho = –.160, p > .05) and SMR standard deviation (rho = .168, p > .05), both of which are associated with motor inhibition and cognitive control. These patterns imply that stress-induced autonomic shifts may lead to reduced cognitive inhibition and greater distractibility during task performance.

The theta/alpha ratio demonstrates significant correlations with MRRINT (rho = .209, $p < .05$), LF/HF ratio (rho = –.220, $p < .05$), HF peak (rho = .193, $p < .05$), and HR mean (rho = –.204, $p < .05$). A near-significant association with PNN50 (rho = .167, $p > .05$) is also observed. The inverse relationship between theta/alpha ratio and sympathetic markers suggests that parasympathetic shifts may promote attentional focus and reduce stress-related interference, while sympathetic activation disrupts this balance.

Significant negative correlations are also observed between the alpha peak frequency mode and several HRV indicators: SDNN (rho = –.205, $p < .05$), total power (rho = –.218, $p < .05$), and LF power (rho = –.208, $p < .05$). Additional near-significant associations are noted with RMSSD (rho = –.162, $p > .05$), LnRMSSD (rho = –.170, $p > .05$), PNN50 (rho = –.175, $p > .05$), and HF power (rho = –.159, $p > .05$). These relationships suggest that autonomic rigidity, reflected in lower HRV, may impair cognitive flexibility and emotional regulation. The alpha peak frequency mode, often associated with cognitive readiness and processing efficiency, emerges as a sensitive marker of stress-related autonomic shifts.

Multiple Regression Analyses for AP and NAP Success Taking Heart Rate and Brainwave Indices as Predictors

Not any variable of heart rate indices and brainwaves significantly predict AP scores either in rest or test mode except for gamma standard deviation in test mode. But some variables both of heart rate and brain waves significantly predict NAP success.

When NAP score variable set dependent, normal P-P plot of regression standardized residuals shows highly positive correlation supporting the normality of the residuals. As for homoscedasticity, scatterplot of standardized residual with standardized predicted values demonstrates almost zero correlation with a shape of a cone with no outfit

Table 4

Stepwise Regression Model Summary

Model Summary[e]

					Change Statistics					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.272[a]	.074	.065	1.74	.074	8.39	1	105	.005	
2	.375[b]	.141	.124	1.69	.067	8.07	1	104	.005	
3	.416[c]	.173	.149	1.66	.032	4.03	1	103	.047	
4	.452[d]	.204	.173	1.64	.031	4.04	1	102	.047	2.503

a. Predictors: (Constant), Heart Rate Variability Mean

b. Predictors: (Constant), Heart Rate Variability Mean, Frequency Domain Low Frequency Peak

c. Predictors: (Constant), Heart Rate Variability Mean, Frequency Domain Low Frequency Peak, Wide beta mean

d. Predictors: (Constant), Heart Rate Variability Mean, Frequency Domain Low Frequency Peak, Wide beta mean, SMR Ss.

e. Dependent Variable: NAP score. (Intuition as extrasensory perception)

Model summary shows adjusted R square and change statistics when each independent variable entered. The first independent variable entered is HRV which represents .065 of dependent NAP scores. The next independent entered is LF peak and the model with both variables represents .124 of change in NAP scores, the third is wide beta mean and with it, the model represents .149 of change and last entered independent is SMR standard deviation and the model turns out to represent .173 of the change in the dependent variable that is NAP scores. All Anova values of change are statistically significant. Durbin Watson value estimated is 2.503 indicating there is no autocorrelation.

Table 5

Stepwise Regression Anova Table

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	25.504	1	25.504	8.395	.005[b]
	Residual	319.000	105	3.038		
	Total	344.505	106			
2	Regression	48.469	2	24.234	8.514	.000[c]
	Residual	296.036	104	2.846		
	Total	344.505	106			
3	Regression	59.610	3	19.870	7.184	.000[d]
	Residual	284.894	103	2.766		
	Total	344.505	106			
4	Regression	70.450	4	17.613	6.555	.000[e]
	Residual	274.054	102	2.687		
	Total	344.505	106			

a. Dependent Variable: NAP score (Intuition as extrasensory perception)
b. Predictors: (Constant), Heart Rate Variability Mean
c. Predictors: (Constant), Heart Rate Variability Mean, Frequency Domain Low Frequency Peak
d. Predictors: (Constant), Heart Rate Variability Mean, Frequency Domain Low Frequency Peak, Wide beta mean
e. Predictors: (Constant), Heart Rate Variability Mean, Frequency Domain Low Frequency Peak, Wide beta mean, SMR Standard Deviation

Anova statistics in the table above displays all independent variables entered stepwise has statistically significant effect on dependent variable. Also the table below displays the standardized beta coefficients when each independent variable entered. All VIF statistics are below 10, tolerance values are above .100 and condition indexes for collinearity diagnostics below 30 proving that no perfect multicollinearity.

Table 6

Stepwise Regression Coefficients

Coefficients[a]							
	Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
Model	B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1(Constant)	11.839	1.214		9.751	.000		
Heart Rate Variability Mean	-.067	.023	-.272	-2.897	.005	1.000	1.000
2(Constant)	10.619	1.251		8.488	.000		
Heart Rate Variability Mean	-.080	.023	-.324	-3.494	.001	.961	1.040
Frequency Domain Low Frequency Peak	17.986	6.332	.263	2.840	.005	.961	1.040
3(Constant)	11.301	1.279		8.835	.000		
Heart Rate Variability Mean	-.082	.023	-.333	-3.639	.000	.959	1.043
Frequency Domain Low Frequency Peak	16.079	6.314	.235	2.546	.012	.940	1.064
Wide Beta Mean	-.116	.058	-.182	-2.007	.047	.971	1.030
4(Constant)	11.348	1.261		8.999	.000		
Heart Rate Variability Mean	-.082	.022	-.334	-3.705	.000	.959	1.043
Frequency Domain Low Frequency Peak	14.103	6.300	.206	2.238	.027	.917	1.091
Wide Beta Mean	-.248	.087	-.390	-2.852	.005	.418	2.394
SMR Standard Deviation	.372	.185	.271	2.009	.047	.429	2.329

a. Dependent Variable: NAP scores

These four variables represent a .173 change in NAP, whereby a decrease in HRV and wide beta mean corresponds with an increase in NAP. As the LF peak and SMR standard deviation rise, the NAP escalates.

DISCUSSION AND CONCLUSION

There is no single scientific answer to the question of what intuition is. In the literature, intuition is sometimes described as the ability to rapidly interpret explicit and implicit cues based on prior experience—essentially an analytical, pattern-recognition-driven process (Simon, 1990; Gigerenzer, 2007; Evans & Stanovich, 2013). In contrast, other scholars and theoretical frameworks define it as a non-analytical form of insight—a spontaneous sense or inner knowing that arises without deliberate reasoning (Damasio, 1994; McCraty, 2015; Holzer, 2022). These divergent perspectives raise the question of whether intuition is a unified faculty or a multifaceted construct with distinct cognitive and physiological bases.

This study approached intuition as a multidimensional construct and examined whether two types of intuitive performance—analytical perception (AP) and non-analytical perception (NAP)—differentially engage the heart–brain axis. Specifically, correlations between heart rate variability (HRV) and EEG signals during rest and task phases were examined, and physiological and neural predictors of AP and NAP performance were identified.

Physiological Patterns Associated with AP and NAP

AP performance showed significant positive correlations with HRV indices such as RMSSD, LnRMSSD, PNN50, HF power, and HRV mean during resting conditions. These markers of parasympathetic dominance suggest that analytical intuition is associated with a calm and regulated physiological state. This aligns with the somatic marker hypothesis (Damasio, 1994) and McCraty and Zayas (2014), who emphasized the role of autonomic balance in enhancing emotional and attentional regulation. Notably, no significant HRV correlations were found for AP during task conditions, implying that its success relies more on baseline readiness than real-time physiological shifts.

In contrast, NAP presented a markedly different physiological profile. At rest, it was positively correlated with heart rate mean and negatively with R-R interval, reflecting elevated arousal. During task performance, NAP scores were negatively correlated with nearly all HRV indices—RMSSD, SDNN, PNN50, LF power, HF power, and HRV mean—and positively with heart rate mean. These patterns are consistent with models linking intuitive insight to sympathetic activation and reduced vagal control (Bechara & Damasio, 2005; Evans & Stanovich, 2013).

Supporting these results, Rezaei et al. (2014) expanded McCraty's protocol (2004a, 2015), showing that intuitive pre-stimulus responses, measured through HRV, can be enhanced in socially coherent dyads. This reinforces the importance of contextual and relational dynamics in intuitive processing.

EEG Correlates of AP and NAP

EEG data further distinguished the two types of perception. AP did not show significant EEG correlations, though a trend-level negative association with SMR standard deviation was observed, suggesting that cortical stability may support AP. In contrast, NAP was associated with increased high beta activity and variability in alpha peak frequency, particularly during testing. These neural markers are typically linked to heightened attentional flexibility and arousal, supporting the non-conscious nature of NAP (Pennington et al., 2019; Sood & Singh, 2018; Azhari & Hernandez, 2016).

Discrepancies in Mean Comparisons

Table 7

Summary of significant and near-significant correlations between AP and NAP task scores and physiological indices (HRV and EEG) during rest and task conditions.

		TYPE OF INDICES			
		Heart Rate		Brain Waves	
		Resting	Testing	Resting	Testing
Correlations (Rho)	Analytical Perception Scores (AP)	+◉ RMSSD +◉ LnRMSSD +◉ PNN50 +◉ HF Power +◉ HRV Mean	NO	+◐ SMR Std.Dev.	NO
	Non-analytical perception (NAP) Scores	-◉ MRRInt +◉ HR mean	-◉ RMSSD -◉ SDNN -◉ LnRMSSD -◉ PNN50 -◉ MRRINT -◉ Total Power -◉ LF Power -◉ HF Power +◉ HR mean -◉ HRV Mean	-◐ High Beta Mean -◐ High Inhibit Mean +◐Alpha Peak Frequency Std.Dev.	NO
Compare Means (MWU)	Analytical Perception (AP) Scores	◐RMSSD $\bar{x}l>\bar{x}h$ ◐LnRMSSD $\bar{x}l>\bar{x}h$ ◐PNN50 $\bar{x}l>\bar{x}h$ ◉HF Power $\bar{x}l<\bar{x}h$	NO	NO	◉Gamma Std. Dev. $\bar{x}l>\bar{x}h$
	Non-analytical perception (NAP) Scores	NO	◉ RMSSD $\bar{x}l>\bar{x}h$ ◐ SDNN $\bar{x}l>\bar{x}h$ ◉ LnRMSSD $\bar{x}l>\bar{x}h$ ◐ PNN50 $\bar{x}l>\bar{x}h$ ◉ Total Power $\bar{x}l>\bar{x}h$ ◉ LF Power $\bar{x}l>\bar{x}h$ ◉ HF Power $\bar{x}l>\bar{x}h$ ◐ HR Mean $\bar{x}l<\bar{x}h$ ◉ HRV Mean $\bar{x}l>\bar{x}h$	◐ High Beta Mean $\bar{x}l>\bar{x}h$ ◐ High Inhibit Mean $\bar{x}l>\bar{x}h$ ◐ Alpha Peak Frequency Ss $\bar{x}l>\bar{x}h$	NO.

◉ *Significant (p<.05),* ◐ *Nearly Significant (p= .05 - .10), "+" positive correlation, "-" negative correlation,*

Table 7 presents a summary of all correlation and disparity findings. Differential analyses showed that during rest, individuals with higher AP scores had significantly lower values in RMSSD, LnRMSSD, and PNN50, but higher HF power. Interestingly, these indices were also positively correlated with AP in correlation analyses. There exists a positive correlation between AP scores and RMSSD during rest mode. In other words, it is concluded that as AP scores rise, the RMSSD value also increases. Nevertheless, differential analyses reveal that the RMSSD values of individuals with elevated AP scores are significantly lower than those with diminished AP scores. This suggests that while AP is associated with overall parasympathetic tone, high performers may display more efficient or "economical" physiological patterns.

In terms of EEG, only gamma standard deviation during the test phase significantly differed, with higher variability observed in the low-performing group, potentially reflecting instability in cortical arousal (McCraty et al., 2004b).

For NAP, significant differences in HRV emerged only during the task phase. High NAP scorers showed lower values in RMSSD, LnRMSSD, total power, LF power, HF power, and HRV mean. Additionally, SDNN, PNN50, and mean heart rate showed trends toward significance. These results underscore the association of NAP with elevated physiological arousal under cognitive demand.

EEG findings for NAP further supported these physiological patterns. Significant differences were found in resting high beta and inhibit mean levels, as well as in alpha peak frequency standard deviation, which was higher in the high NAP group. These differences suggest increased cortical excitation and flexible frequency modulation as neural traits that accompany non-analytical processing (Soosalu et al., 2019).

Heart-Brain Interaction Insights

The interplay between HRV and EEG activity was also analyzed to understand heart-brain synchrony. At rest, LF peak showed significant negative correlations with slow-wave EEG patterns such as theta mean, theta/alpha ratio, and theta/SMR ratio, as well as with delta and theta standard deviations. This suggests that elevated sympathetic activity may suppress slower rhythms linked to emotional processing and memory (Lacey & Lacey, 1978; Tiller et al., 1996).

Conversely, HF peak positively correlated with wide beta mean and alpha peak frequency mode, suggesting that parasympathetic activity facilitates cognitive alertness. However, negative associations between HF peak and theta-related ratios imply that excessive vagal tone may disrupt introspective or memory-linked processes. These dynamics highlight the importance of autonomic flexibility in emotional and attentional regulation (McCraty, 2000; Dunn et al., 2010).

Under task conditions, a positive correlation was found between the theta/alpha ratio and mean R-R interval (MRRINT), and a negative one with the LF/HF ratio. This suggests that parasympathetic dominance enhances attentional control, whereas sympathetic activation impairs it. Additionally, alpha peak frequency mode negatively correlated with SDNN, LF power, and total power, supporting the notion that physiological rigidity undermines mental efficiency (Zion-Golumbic, 2007).

Consistent findings across rest and task conditions point to the theta/wide beta ratio as a critical balancing metric. Its positive correlations with HRV indices highlight the role of autonomic flexibility, while its negative associations with LF and HF peaks imply that extremes in autonomic activation can destabilize attentional control.

Wide beta standard deviation exhibited strong negative correlations with HRV measures, implying that increased variability in this band, often linked to stress and cognitive overload, reduces autonomic adaptability and emotional resilience.

Regression-Based Predictors of Intuition

Regression analyses revealed four physiological predictors that together explained 17.3% of the variance in NAP scores. Specifically, HRV mean (negative), LF peak (positive), wide beta mean (negative), and SMR standard deviation (positive) emerged as significant contributors. These findings suggest that non-analytical intuitive performance is supported by a unique blend of heightened sympathetic arousal (LF peak), cortical modulation (SMR variability), and reduced physiological coherence (low HRV mean). Notably, no significant predictors emerged for AP performance, reinforcing the idea that its effectiveness may be grounded in stable physiological coherence rather than dynamic task-related fluctuations.

Educational Significance of Intuitive Thinking in the Post-Technological Era

Beyond its theoretical implications, the present findings carry meaningful relevance for education, teacher training, and school leadership. The differentiation between analytical and non-analytical intuition observed in the physiological data suggests that intuition is not a vague or mystical construct, but a measurable and trainable aspect of human cognition. In educational contexts, fostering intuitive awareness alongside analytical reasoning may enhance teachers' and learners' capacity to make rapid, context-sensitive decisions—skills that are increasingly vital in complex learning environments. As artificial intelligence and digital technologies progressively assume routine, analytical, and data-driven tasks, the uniquely human capacities for creativity, intuitive judgment, and emotional attunement gain heightened importance. Developing these capacities through reflective pedagogical practices and teacher education programs can help prepare individuals for a post-technological era in which human intuition and adaptive insight complement, rather than compete with, intelligent systems. Thus, the current study contributes to the growing body of evidence supporting the integration of intuitive thinking as a critical component of educational innovation and professional development in the age of AI.

Implications and Future Directions

Collectively, these results suggest that elevated HRV—an index of autonomic balance—supports attentional regulation and emotional resilience, whereas dysregulated HRV is linked to disruptions in EEG patterns critical for intuitive cognition. These findings echo previous work (e.g., Rein et al., 1995) on the regulatory role of heart rhythms in emotional and stress responses.

In conclusion, AP and NAP represent distinct modes of intuitive cognition with unique neurophysiological signatures. AP is supported by baseline parasympathetic regulation and coherence, whereas NAP relies on heightened arousal and dynamic brain activity. This differentiation advances embodied cognition theory and offers practical strategies to enhance intuitive functioning through physiological training.

Future studies should consider integrating IQ measures to explore their interaction with intuition. Test item design could be expanded to improve discrimination between AP and NAP processes. Additionally, allowing HRV and EEG data collection during separate task phases may yield cleaner results. Broader demographic sampling and longitudinal designs would further support the generalizability of the physiological markers identified here.

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Conflict of Interest Statement

The author declares that there are no conflicts of interest or competing interests associated with this study.

Ethical Approval Statement

Throughout the entire process of planning, conducting, data collection, and analysis, all ethical principles outlined in the *Higher Education Institutions Scientific Research and Publication*

Ethics Directive were strictly followed. None of the acts specified under the section titled "Actions Contrary to Scientific Research and Publication Ethics" were committed. During the writing process, scientific ethical standards and citation rules were observed, no manipulation was performed on the collected data, and this study has not been submitted to any other academic publication platform for evaluation.

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Supplementary Tables

Supplementary Table 1.

Heart Rate Indices

Time Domain Indices
RMSSD (Root mean square of successive RR interval differences)
SDNN (Standard deviation of NN intervals)
LnRMSSD (Natural Logaritm of Root mean square of successive RR interval differences)
PNN50 (Percentage of successive RR intervals that differ by more than 50 ms)
MRRINT (Mean of ***interbeat intervals* (IBI) *between all successive heartbeats)***
Frequency Domain Indices
Total Power (Total ***Power*** is the signal energy found within a frequency band)
LF/HF Ratio (Ratio of LF-to-HF power)
LF Power (Relative power of the low-frequency band, 0.04–0.15 Hz, in normal units)
HF Power (Relative power of the high-frequency band (0.15–0.4 Hz) in normal units)
LF Peak: Peak frequency of the low-frequency band (0.04–0.15 Hz)
HF Peak: Peak frequency of the high-frequency band (0.15–0.4 Hz).
Heart Rate Indices
HR Mean (Heart rate mean a minute)
HRV Mean (Heart rate variability mean).

(Schafer and Ginsberg, 2017)

Supplementary Table 2.

Brain Wave Indices and Their Functions

Brain Waves (Campbell et al., 2021).
Delta (0.5–4 Hz): are linked to deep sleep and restorative processes
Theta(4–8 Hz: are associated with drowsiness and creativity
Alpha (8-12 Hz): indicate a relaxed yet alert state
SMR- Sensorimotor Rhythm (11-14 Hz): is associated with a calm, focused state, active intelligence.
Wide Beta (12-30 Hz): are related to active thinking and problem-solving
High Beta (21-30 Hz)
Gamma (30-90 Hz): are involved in high-level cognitive functions such as perception and consciousness
Some other EEG Metrics

Low Inhibit (Theta): reflect the intricate balance of excitatory processes in the brain and is associated with increased neuronal activity and higher frequency waveforms (Taylor et al., 2023).
Reward Positivity (SMR): linked to the processing of positive feedback or rewards and is indicative of dopaminergic signaling and is sensitive to the value of rewards, highlighting its role in learning and decision-making processes (Allen et al., 2020).
High Inhibit (High Beta) : reflects the balance of inhibitory processes and leads to reduced activity characteristic suppression patterns (Taylor et al., 2023).
Theta/Alpha ratio: reflects the balance between the slower Theta waves, which are associated with daydreaming and inattention, and the faster Alpha waves. High ratio indicates a potential marker for cognitive dysfunction and attentional issues (Clarke et al., 2002; Becerra et al., 2006; Fernández et al., 2003).
Theta/Wide beta ratio: provide insights into cognitive workload and mental engagement. Increased Theta activity relative to beta waves can indicate a state of cognitive overload or distraction (Rojas et al., 2020; Raufi & Longo, 2022).
Theta/SMR (Sensorimotor Rhythm) ratio: Higher Theta relative to SMR can indicate increased anxiety or cognitive disorganization (Kopańska, 2023; Reichert et al., 2016). Decrease in Theta/SMR ratio can lead to improved performance in tasks requiring concentration and reduced anxiety levels (Reichert et al., 2016; Fernández et al., 2015)

GENİŞ ÖZET

Giriş

Sezgi, felsefe ve psikoloji kesişiminde çok yönlü bir kavramdır. Felsefi açıdan sezgi, doğrudan ve aracısız hakikati kavrama biçimi olarak tanımlanırken (Gündoğan, 2024; Bibika, 2024; Soyaslan, 2024), psikoloji literatüründe hızlı, bilinçdışı ve duygusal temelli bir süreç olarak görülmektedir (Hammond, 1996; Pretz ve ark., 2014). Çift süreçli teoriler, sezgiyi bilinçdışı, otomatik ve evrimsel olarak uyum sağlayıcı bir mekanizma olarak ele alır (Gore & Saddler-Smith, 2011; Cai Shi & Lucietto, 2022). Bununla birlikte sezgi, tek boyutlu bir yapı değil; bağlam, işlev ve bilişsel süreçlere göre çeşitlilik gösteren çok yönlü bir olgudur (Glöckner & Witteman, 2010; McCraty, 2015). Bu nedenle sezgi; analitik algı (AP), yani daha çok deneyim ve şemalara dayalı, bilinçli işleme yakın süreçler; ve analitik olmayan algı (NAP), yani duygusal, bedensel ipuçlarına dayalı, bilinçdışı sezgisel süreçler şeklinde iki boyutta incelenmektedir.

Son yıllarda özellikle kalp-beyin etkileşiminin sezgisel süreçlerde rol oynadığına dair bulgular ön plana çıkmıştır (Damasio, 1994; Holzer, 2022; McCraty, 2015). Kalp atım hızı değişkenliği (HRV) ve elektroensefalogram (EEG) göstergeleri, sezginin fizyolojik karşılıklarını anlamada önemli araçlar olarak kullanılmaktadır. McCraty ve Zayas (2014), kalp ritmindeki uyumun duygusal düzenleme ve sezgisel erişimi kolaylaştırdığını belirtirken; Azhari ve Hernandez (2016) EEG çalışmalarında sezgisel bireylerde artan theta ve alfa aktivitelerine dikkat çekmiştir. Bu noktadan hareketle, çalışmanın önemi, sezgisel süreçlerin yalnızca bilişsel değil, aynı zamanda fizyolojik dayanaklara sahip olup olmadığını araştırmasıdır. Bu bağlamda araştırmanın amacı, AP ve NAP'ın kalp-beyin eksenindeki farklı fizyolojik yansımalarını incelemek, HRV ve EEG göstergelerinin bu iki sezgi türüyle ilişkisini ortaya koymak ve olası yordayıcı değişkenleri belirlemektir.

Yöntem

Araştırma, Kocaeli Üniversitesi Eğitim Fakültesi öğrencileri üzerinde yürütülmüştür. Çalışmaya 19–23 yaş aralığında, farklı bölümlerden 147 öğrenci katılmış, psikolojik sağlık düzeyi belirlenen eşik değerin altında kalan veya psikiyatrik tanısı olan katılımcılar çıkarıldıktan sonra analizler 110 sağlıklı öğrenci üzerinden yapılmıştır. Araştırma deseni ilişkisel tarama modeline dayanmaktadır. Katılımcılar hem dinlenme hem de test koşullarında iki tür görev tamamlamışlardır: AP görevleri görünür ipuçlarına dayalı analitik çözümlemeyi, NAP görevleri ise herhangi bir ipucu içermeyen tamamen sezgisel yanıtları ölçmüştür. Görevler uzman görüşü ve pilot uygulamalarla geçerlikten geçirilmiş, nihai testte AP için 12, NAP için 18 madde yer almıştır.

Veri toplama sürecinde KYTO2935 HRV sensörü ve Elite HRV uygulaması ile kalp atım hızı verileri, Procomp Infiniti EEG cihazı ve Biograph Infiniti yazılımı ile beyin dalgaları kaydedilmiştir. Ölçümler katılımcıların kulak ve baş bölgelerinden, dinlenme ve test sırasında beşer dakika süreyle alınmıştır. Veriler SPSS 27 yazılımında analiz edilmiştir. Korelasyon analizlerinde Spearman rho, grup karşılaştırmalarında Mann Whitney U, yordayıcı değişkenlerin belirlenmesinde ise adımsal regresyon analizi kullanılmıştır.

Bulgular

Analizler, AP ve NAP'ın farklı fizyolojik profillere sahip olduğunu ortaya koymuştur. Dinlenme durumunda AP puanları RMSSD, PNN50, HF gücü ve HRV ortalaması gibi parasempatik etkinlik göstergeleriyle pozitif ilişkili bulunmuştur. Bu sonuç, analitik sezginin daha çok sakinlik, düzenli kalp ritmi ve otonom dengeyle bağlantılı olduğunu göstermektedir. Buna karşın NAP puanları test sırasında çoğu HRV göstergesiyle negatif yönde, ortalama kalp atım hızıyla pozitif yönde ilişkilendirilmiştir. Yani, yüksek NAP performansı, artmış uyarılma ve azalmış otonom esneklik ile ilişkilidir.

EEG bulguları AP için belirgin bir korelasyon göstermemiştir; ancak SMR standart sapmasıyla negatif yönde eğilim düzeyinde bir ilişki gözlenmiştir. NAP ise yüksek beta aktivitesi ve alfa tepe frekansı değişkenliği ile ilişkili bulunmuştur. Bu durum, NAP'ın daha çok kortikal uyarılma ve esneklikle desteklendiğini işaret etmektedir. Grup karşılaştırmalarında, yüksek ve düşük başarı düzeyine sahip katılımcılar arasında özellikle test koşullarındaki HRV değerleri ve dinlenme sırasında EEG desenlerinde anlamlı farklılıklar ortaya çıkmıştır.

Adımsal regresyon analizleri sonucunda NAP puanlarını anlamlı düzeyde yordayan dört değişken belirlenmiştir: HRV ortalaması (negatif), LF tepe değeri (pozitif), geniş beta ortalaması (negatif) ve SMR standart sapması (pozitif). Bu model, NAP varyansının %17,3'ünü açıklamaktadır. Buna karşın AP için anlamlı bir yordayıcı bulunmamıştır.

Sonuç ve Tartışmalar

Araştırmanın sonuçları, AP ve NAP'ın kalp-beyin etkileşiminde farklı fizyolojik mekanizmalarla desteklendiğini ortaya koymuştur. AP, dinlenme halinde yüksek parasempatik etkinlik ve düzenli kalp ritmiyle bağlantılıdır. Bu, daha sakin ve istikrarlı bir otonom sistemin analitik sezgiyi desteklediğini göstermektedir. NAP ise artmış kalp atım hızı, düşmüş HRV göstergeleri ve yüksek kortikal uyarılmayla ilişkili bulunmuştur. Dolayısıyla analitik olmayan sezgi, dinamik uyarılma ve nöral esneklik üzerinden işlev görmektedir.

Bu bulgular, sezgiyi tek bir bilişsel süreç yerine çok boyutlu bir yapı olarak kavramsallaştırmayı desteklemektedir. Ayrıca, kalp-beyin etkileşiminin sezgisel karar verme süreçlerinde oynadığı rolü vurgulamakta ve sezginin fizyolojik dayanaklarını ortaya koymaktadır. McCraty (2000, 2015) ve Damasio'nun (1994) kalp ve duyguların karar verme süreçlerindeki rolünü ön plana çıkaran çalışmalarıyla tutarlılık göstermektedir. Özellikle NAP'ın artmış uyarılma ve yüksek beyin dalgası değişkenliği ile desteklenmesi, beden sinyalleri ve duygusal süreçlerin sezgisel başarıdaki önemini pekiştirmektedir.

Sonuç olarak, çalışma analitik ve analitik olmayan sezgiyi ayırt eden fizyolojik göstergeleri ortaya koyarak sezgi araştırmalarına katkı sağlamaktadır. Eğitim, klinik uygulamalar ve karar verme alanlarında, bireylerin sezgisel yetkinliklerini geliştirmeye yönelik fizyolojik farkındalık ve düzenleme stratejilerinin önemine işaret etmektedir. Gelecek araştırmaların farklı yaş ve kültürel gruplarda tekrarlanması, uzunlamasına tasarımlar ve daha ayrıntılı görev çeşitlendirmeleriyle bu bulguların genellenebilirliği artırılabilir.