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Challenge and Threat Appraisal of Tests in High School: Integrating Educational Psychology and Biopsychology Improves Understanding of How Students Take Tests

SUPPLEMENTARY MATERIALS

Roger Kennett[1], Andrew J. Martin[1], Joel Pearson[1], Emma C. Burns[2], Rebecca J. Collie[1]

[1] University of New South Wales, Australia
[2] Macquarie University, Australia

Physio-psychological Measures: Sympathetic Arousal via EDA

Electrodermal Activity (EDA) provides an accessible measure from which sympathetic arousal can be inferred. The "fight-or-flight" response is a neurological reaction that significantly impacts physiology by preparing an individual to respond to a stressor. This response is a fundamental manifestation of approach or avoidance behavior, conserved across nearly all animals (McCarty, 2016). Within the brain, the amygdala processes sensory information and signals the hypothalamus. Upon perceiving a stressor, the sympathetic nervous system primes the body for action, evident through increased heart rate, breathing rate, and glucose release, regardless of whether the subsequent appraisal leads to fighting or fleeing. Relevant to the present investigation, sympathetic arousal indicates the intensity of the fight-or-flight response (Pijeira-Díaz et al., 2019).

Importantly, sympathetic arousal is not synonymous with challenge and threat, as it operates independently for two primary reasons. First, it does not convey information about whether the action will be to fight or flee (Wilhelmsen, 2000). Second, it is an immediate and subconscious response, potentially moderated later by cortical brain areas (Derakhshan et al., 2019; Tranel & Damasio, 1994). Originating in the brain, sympathetic arousal falls under the domain of neuroscience (Harmon-Jones & Van Honk, 2012); however, due to its measurement through physiological responses, it is categorized as a physio-psychological measure.

Given its direct relevance to student appraisals and its potential to uncover a unique dimension related to their orientation toward science tasks (Gillies et al., 2016; Kennett, 2020; Kennett et al., 2023; Martin, Ginns, et al., 2021; Martin, Kennett, et al., 2021; Martin et al., 2023), the present research utilized a measure of sympathetic arousal inferred from EDA analysis. EDA is one of the least invasive and most accessible measures, exclusively innervated by the sympathetic nervous system (Kreibig, 2010). Justifying the use of EDA to derive sympathetic arousal necessitates a comprehensive understanding of the origins of EDA, along with an analysis of the signal and the pragmatics of signal and noise separation.

It Starts in the Brain

In his 2002 review, Critchley summarized studies on the correlation between EDA and brain activity. He used evidence to demonstrate that the skin is highly connected to the central nervous system and brain activity, including arousal and task engagement. Mediated by the hypothalamus, these signals to the sweat glands are part of the sympathetic nervous system and play a vital role in homeostasis. Notably, control of sweat glands, and hence measures of EDA, is one of the few autonomic actions solely under the control of the sympathetic nervous system without innervation by the parasympathetic nervous system.

Empirical evidence for the connection between the skin and the brain was established by Critchley et al. (2000), who used fMRI to monitor active brain regions as subjects engaged in demanding cognitive tasks, specifically a gambling exercise that required attention and complex decision-making, while simultaneously recording their electrodermal activity (EDA). Critchley demonstrated a correlation between the decision's risk level, fMRI indicators of arousal, and, notably, EDA levels.

Since then, EDA and other measures of autonomic correlation with emotion have been extensively investigated. Kreibig (2010), in a meta-analysis of 134 studies on the autonomic correlates of emotion, found that 88 published studies used at least one measure of EDA, making it nearly as prevalent as cardiovascular measures. While there is still much to be understood, EDA remains an accessible, non-invasive, and valid measure of the sympathetic branch of the autonomic nervous system from which sympathetic arousal can be reasonably inferred. This measure is particularly appropriate for studies involving student samples in naturalistic settings, such as classrooms.

Getting Under Our Skin

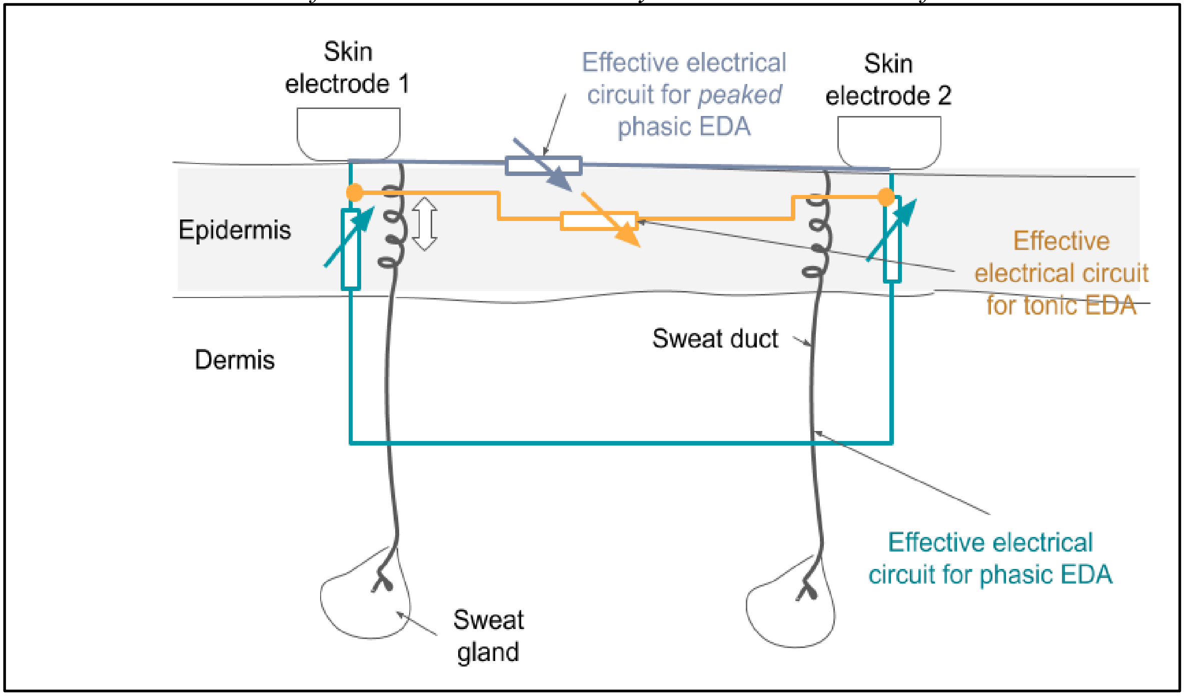
Having established the neurological origins of EDA, it is helpful to outline the relevant physiology of the skin to understand the various components of EDA. This understanding is significant when justifying the use of a specific component, phasic EDA, to operationalize sympathetic arousal relevant in academic tasks and assessments (Posada-Quintero & Chon, 2019).

Mechanisms Driving EDA. In his volume on EDA, Boucsein (2012) outlined the origins of the skin's electrical activity. The sweat gland contracts due to the firing of the sudomotor nerve, which has been observed to fire at frequencies up to 2 Hz (Boucsein, 2012). Sweat rises in the duct, and when it reaches the epidermis, the column of sweat provides a conductive pathway between an electrode on the skin surface and the more conductive dermis. The electrical pathway continues through the dermis to another filled sweat duct, completing the circuit to a second skin electrode.

Rather than acting as a simple switch, this phenomenon functions more like a variable resistor. The closer the columns of sweat get to the skin surface, the higher the conductivity, even if the sweat does not reach the surface itself. Thus, the conductivity of this pathway is proportional to the height of the sweat in the duct. The spiral region of the duct is porous, allowing sweat to slowly move out and permeate the horny layer, reducing its electrical resistance. Consequently, the dampened horny layer has increased conductivity even after the column of sweat has returned to the gland. This moistened horny layer provides an alternative electrical pathway. Over time, this moisture evaporates, and the dried-out epidermis returns to its lower conductivity state.

These different mechanisms of electrical conduction are illustrated in Figure S1 and discussed in more detail below.

Figure S1
Effective Electrical Circuits for EDA Overlaid on a Stylized Cross Section of the Skin



Critchley (2002) described two broad patterns evident in EDA: “basal” change and “phasic” change. Basal change, also known as "tonic EDA," is the slow, gross change in the electrical conductivity of the skin that occurs over a relatively long time (from one or two minutes up to tens of minutes). This change is best understood as the electrical resistance of the skin's horny layer altering due to sweat infusion, represented by the upper pathway in Figure S1. Conversely, phasic changes are more rapid, occurring over a time frame of tenths of seconds to several seconds. These changes are attributed to the oscillating columns of sweat in the spiral sections of the duct, which act as a variable resistor between two skin electrodes, changing resistance almost instantaneously, as illustrated by the lower pathway in Figure S1. Additionally, an electrical pathway is formed when liquid sweat exits the top of the duct and flows over the skin. This salty liquid creates a highly conductive pathway, forming a rapid peak in the signal known as "peaked skin conductance response" which is superimposed on the phasic EDA signal (Benedek & Kaernbach, 2010).

EDA is an Established Measure in Psychology. EDA is an established and frequently used measure of sympathetic arousal (Baukal et al., 2017; Gillies et al., 2016; Kreibig, 2010; Martin, Ginns, et al., 2021; Martin, Kennett, et al., 2021; Martin et al., 2023) and is the measure used in the present investigation. It is thus appropriate to explore studies that demonstrate the use of EDA and highlight relevant lessons from these studies. Two aspects were the focus here: evaluating tonic versus phasic EDA and addressing signal-to-noise challenges in ecological environments, such as classrooms.

In a relevant study, Drachen et al. (2010) measured EDA and heart rate in 16 participants playing first-person shooter computer games. Using the In-Game Experience Questionnaire, participants self-reported their level of engagement (immersion, flow, competence, tension, challenge, negative emotions, and positive emotions). Significant correlations were found between each self-reported engagement measure and heart rate, as well as between EDA and negative emotions such as frustration. However, this study did not differentiate between tonic and phasic changes in EDA, using relatively simple measures (maximum, minimum, average in each interval) that may have been confounded by both tonic and phasic signals.

The importance of differentiating phasic and tonic EDA was highlighted in a study on stress in deep-sea divers (Posada-Quintero et al., 2018). The authors found that tonic changes were not correlated with stress, but using spectral analysis (Fast Fourier Transform), they showed a correlation between cognitive stress and phasic EDA in divers undergoing a Stroop task. These studies emphasize the value of using analytical tools to generate measures of phasic changes distinct from tonic changes in EDA, establishing a correlation between phasic EDA and stress-related sympathetic arousal.

Regardless of the measure of EDA, sophisticated methods are needed to separate the signal from noise. Motor nerves generate artifacts, as does the inadvertent repositioning of wrist electrodes from hand movements. These motion artifacts are more problematic in naturalistic settings compared to laboratory environments. This theme of extracting the signal from noise is increasingly important as the use of EDA to explore sympathetic arousal in realistic settings rises. Small wristband devices, such as the *Empatica E4*, have increased access and facilitated the transition from laboratory to classroom settings. The *E4* incorporates electrodes that contact the ventral surface of the wrist and a photoplethysmograph that illuminates the dorsal surface and measures blood perfusion of the superficial capillaries.

Gillies et al. (2016) used the *Empatica E4* in a Year 6 science classroom to measure engagement through sympathetic arousal. Only tonic EDA was extracted from the signal and was found to correlate with other measures of engagement derived from video recordings. They used band-pass filtering and signal smoothing to reduce noise in the tonic EDA recording, which was aggregated over time to a single measure per student. However, in a later study, the same research team (Carroll et al., 2019) computed an RMS (root-mean-square) value based on changes in the tonic EDA signal to measure the "physiological reactivity" of the student. The RMS value likely reflected both tonic and phasic components, indicating a progression from a simple tonic EDA measure to a more sophisticated approach that includes phasic EDA.

In an experiment evaluating peer teaching's effectiveness, Hoogerheide et al. (2019) used EDA among other measures. Despite a modest sample size ($N = 61$), the naturalistic conditions resulted in high noise rates. Using the *Empatica E4*, some students had as little as 5% of useful recording time. Only tonic EDA was analyzed, reducing time periods to single sets of statistics. Noise and artifacts significantly impacted their results, highlighting the importance of robust techniques to extract the signal from the noise.

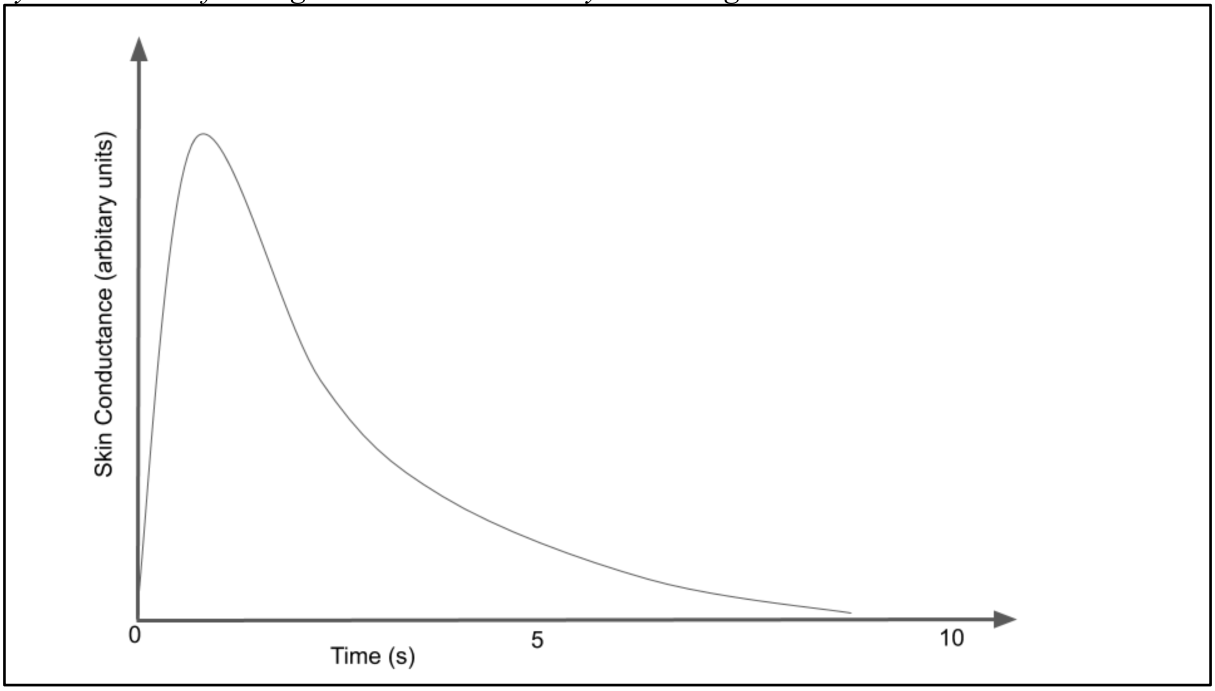
A relatively novel approach to EDA interpretation was adopted by Ahonen et al. (2018) using the minimum-width envelope (MWE) method. By comparing changes in skin conductivity within a 10-second window around an event, they characterized changes and their valencies rather than tonic levels. While useful for event-related changes in controlled environments, this method is less relevant in naturalistic settings. Nevertheless, it highlights the diversity of methods used to extract meaningful indicators from raw EDA recordings and the insufficiency of purely tonic EDA measures.

Pijeira-Diaz et al. (2016) investigated physiological coupling between students engaged in collaborative learning, comparing various coupling indices to extract the signal from noise. Using *Empatica E4* wristbands, they used tonic EDA as their measure of interest. In a subsequent study measuring arousal in a physics classroom (Pijeira-Díaz et al., 2018), they used *Ledalab*'s curve matching approach to extract deconvoluted events constituting phasic EDA (Benedek, n.d.). Despite involving relatively few students ($N = 24$), this study illustrated the trend of moving from tonic to phasic EDA, finding a strong correlation ($r = .66$) between phasic EDA and achievement. A further study (Pijeira-Díaz et al., 2019) investigating sympathetic arousal contagion among group members also used *Ledalab*'s phasic EDA measures, affirming its superiority for measuring sympathetic arousal and extracting phasic EDA from noisy signals.

Hunting the Pure Signal in EDA. One method for extracting the phasic EDA signal involves using a Fourier Transform to convert the signal from the time domain to the frequency domain and then measuring the power across a frequency band typically between 0.1 and 2 Hz. While this method is valid, artifacts may contribute to the power in this range, necessitating a more sophisticated approach. *Ledalab* (Benedek, n.d.; Benedek & Kaernbach, 2010) employs a curve-fitting approach, which differs significantly from a Fourier Transform. A single, isolated sudomotor event produces a predictable change in skin conductivity over time, as illustrated in Figure S2.

Figure S2

A Stylized Model of Changes in Skin Conductivity Following an Isolated Sudomotor Event



The overall shape of this curve is determined by underlying biophysics, while specific features are described by two person-specific parameters (Benedek & Kaernbach, 2010). However, the stylized event depicted rarely occurs as sudomotor events are seldom isolated, with new events often occurring before the previous one has fully decayed. This results in a cascade of events piling up on each other. *Ledalab* utilizes deconvolution to reconstruct each event from the sum of events in the recording. Deconvolution is a method of disentangling a single sudomotor event from the superposition of multiple events, noise, and tonic EDA recorded by the skin electrodes. Intense firing occasions may lead sweat to reach the skin surface, creating an additional conductive pathway and resulting in a different shape known as peaked skin conductance response (peaked SCR), which must also be accounted for.

Once the deconvolved signal has been reconstructed into individual events, a first pass identifies probable events in an individual's recording and optimizes the two parameters of the rise-fall curve, creating a target curve for that individual. Probable events are those that follow the general rise-fall shape. A second pass then matches this target curve with the deconvolved signal and records curves that fit the target, including peaked SCR events. This conservative approach may result in non-identification of valid events or false negatives, potentially leading to issues when measuring event frequency in areas with significant noise. To mitigate these consequences, the present research focused on measuring the amplitude of identified events rather than their frequency.

The *Empatica E4* measures EDA from AgCl skin electrodes at a sample rate of 4Hz, applying a voltage-limited EMF in pulses at 8Hz across the electrodes. However, the pulsed signal is considered switched DC, measuring only skin conductivity and not electrical impedance or admittance. The *E4* records these data to local memory in a time-stamped data file, uniquely identified for subsequent data matching.

Electrodermal Activity Analysis. Skin conductance can be calculated from the known potential across the electrodes and the measured current. Conductivity is the inverse of resistance, G = 1 / R (where G is conductivity in Siemens, R is resistance in Ohms) (Boucsein, 2012). Since V = IR (Ohm's law), it follows that G = I / V (where I is the measured current in Amperes and V is the known EMF in Volts). The *E4* samples skin conductivity (SC) at 4Hz, calibrated in milli Siemens, and stores this in a UTM time-stamped csv file. All data files from the *E4* are saved in a folder also UTM time-stamped and include a unique Media Access Control Address expressed as a hexadecimal (MAC Address). Exclusive use of UTM timestamps (e.g., 1509314436 representing the number of seconds after midnight 1970 in GMT) avoided time zone confusion and potential errors in analysis (*UnixTime—Wolfram Language Documentation*, n.d.).

As mentioned, *Ledalab* was employed to separate the tonic EDA signal from the phasic and provide signal from noise discrimination. The raw data were incorporated into the automated signal pipeline, batch-processed outsourced to *Ledalab* for deconvolution, and the processed data flowed back into the signal pipeline.

Neuropsychological Indicators: Internal Attention and Working Memory Activity

This section explores the integration of neurological measures within a study such as this, outlines the process of selecting the two target measures, and explores the scientific basis for the inference of *internal attention* and *working memory activity* from EEG-alpha and EEG-theta.

At the outset, it is worth addressing some questions which surround the emerging discipline of educational neuroscience. There are questions about whether educational neuroscience is capable of enhancing the persuasive and communicative pursuit of education without reducing it to impersonal brain engineering (Bakhurst, 2008). There are also questions as to whether it offers anything beyond what behavioral studies in psychology have already revealed (Bowers, 2016). These fundamental questions and concerns emanate in part from assertions that educational neuroscience has not only failed thus far, but is so flawed in principle as to render it perpetually impotent (Bowers, 2016).

In seeking to reconcile educational psychology and neuroscience, it is important to understand the levels at which each predominantly operates. On the one hand, educational psychology operates at the level of the mind and behavior. On the other hand, neuroscience tends to operate at the level of neurons, neural networks and other measures of neural activity. Notwithstanding these apparent disconnects, neuroscience has done much to expand our understanding about how the brain functions, even if it is not a complete description of the mind (Bakhurst, 2008; Katzir & Pare-Blagoev, 2006). This being so, some academics (e.g., Szűcs & Goswami, 2007; Tolmie, 2015) strongly argue for the utility of educational neuroscience in assisting our understanding of human learning, seeking to use neuroscience to study "mental representations", or signatures in the neurological data, which are associated with particular learning modes. These mental representations may not in the first instance be related to modes of thinking typically identified by applied psychology. However, tracking their normative development and studying these representations can add to a fuller understanding of learning.

These questions of neuroscience and educational psychology were addressed by a taskforce formed to evaluate and map the future of this new discipline of educational neuroscience (Fischer et al., 2010). The taskforce proposed the pursuit of a strongly evidence-based and functional connection between educational psychology and neuroscience and emphasized *functional interdisciplinarity* between educational psychology and neuroscience. Rather than attempting to define a hierarchy of knowledge systems whereby educational psychology is subsumed within a neuroscientific description of learning, the taskforce called for a symbiosis as a credible pathway to address the criticisms (Howard-Jones et al., 2016). The first step towards functional interdisciplinarity is measurement and observation (The Royal Institution, 2017) and to do so within the ecological setting of a real classroom (Shamay-Tsoory & Mendelsohn, 2019). A person's expectancies, drawn either from distal or proximal prior experiences, do alter their neurological networks and therefore their sensory processing and their network responses as measurable by EEG, and vice versa (Fontanini & Katz, 2008; Munakata et al., 2004; Stiles & Jernigan, 2010). This lends weight to the potential yield of educational neuroscience as applied in the present research.

Thus, while recognizing some of the limitations of neuro-psychological research, it is important to note that the synergy between, and integration of, neuroscience and psycho-educational science has increasing rigor and utility (Katzir & Pare-Blagoev, 2006; Willingham & Lloyd, 2007). More recently, a systematic review of educational neuroscience tracks this increasing rigor and provides a helpful perspective for incorporating neuroscience within educational psychological studies (Gkintoni et al., 2023). With that being said, we moved our consideration to neuroscientific measures which can be meaningfully incorporated within an educational neuroscientific study such as the present one.

Selecting Neuro-Psychological Measures

Four criteria were used to select neuro-psychological measures for this research (Kennett, 2020; Kennett et al., 2023):

(a) Potential to enhance understanding of students' challenge and threat states by providing unique information.
(b) Compatibility with portable EEG devices.
(c) Strong empirical and theoretical basis for inferring from EEG data.
(d) Ability to be meaningfully aggregated over time in an observational study.

For criterion (a), measures must deepen understanding of students' challenge and threat states during academic tasks, focusing on cognitive processing and engagement. A plausible connection between these states and the measured quantity is essential. The discussion below identifies cognitive functions involved in science tasks and related neuro-psychological indicators. Criterion (b) excludes measures needing precise brain signal localization due to the limitations of portable EEG devices. Also excluded were those requiring millisecond timing or relative phase, and those exceeding device frequency specifications. For criterion (c), only a few measures with adequate empirical support in ecological observational studies were considered. Criterion (d) excludes event-related potentials, as the observational study design does not involve stimulus manipulation and precise brain response recording. Measures must remain meaningful when averaged over extended periods. Dominant brain rhythms, such as alpha rhythms, were identified as having the greatest potential.

Establishing Realistic Expectations. We need to establish realistic expectations of what can be inferred when using measures derived from an EEG as well as measures likely to add value to the research aims of this investigation. After iteratively applying the preceding criteria, two candidate measures were ultimately selected: *internal attention* via alpha rhythms and *working memory activity* via theta rhythms. Each of these is briefly outlined below with special focus on criterion (a), the potential meaningful yield of these measures.

Internal Attention. The ability of the mind to selectively attend to particular aspects of the sensory stream and to alternate between external stimulus-centered attention and internal attention is critical for task completion (Foxe & Snyder, 2011). The exercise of endogenous attention is related to engagement with a task, although in a complex and nuanced manner. The ability of a learner to focus attention is critical in their extraction of meaning from complex text (Van Den Broek, 2010). However, even this is nuanced, as research has demonstrated that having an overly narrow attentional focus on only parts of a scientific communication (e.g., a graphic) inhibits students in attaining an overall understanding of the information (Holliday, 1981).

Challenge and threat states can also impact attentional focus, with a challenge state being associated with more efficient attentional focus and a threat state associated with maladaptive "fixations" on irrelevant information (Frings et al., 2014). Anxiety, which is closely related to a threatened state, has also been shown to impact attentional focus (Schmidt & Trakowski, 1999) and challenge and threat states can impact on the processing of affective dimensions (Sassenberg et al., 2015).

Taking together the above caveats and nuances, it is nevertheless plausible that endogenous attentional processes are important in students' engagement with a science task and that attentional focus may also be implicated in challenge and threat states. For these reasons, a measure of attentional focus, *internal attention*, was selected.

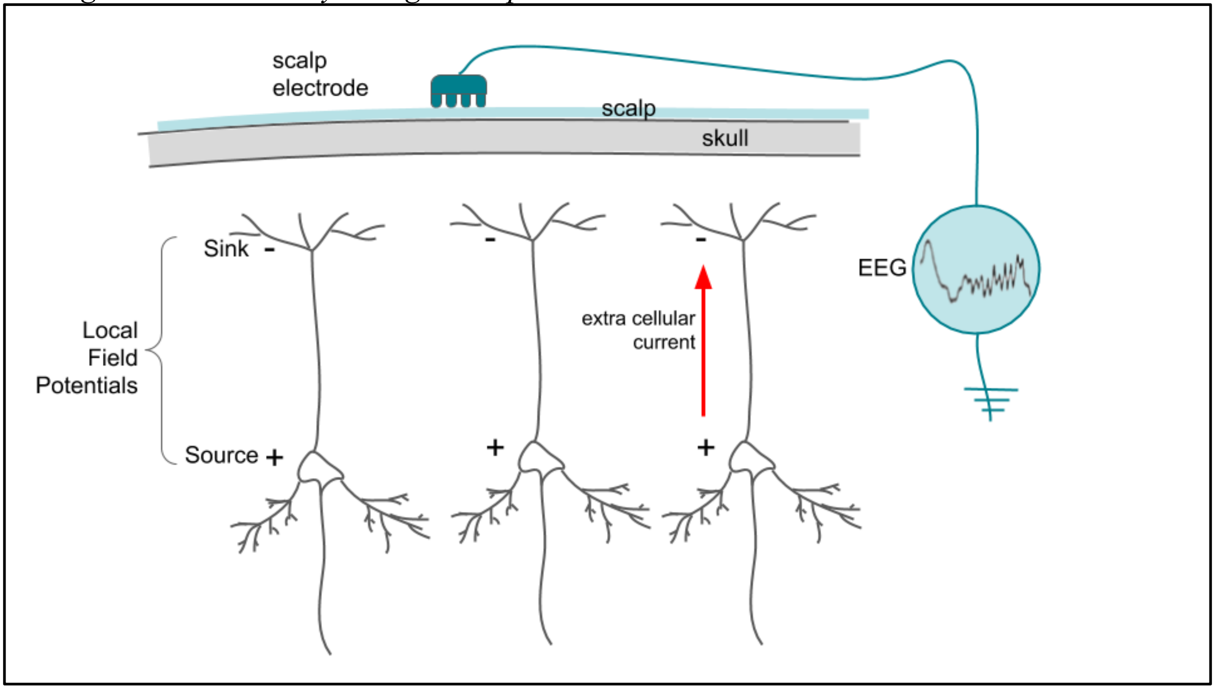
Working Memory Activity. Working memory is a limited cognitive resource needed to actively hold information in a dynamic manner. Adults typically hold around seven items (plus or minus two) in their working memory, as has been demonstrated in the work on cognitive load theory (Sweller et al., 2011). Working memory is relevant to a student's challenge and threat state, particularly anxiety. Individuals with dispositional anxiety divert working memory resources to threat-related information, reducing capacity for task-related information (Stout et al., 2017). This relationship is bi-directional; anxiety can increase working memory demands, and working memory stress can increase anxiety (Berggren et al., 2012; Chen & Chang, 2009).

Capturing the Mind

Having chosen candidates for neuro-psychological measures, we turn our attention to how these measures might be inferred from electrical recordings of the brain. Since Hans Berger's first human EEG recording in 1924, the goal of "reading the human mind" from EEG data alone remains unattainable. However, EEG has provided valuable insights into brain function. EEG measures electrical activity from scalp electrodes non-invasively with high temporal resolution. Only neurons with axons oriented perpendicular to the skull generate scalp measurable potentials, primarily from pyramidal cells (Figure S3) (Cutmore & James, 2007; Olejniczak, 2006). Spatial resolution is limited by volume conduction, where three-dimensional information is projected onto the two-dimensional scalp surface, further complicated by the skull's effects.

Figure S3

Recording Electrical Activity Using a Scalp Electrode



Note. The electrical potential recorded at a scalp electrode is the sum of the Local Field Potentials generated by pyramidal cells, modified by volume conduction, attenuated by the skull and collapsed to the 2D surface of the scalp.

These limit the ability to reconstruct the origin of a specific signal from EEG and therefore EEG does not have the high spatial resolution of computed axial tomography (CAT) or functional magnetic resonance imaging (fMRI) technologies. However, with sufficient electrodes (256 or more) in contact with the scalp, the spatial resolution of EEG can be enhanced by sophisticated signal analysis and thereby provide reasonable localization of a signal's source (Seeck et al., 2017). However, the equipment in this study had insufficient electrodes and spatial information was excluded.

Targets in the Signal: Event Related Potentials Versus Rhythms. Studying event-related potentials (ERPs) is a popular EEG analysis method. ERPs refer to voltage changes over time around an event, such as a flash of light, or a response to an image (Kropotov, 2009). This approach is effective for examining small or "atomized" activities. Another method is event-related synchronization (or desynchronization), which focuses on changes in power across a frequency band around an event (Neuper & Klimesch, 2006). In ecological settings, small event-related changes are less relevant, but synchronization can be aggregated over many events. Task-related synchronization, an extension of event-related synchronization, involves changes in power during a task compared to a non-task baseline (Razoumnikova, 2000).

The first EEG components identified were oscillations at certain frequencies (Olejniczak, 2006). Large neuron networks firing in synchrony amplify the signal, similar to how many violins playing together produce a louder sound (Olejniczak, 2006). This "music of the brain" dominates EEG signals. The study of EEG is regaining popularity as EEG moves to ecological environments like classrooms (Goswami, 2016). Early EEG rhythm identification was manual, but modern analysis transforms data from the time domain to the frequency domain using techniques like Fourier Transform or wavelet analysis. Power across a frequency band can be integrated and compared between task and baseline to measure task-related synchronization.

Delahunty et al. (2018) used the EPOC+ headset to collect EEG data during students' problem-solving in STEM education. They found that a 14-electrode EEG could assess cognitive function correlates, even in a natural learning environment with potential electrical noise. Despite challenges in signal extraction, they demonstrated significant relationships between problem types and neural signatures of cognitive responses (Szűcs & Goswami, 2007). Their approach focused on task-related changes rather than ERPs. They used conventional frequency bands—theta (4-8 Hz), alpha (8-13 Hz), and beta (13–30 Hz) (Klimesch, 1997; Razoumnikova, 2000)—and applied Fast Fourier Transforms and Independent Component Analysis to remove noise and artefacts.

To calculate power changes related to a task, a baseline where participants are not engaging in a task is required. This baseline is subtracted from the task EEG data, allowing the difference to indicate activity across brain regions and frequencies. This method, creating task-related synchronization measures relative to a person-specific baseline, was adopted in the present research.

Using Alpha Rhythms of the Brain to Infer Attention. As discussed previously, the ability to selectively focus was chosen as a neuro-psychological measure for the present study, so an explanation of how this can be achieved is relevant. Alpha rhythm refers to a peak in scalp potential power within the 8-13 Hz frequency range. This peak occurs when neurons within a local network and across networks fire in phase. The alpha peak is typically more pronounced with eyes closed and diminishes when eyes are open, leading to its early characterization as "cortical idling" (Pfurtscheller, 1992). The exact frequency of the alpha peak can vary with age and gender, between individuals of the same age and gender, and can simultaneously present as two distinct frequencies (Chiang et al., 2011).

The observations above indicate that the amplitude of the alpha peak in specific regions of neural networks is relevant to endogenous attention. Alpha synchronization acts as a gate for sensory information to different brain areas. This gating by alpha rhythms can be induced by cuing the brain to ignore distracting or irrelevant information (Foxe & Snyder, 2011). The concept of "irrelevant" implies an executive or "top-down" directive to focus on specific parts of the sensory stream, allowing attention to shift to brain regions processing relevant information. This cueing can be endogenous, with alpha synchronization suppressing the responsiveness of certain networks to sensory information. Research shows that cuing participants to attend to either auditory or visual stimuli before the actual stimulus increases alpha rhythms in the networks opposite to the expected sensory modality. For example, anticipating auditory information increases alpha rhythms in the parietal-occipital (visual) regions (Foxe & Snyder, 2011). In their study, Foxe and Snyder (2011) found that cuing participants to expect visual information in one hemisphere increased alpha rhythms in the contralateral hemisphere. This pattern was replicated with auditory tasks, where participants cued to attend to one of two simultaneous conversations showed increased alpha rhythms in networks that would have processed the distracting conversation.

The large "eyes-closed" alpha band peak reflects this gating or suppression of the visual cortex, as the posterior parietal areas of the fast dorsal visual stream control the flow of visual information to the thalamic relay nuclei (Foxe & Snyder, 2011). This alpha band peak is particularly prominent in scalp electrodes over the parietal regions, shifting our view of alpha rhythms from indicating cortical idling to playing a critical role in sensory gating as part of the brain's selective attentional mechanisms. The idea that alpha rhythms represent a brain idling and waiting for sensory input has been largely discounted and replaced with a view of the brain as an active organ with intrinsic or spontaneous activity. The brain's intrinsic activity shapes and is shaped by external stimuli, with its endogenous ability to focus attention on select components of the sensory stream being crucial (Gómez-Ramírez et al., 2017). The ability to control attention to certain foci while ignoring others is essential for cognition (Markram & Markram, 2010).

A localized high alpha rhythm may indicate that networks in alpha synchronization are not inactive, but that the external sensory stream to those networks is suppressed. This suppression allows priority processing of sensory information in other unsuppressed networks associated with relevant parts of the sensory stream and cortex. Higher magnitude alpha rhythms may also indicate a priority of top-down predictions, enabling networks to process predictions, consider alternatives, and engage in functions related to developing new ideas or deriving meaning (Seth et al., 2012; Sherman et al., 2016).

Thus, internal attention may be inferred from the level of alpha rhythms. Attention may be directed towards bottom-up sensory information or ongoing internal processes such as top-down predictions, pattern recognition, or daydreaming (Foxe & Snyder, 2011; Seth et al., 2012). The present investigation inferred internal attention from alpha rhythms. High alpha task-related synchronization indicates a focus on internal processes (high internal attention), while low alpha task-related synchronization indicates a focus on external stimuli (low internal attention). Task-related synchronization was computed by integrating power across the alpha frequency band during the task and comparing it to a non-task baseline. The next step is defining the alpha band.

Person-Specific Peak Alpha Frequency. The distinctive resonance in the alpha band causes a peak in signal power at a given frequency, which varies with age and can be influenced by individual brain morphology (Chiang et al., 2011; Richard Clark et al., 2004). While researchers have previously summed the power of an arbitrary frequency range (often 8-14 Hz, with some variation), concerns about fixed frequency bands exist due to variations in age, neuromorphology, memory performance, and other factors (Klimesch, 1999). A more valid approach is using person-specific frequency bands based on the frequency of peak power in the alpha band for an individual, with other frequency bands determined relative to this. For this study, the theta band is defined as 6 to 4 Hz below the alpha peak frequency. Identifying the alpha peak can be complex due to phenomena like split alpha frequencies (Chiang et al., 2011), possibly due to the two origins of alpha rhythms proposed by Ben-Simon et al. (2008). Klimesch (1999) proposed determining the person-specific alpha peak frequency by identifying the peak at the lowest frequency demonstrating desynchronization during a task compared to a resting baseline, providing an unambiguous criterion for determining the peak alpha frequency. This approach can be translated to an automatic algorithm, necessary for gathering EEG data in naturalistic settings across large sample sizes, despite operational difficulties in determining the person-specific alpha peak frequency.

In summary, attention selection between the sensory stream and internal processes can be inferred from alpha rhythm analysis. The change in power in the alpha band relative to a person-specific baseline measurement provides a measure of task-related synchronization, correlated with internal focus of attention. Therefore, this research proposes determining a person-specific alpha frequency and calculating a measure of task-related synchronization to infer internal attention. This measure, alongside indicators like self-efficacy, anxiety, and EDA, were used in latent profile analyses. The final indicator relates to students' working memory, inferred from measures of their theta rhythms.

Using Theta Band Rhythms to Infer Working Memory. In his comprehensive review of brain oscillations, Klimesch (1999) not only covered alpha rhythms but also addressed lower frequency theta rhythms. His analysis suggested that theta rhythms are linked to the encoding of new information. Specifically, theta oscillations within hippocampo-cortical feedback loops were associated with encoding, showing a contrasting pattern to alpha rhythms. Higher power in the theta band indicated more efficient functioning of memory circuits. Subsequent advancements in technology were utilized by Mollë et al. (2002) to confirm that intentional learning relies on coordinated regulation of thalamo-cortical and hippocampo-cortical circuits, with increased theta power specifically associated with intentional encoding. Brain oscillations synchronize distant neural networks, facilitating neural plasticity necessary for both encoding new information and coordinating memory reactivation (Hanslmayr et al., 2012). This role of theta oscillation is supported by various studies and reviews (Axmacher et al., 2006; Berger et al., 2014; Düzel et al., 2003; Nyhus & Curran, 2010). Delahunty et al. (2018) and other studies have demonstrated that analyzing synchronized oscillations can provide real-time insights into cognitive load during tasks (Antonenko et al., 2012; Sweller et al., 2011). Increased access to working memory has been associated with higher theta oscillations (Castro-Meneses et al., 2020; Klimesch, 1999; Razoumnikova, 2000). Theta rhythms, measurable via scalp electrodes, reflect synchronized activity across numerous neural networks. While theta synchronization is linked to working memory, it is not the sole determinant, necessitating cautious interpretation. Nonetheless, it remains a potentially valuable indicator, particularly when considered alongside other metrics, as in the current study.

Despite these considerations, a growing body of evidence supports the relationship between theta oscillations and working memory activity. Castro-Meneses et al. (2019) identified a correlation between theta power and cognitive load, suggesting theta oscillations could serve as a real-time measure of changes in working memory activity, ideally referencing an individual's baseline. Given the existing research linking theta oscillations to working memory and the need for ecological investigations, utilizing theta oscillations as a measure of working memory in classroom settings appears promising. Therefore, the present research exploratively included this inferred measure of working memory activity, defined within the theta range of -6 to -4 Hz from the individual's peak alpha frequency.

Science Achievement Test

For science achievement, all students completed a standardized set of questions derived from the NSW Stage 4 and 5 syllabuses. The assessment was divided into two halves, each covering similar units: one administered before an online science survey and the other afterward. Both halves measured selected content outcomes aligned with the NSW Stage 4 and Stage 5 science curriculum.

The assessment was designed by a team of experienced NSW science teachers (8-26 years of experience) to mirror the structure and format of a typical school science test. Each question was based on a syllabus unit, featuring introductory information supported by visual aids. Example units with associated questions are provided below.

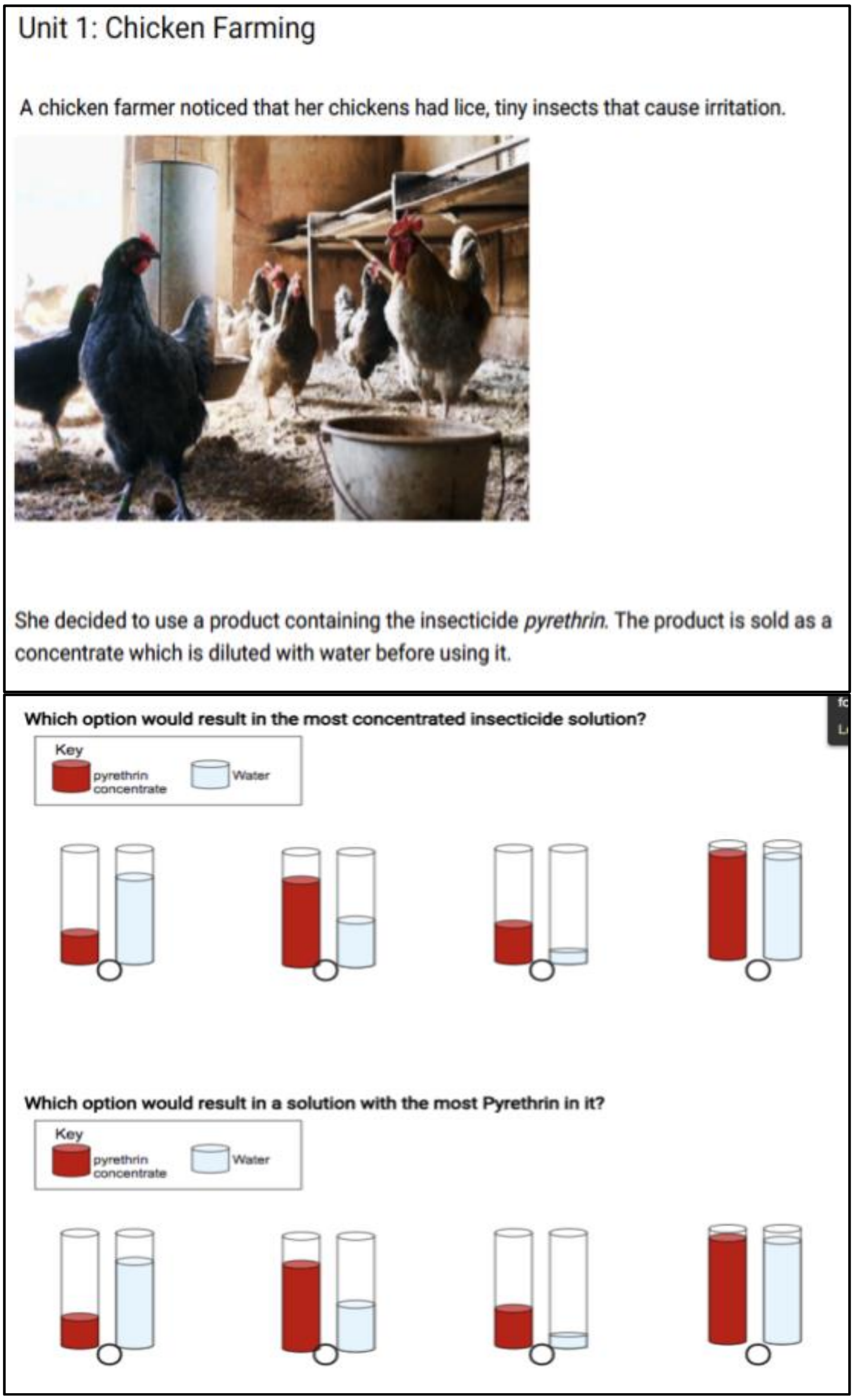
Questions were developed by a lead science teacher with 26 years of experience and reviewed by a panel of five science educators for appropriateness in difficulty level and alignment with the syllabus. An additional review ensured linguistic accessibility for students from non-English speaking backgrounds (NESB). This iterative review process ensured content, format, structure, and accessibility met the panel's satisfaction and included a spread of difficulty levels typical of science assessments.

All assessment items were coded dichotomously, where 0 indicated an incorrect response and 1 a correct response. Scores were summed to generate a total science test score, standardized by year level to facilitate uniform analysis across the sample. This standardized measure was used to summarize statistics and reliabilities of the science outcome indicators in the results section. Scientific knowledge and skills, measured by achievement, were considered the primary outcome, aligning closely with the study's educational objectives.

The following example in Figure S4 demonstrates one unit of the science achievement test as it was presented to the students using *Qualtrics*.

Figure S4

Sample Achievement Test


Unit 1: Chicken Farming

A chicken farmer noticed that her chickens had lice, tiny insects that cause irritation.

She decided to use a product containing the insecticide *pyrethrin*. The product is sold as a concentrate which is diluted with water before using it.

Which option would result in the most concentrated insecticide solution?

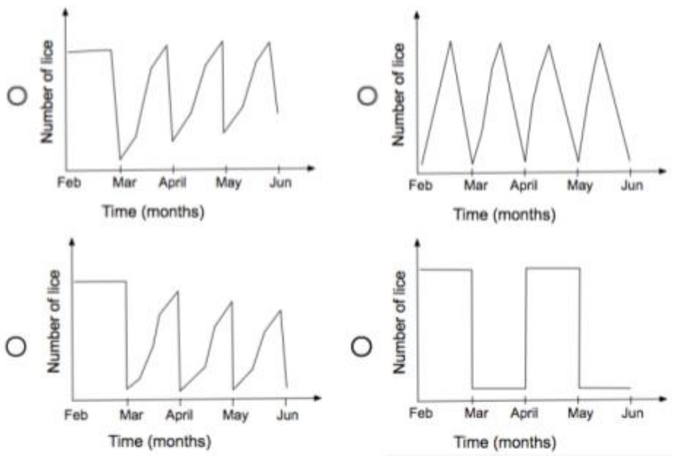
Key
pyrethrin concentrate
Water

Which option would result in a solution with the most Pyrethrin in it?

Key
pyrethrin concentrate
Water

In March, she made up 25 litres of insecticide and sprayed the chicken coup and their nests with 5 litres. This killed almost all the lice. However, after a month, the remaining lice reproduced and their numbers returned to the previous level.
Over the next 3 months, she used up the original batch of insecticide, spraying 5 litres each month.
The farmer noticed that each month, fewer of the lice were killed.

Which graph best represents this situation?



The farmer's hypothesis was;
"Once the insecticide is mixed with water, it decomposes over time."
In June, she decided to perform an experiment to test her hypothesis.

Identify the variables correctly

	percentage of lice killed	concentration of solution	time after solution is mixed
independent (changing)	○	○	○
dependent (measuring)	○	○	○

What would need to be controlled (control variables) for this to be a fair test.

Choose all the correct options

- ☐ type of insecticide
- ☐ concentration
- ☐ age of insecticide solution
- ☐ number of lice killed

Which alternative explanation is most plausible (likely to be true) to explain the fewer lice being killed each month?

- ○ The insecticide made the chickens more resistant to lice
- ○ Someone was secretly diluting the insecticide each time without the farmer noticing
- ○ The lice grew resistant to the insecticide because they became used to it
- ○ Lice with some resistance to the insecticide were surviving and reproducing

Signal Pipeline Tool

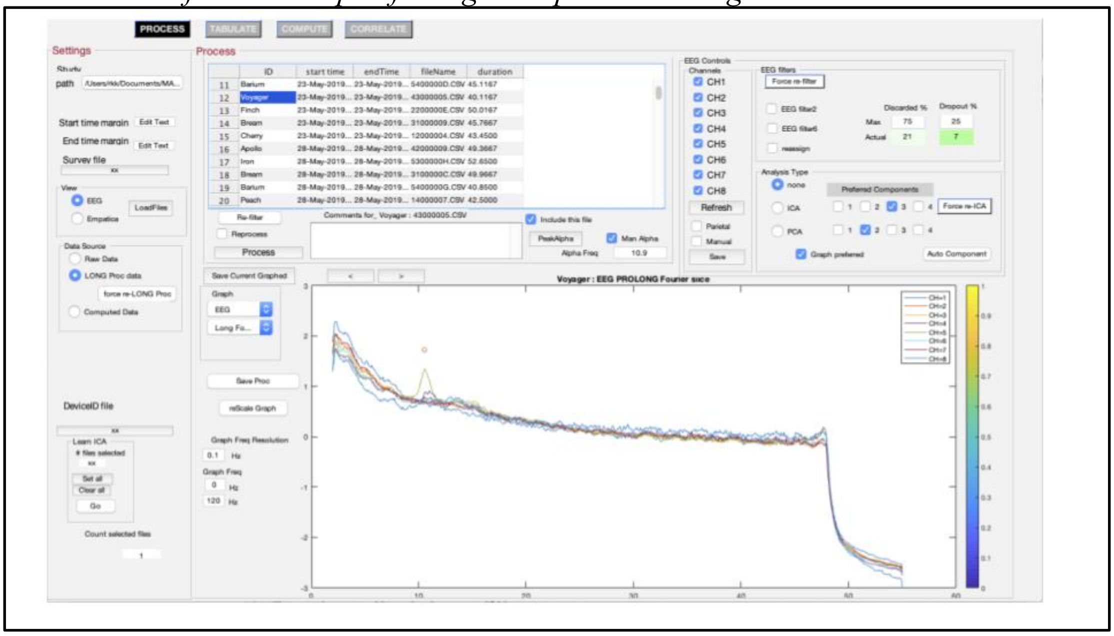
The term "pipeline" captures the autonomous nature of this program where the raw signals from the *Empatica E4*, the *CytonRK* headsets, and the *Qualtrics* survey data are fed into one end and a synchronized and processed dataset exits at the other end without requiring subjective human intervention in between (Kennett, 2020; Kennett et al., 2023).

Matlab was chosen as the programming environment due to the existence of established signal processing algorithms, Fourier and wavelet transforms, and extensive file reading and writing abilities. It was designed with an independent database for each recording where the subsequent layers of processing were added, and each step was retained. This allowed for a return to the raw data, or indeed any step along the way, without any of the data being lost or overwritten. Since some of the steps, such as the Fourier transform into different time slices, took nearly 10 hours to process, the data were stored in these individual files so that participants could be added without the entire database being re-computed.

A visual interface was constructed so that manual inspection of the data was possible at each stage, which allowed for visual confirmation of the results of each step of signal processing. Figure S5 presents a screenshot of the graphical user interface (GUI) developed by the lead author which demonstrates the ability to inspect each signal (either EEG or EDA) and visualize the effect of various signal and noise treatments (Figure S6) as well as confirming aspects such as the automated identification of the peak-alpha frequency for each student.

Figure S5

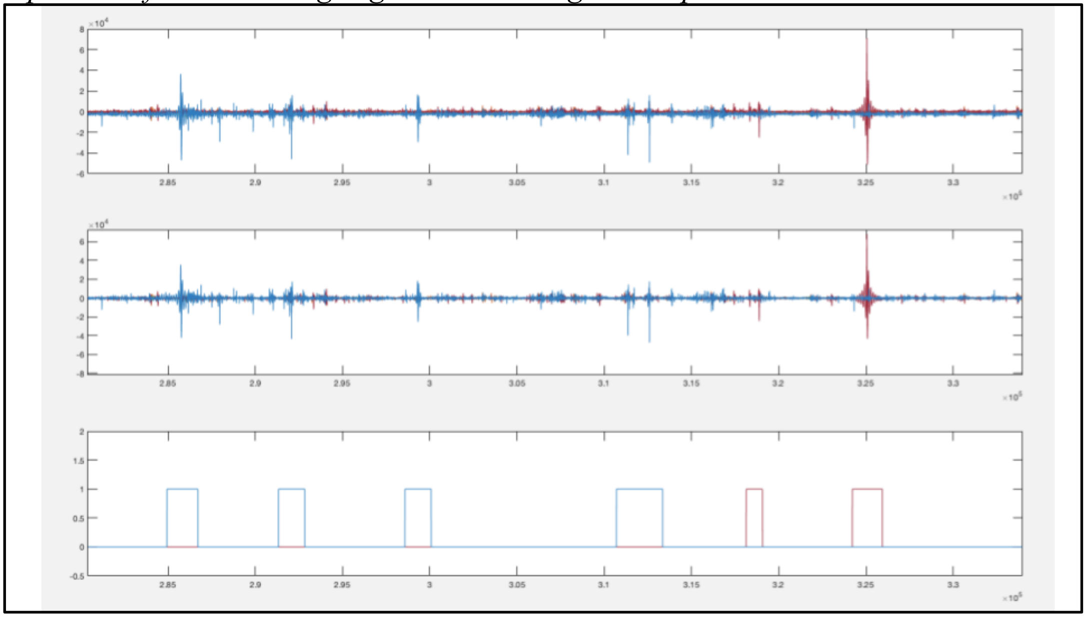
Graphical User Interface Developed for Signal Pipeline Oversight



Note. The small circle visualized the automated choice of peak alpha frequency for an individual EEG recording in the time domain for the entire relevant (task and baseline) recording. The peak alpha rhythms are most dominant in the parietal electrodes (electrodes 4 and 5) depicted in green and purple in the graph.

Figure S6

Visual Inspection of Noise Gating Algorithms During Development



Development of the CytonRK Portable EEG

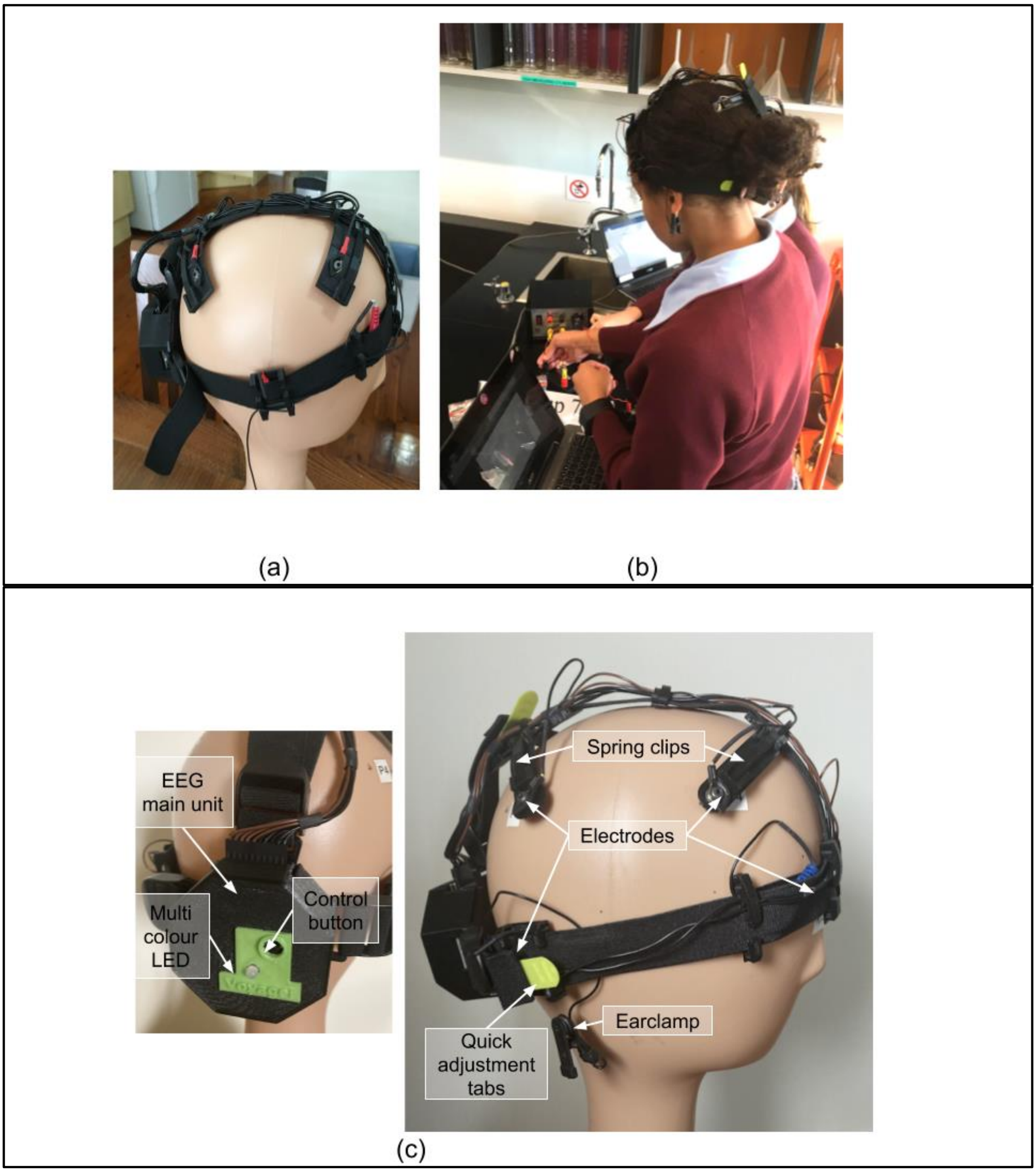
The commercially available portable EEG devices during the study period utilized Bluetooth for connecting each device to a paired recording device. Given the requirement for one recording device per sensor, using up to 26 EEG devices in a single classroom rendered Bluetooth connectivity impractical and technically challenging. While a few low-bandwidth Bluetooth devices can coexist (e.g., headphones, computer mouse), the high bandwidth needed for neuro-psychological measurements would have overwhelmed and potentially disrupted Bluetooth connections.

Attempting to pair 26 laptops with numerous devices was also impractical even if wireless transmission were feasible. WiFi was considered as an alternative due to its capability to manage required bandwidth and connections, but this approach would have necessitated setting up WiFi networks in each classroom. In addition, concerns about security measures in schools blocking unauthorized wireless networks made this option even less feasible. Consequently, the decision was made to utilize local memory recording within each EEG device as the most reliable data recording method for classroom use.

At the time of the study, no commercially available device met these requirements, prompting the development of a custom solution by the lead author (Kennett, 2020; Kennett et al., 2023). The cornerstone of this bespoke device was the OPENBCI Cyton board (Open Source Biosensing, n.d.), known for supporting open-source development of Brain-Computer-Interfaces. The firmware source code, being open source, was re-engineered using the Arduino Integrated Development Environment (IDE). The signal front end utilized the ADS1299 Low-Noise, 8-Channel, 24-Bit Analog-to-Digital Converter from Texas Instruments, capable of recording 8 channels with two references connected to the ear lobes.

For this application, a sample rate of 250Hz was chosen to balance recording speed with file size and performance considerations, capturing the highest frequencies of interest. Additional components such as real-time clock, lithium battery pack, and controls were integrated into the design by the lead author to create the CytonRK, a head-mounted portable EEG device (see Figure S7, with the student pictured on the right).

Figure S7
The CytonRK EEG Headset



Note. The *CytonRK* EEG: (a) early prototype, (b) final model during data collection in a parallel study, (c) final model physical features.

The main processor of the CytonRK was the PIC32MX250F128B Microcontroller with the chipKIT UDB32-MX2-DIP bootloader from Microchip (Kennett, 2020; Kennett et al., 2023). Motherboards were initially sourced from OPENBCI, although modifications were necessary as the Cyton motherboard lacked an essential real-time clock for local recording. The lead author subsequently constructed a supplementary electronics board featuring a battery-backed DS3234 IC from Microchip, ensuring high precision with a +/-1.0 seconds accuracy. This board also included an input button for local control (start/stop recording) and a tri-color LED indicator (blue for standby, green for recording in progress without errors, and red for error alerts).

To power the device, a 600mAh lithium polymer battery and a designated charging controller were integrated, providing up to 8 hours of continuous recording time and allowing for convenient recharging via a microUSB cable.

A custom-designed case was developed to house the electronics at the rear of the head, specifically at the inion, forming an integral part of a 25mm elasticized head harness. This harness secured the EEG case to the participant's head and supported the electrodes. Electrodes were strategically placed on the left hemisphere at T3, FP1, F3, P3, and mirrored on the right at T4, FP2, F4, P4. The electrodes at FP3 and FP4 were Silver Chloride dry electrodes with a flat presenting surface, while the temporal, frontal, and parietal electrodes utilized 5mm comb dry Silver Chloride chemistry electrodes. The comb design facilitated better contact with the scalp through hair, a necessary feature for the naturalistic classroom-based research design that aimed for minimal invasiveness. To maintain wearability and reduce discomfort, small housings connected these electrodes to the elasticized 25mm straps.

The harness included two straps: one circumnavigating the head above the ears and a central strap running from nasion to inion. The central strap featured two semicircular springs connected to electrodes P3, P4, F1, and F2, applying gentle downward pressure to assist the comb electrodes in penetrating hair. The design of the spring clips minimized upward movement in thick hair, ensuring optimal electrode contact pressure.

Iterative testing and revision of the physical design, with input from the Future Minds Lab at UNSW, preceded the final implementation. Numerous prototypes and structural components were manufactured using a 3D printer and PLA, a compostable plastic derived from cornstarch.

Early in the study, adjustments to electrode placement were made in response to participant feedback regarding pressure irritation at the temples. Specifically, the temporal electrode was relocated from just in front to just behind the ears, resulting in improved comfort and reduced participant withdrawals thereafter.

Neurometric performance testing occurred at UNSW's Future Minds Lab. During these tests, a participant was exposed to 12Hz white flicker in a darkened room, resulting in observed event-related oscillations in the frequency domain at 12Hz from electrodes O1 and O2. These oscillations disappeared when the flickering stimulus ceased. Additionally, alpha peaks were observed with eyes closed and diminished upon eye opening at parietal electrodes, consistent with typical EEG signals.

Firmware modifications by the lead author enabled local control and data capture to a micro-SD card, with the firmware also managing real-time clock synchronization and file management. Each recording session was time-stamped at the beginning and end, facilitating synchronization with participant interaction in the Qualtrics survey and detection of data dropouts. Unique machine addresses and file naming conventions ensured data integrity and facilitated subsequent analysis, supported by the use of Class 10 microSD cards to manage high data rates without risk of overrun or errors.

Data Transformation

To determine the person-specific alpha peak frequency, data from the entire recording session were analyzed using an algorithm developed by the lead author. This algorithm identified the dominant peak within the range of 7.5-12 Hz, primarily using parietal electrodes which are known to capture alpha rhythms most distinctly according to the literature. However, in cases where data from the parietal electrodes were insufficient, data from other electrodes were utilized.

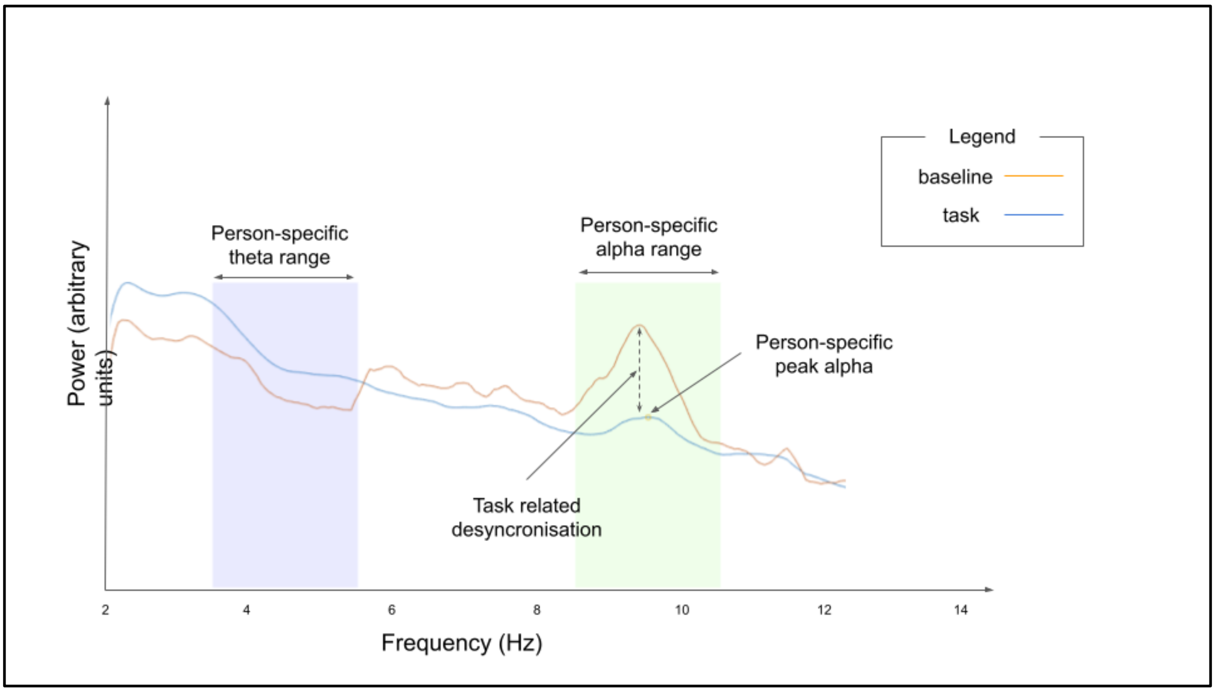
For many participants, the alpha peak was clearly identifiable, and the algorithm accurately pinpointed it automatically. Yet, some individuals exhibited ambiguous results with multiple alpha peaks, a phenomenon noted by other researchers (Chiang et al., 2011). To address this, each participant's power-frequency graph for both the task and baseline conditions was analyzed, applying Klimesch's principle. This principle determines the lowest frequency where task-related desynchronization is observed, thereby resolving ambiguity regarding the dominant alpha frequency.

In most cases, the automated algorithm incorporating Klimesch's principle effectively identified the alpha peak. All results underwent visual inspection, and in rare instances where the algorithm misidentified the peak, manual adjustments were made. Figure S8 exemplifies a typical alpha peak at 9.56 Hz, confirmed by the presence of task-related desynchronization evident in the difference between task and baseline spectra, correctly identified by the automated algorithm.

Once the individual's alpha peak frequency ($alpha_{person}$) was established, it served as the basis for defining frequency band cutoffs. The theta band was defined as $alpha_{person}$ - 6 Hz to $alpha_{person}$ - 4 Hz, while the alpha band spanned from $alpha_{person}$ - 1 Hz to $alpha_{person}$ + 1 Hz. These band definitions are illustrated in Figure S8 by shaded regions, highlighting their respective frequency ranges.

Figure S8

Identifying Person-Specific Alpha Peak Frequency



Note. An example of algorithmic identification of the peak alpha frequency by local prominence location and comparison of prominences between task and baseline for an individual.

Once the person-specific frequency ranges were identified for each participant, the theta band was then processed to infer working memory activity and the alpha band was processed to infer a measure of internal attention. These are explained in detail below.

Computing EEG-theta (Working Memory Activity)

Used to infer working memory activity, the EEG power was integrated over the person-specific frequency band of theta and the total power averaged over the time dimension within the period of interest. The frontal and prefrontal electrodes were preferentially used for all theta computations. The degree of task related synchronization (TRS) (Razoumnikova, 2000) in the theta band was computed using the equation below to derive a measure of the increase in mean band power during the time on task (completing the test) compared to the mean band power during the baseline measurement. To account for variations between individual recordings due to a range of factors such as scalp thickness, electrode connection, etc., this measure was made proportional to the mean band power for that individual over the entire time of the exercise and the resulting statistic was named EGG-theta.

$$EEG_{theta} = \frac{TaskPower_{theta} - BaselinePower_{theta}}{abs(meanPower_{theta})}$$

EEG-theta is a dimensionless statistic, representing the difference in theta power during the task and baseline power and proportional to the total theta power for that person. Simply, the larger EEG-theta, the greater the working memory activity.

High working memory activity is correlated with cognitive processing effort (Castro-Meneses et al., 2020) and may reflect a student relating items in working memory with long-term schema, adding new items from sensory input or editing and updating schemas in long-term memory. These are activities often related to developing understanding. It is relative to an individual and it is possible that two individuals processing the same stimuli may have differing working memory activity due to difference in the efficiency of pre-existing schemas.

Computing EEG-alpha (Internal Attention)

Utilized to infer internal attention, the signal within the alpha frequency band was analyzed similarly, with a key distinction. As previously noted, alpha measurements primarily utilize parietal electrodes. Typically, an individual's alpha frequency peak is discernible in the power-frequency graph (Olejniczak, 2006). Previous research has emphasized changes in the prominence of this peak during various mental tasks to gauge internal attention levels.

To quantify this, a *Matlab* algorithm developed by the lead author identified the dominant peak within the alpha range and computed its prominence relative to the overall power in the alpha band. The measure of prominence was determined by subtracting the mean power across the entire alpha band from the height of this peak, expressed by the equation:

$$Prominence = peakheight - meanPower$$

Figure S9

Calculating the Prominence of the Alpha Peak Frequency

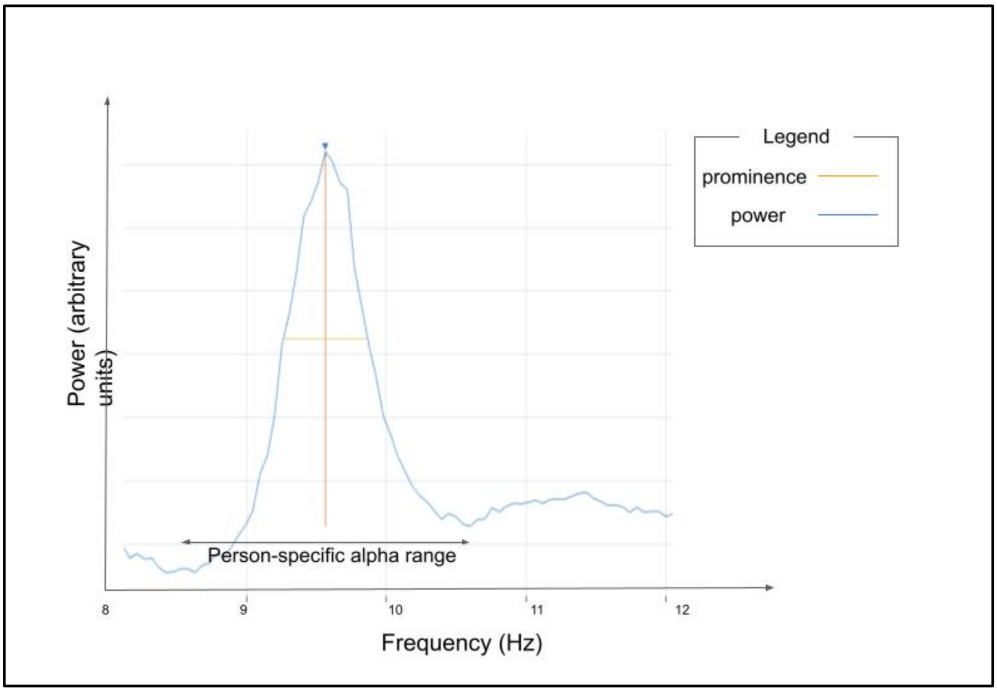


Figure S9 demonstrates this graphically with an alpha peak from a participant. The difference in prominence of the task-related and baseline peaks was then computed. This was made proportional to the mean alpha power for that participant across their entire recording, for the same reasons as for EEG-theta. The equation for calculating this task related synchronization (named EEG-alpha) is shown below:

$$EEG_{alpha} = \frac{TaskProminence_{alpha} - BaselineProminence_{alpha}}{abs(meanpower_{alpha})}$$

EEG-alpha is also a dimensionless statistic. As previously discussed, TRS in the alpha band is caused by multiple networks of neurons oscillating in phase with each other. When attention shifts to processing incoming sensory data, the TRS typically decreases, a phenomenon often referred to as desynchronization. In the context of alpha waves, this decrease signifies a suppression of external sensory stimuli in the cortical region where the TRS is observed (Klimesch, 1999). While this desynchronization may suggest cortical idling (e.g., daydreaming) (Pfurtscheller, 1992), it is also associated with creative ideation (Fink & Benedek, 2014). Therefore, a higher EEG-alpha statistic indicates that attention is focused internally rather than on external stimuli.

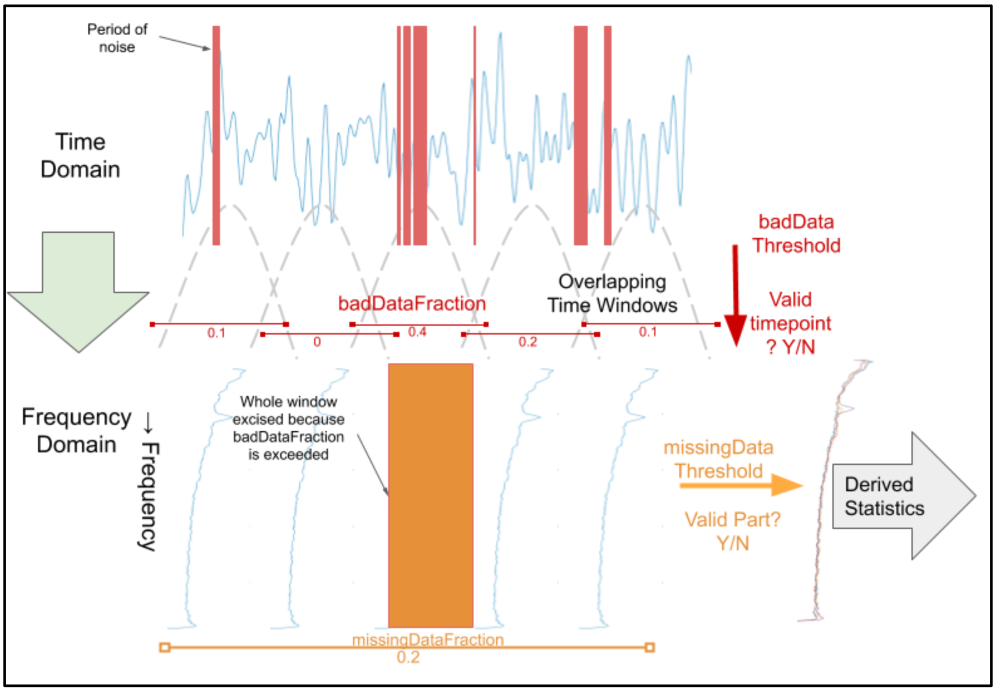
Handling Noise and Resulting Signal Loss in Neuro-physiological Data

Using portable, dry-coupled electrodes in EEG devices in a typical classroom was likely to lead to noise artefacts and this proved to be the case. An automated algorithm in the signal pipeline was developed to remove electrode decoupling events which were a major source of noise. Once gated out, these represent periods of signal loss.

However, since these data were transformed from the time domain to the frequency domain there no longer existed a one-to-one relationship between these excised events and the final signal. Instead, small sections of missing data in the time domain resulted in lower frequency resolution in the time domain for that overlapping time-slice of the frequency domain. As a result, small sections of signal loss could be tolerated without significant impairment, provided the resulting frequency resolution remained above the frequency bands of interest in this study. As shown in Figure S10, the gated periods of noise were tracked in the database and where a threshold was exceeded within a time window, that time window was removed. Since many overlapping time windows contributed to the time a student was working on a task, a second threshold was established for this aggregation. Where this was (rarely) exceeded, the corresponding aggregated statistic for that student-time-period was removed and then treated as missing data within M*plus*.

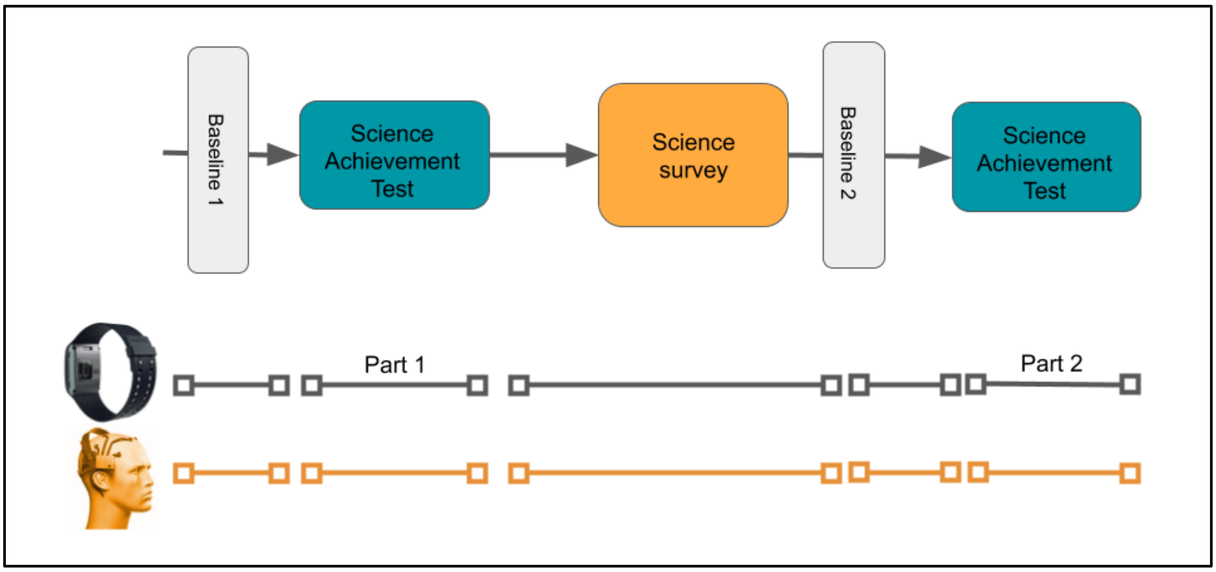
Figure S10

Handling Noise and Resulting Missing Data



Note. A simplified overview of the early part of the signal pipeline for managing missing data and noise excision prior to deriving EEG-alpha and EEG-theta.

Figure S11. *Overview of Procedure*



Results

Background Attributes

In addition to examining psychological indicators and science outcome measures, this study also considered various background attributes. These attributes were investigated to understand their association with the challenge-threat profiles derived from the data. Additionally, they were used to account for any variance in key analyses. The background attributes included socio-economic status (SES), which was based on the Australian Bureau of Statistics socio-economic index of home postcode (with a national mean of 1000 and a standard deviation of 100), year level in high school (treated as a continuous variable), and gender (coded as 0 for male and 1 for female).

Analysis

Latent Correlations and Factor Loadings: CFA

Confirmatory Factor Analysis (CFA) was utilized to examine the measurement properties of the hypothesized factors (previously identified as measures) and to reveal latent correlations among them. In a first-order CFA, the five factors (challenge, threat, sympathetic arousal, internal attention, and working memory activity) were each measured by four items (as detailed in the Materials section of the main article. CFA was conducted using M*plus*, with missing data imputed through Full Information Maximum Likelihood (FIML), the software's default setting. Upon establishing sound measurement properties (see Results in the main article for model fit statistics), this CFA served as the foundation for the subsequent Latent Profile Analysis (LPA). The factor scores, representing a unique score for each individual for each of the five indicators, were then exported from M*plus*. These scores, now referred to as “indicators”, were used as input for the LPA process, also performed in M*plus*. In summary, three steps were employed to prepare the data for LPA: (a) the four items per factor were used to generate a CFA model that quantified the five latent factors, (b) the latent factor scores were exported from this model, and (c) these factor scores were then used as the five indicators for the LPA.

Latent Profile Analysis

LPA facilitates a person-centered rather than a variable-centered approach, identifying groups of students based on the five indicators. A primary objective of the investigation was to explore the relationships between these profiles and outcomes such as science achievement and enjoyment, with the latter considered as distal outcomes in the LPA analysis. Background attributes such as gender and prior achievement were also controlled for in this analysis, ensuring that the findings related to the outcomes are free from variance attributable to these background factors.

The process for incorporating distal outcomes within LPA is an evolving area of research. Nylund-Gibson et al. (2019) highlight in their recent literature review that they advise against using classify-analyze approaches and pseudo class draws, despite previous recommendation and common usage. They provide evidence that the automated processes currently employed in M*plus* (version 8.0) impose restrictive assumptions regarding the relationship between predictors and outcomes in latent profile membership and do not account for classification error associated with non-perfect alignment of individuals with profiles. The LPA conducted here follows the manual three-step method recommended by Vermunt (2010). Readers are referred to their article for the recommended method and examples of M*plus* syntax. Since the manual method recommended by Vermunt (2010) preserves the probabilities of group membership for each student, it allows for some minor group adjustments when including outcomes to ensure the overall final solution is optimal. Provided this membership shift is relatively minor, it is considered acceptable.

Tests of Significance Between Profiles for Indicators and Outcomes

To determine which profile differences are meaningful, Wald tests were conducted for each indicator across different profiles. For instance, a Wald test was used to compare threat levels between Profile #1 and Profile #2, with significance set at $p < .05$. This procedure was repeated for threat levels across all pairs of profiles and for each of the five indicators. To assess interpretable differences in achievement and enjoyment outcomes as a function of profile membership, the final step of the approach involved applying a model constraint. Similar to Wald tests, this step tested the significance of differences in outcomes between each profile. Importantly, this method controlled for variance attributed to background factors such as gender, socioeconomic status (SES), and year level.

Relationship Between Background Attributes and Profile Membership

The inclusion of background attributes into the LPA was to examine how these attributes were associated with profile membership (e.g., whether males or females are more or less likely to be *Confident Striders*, etc.). In this study, girls were more likely to be *Fearers* than *Confident Striders* (multinomial logistic regression coefficient, $b = 0.47$; odds ratio, $OR = 1.6$; $p < .05$) or *Confident Battlers* ($b = 0.93$; $OR = 2.53$; $p < .05$) and more likely to be *Ambivalents* than *Confident Battlers* ($b = 0.85$; $OR = 2.34$; $p < .05$). There was no correlation between either year level nor socioeconomic status and group membership.

Relationship Between Profile Membership and Academic Outcomes

After examining student profiles based on five indicators, the analysis focused on how these profiles relate to crucial outcomes such as enjoyment and achievement, which are pivotal for understanding student engagement and persistence in science (Ainley & Ainley, 2011). This study aimed to investigate the associations between the identified profiles and these key outcomes. As outlined in the Methods section of the main article, incorporating distal outcomes into LPA remains an evolving area of research. As noted above, the current recommended approach, following Vermunt (2010), involves a manual three-step method that preserves probabilities of group membership even when distal outcomes are considered, potentially resulting in slight changes in profile membership, although such changes were minimal in this instance.

Before delving into these outcomes in relation to the profiles, it was noteworthy that there existed a positive correlation between enjoyment and achievement. Specifically, higher levels of achievement were associated with higher reported enjoyment ($r = .19$, $p < .01$). Additionally, it is important to acknowledge that there was considerable variance within each profile regarding these outcomes. Therefore, while insights can be drawn from average group scores on these outcomes, it is crucial to consider the significant variance within each profile.

It is important to note that the analyses exploring connections between profiles and outcomes controlled for students' background attributes as covariates (see above for details on the three-step approach). This approach ensured that the profile findings regarding enjoyment and achievement reflect differences purged of variance attributed to gender, year levels, and socioeconomic status. In other words, the values presented in Table S1 for these outcomes represent differences after accounting for the variance due to these background attributes.

Table S1 summarizes tests for significant differences in outcomes between profiles. For instance, *Confident Striders* reported significantly higher levels of enjoyment compared to *Ambivalents* ($p < .01$) and *Fearers* ($p < .01$). However, there was no significant difference in enjoyment between *Confident Striders* and *Confident Battlers* (though Table 4 of the main manuscript shows that while both were high in enjoyment, *Confident Striders* were significantly above the study average for enjoyment but *Confident Battlers* were not). *Fearers* demonstrated the lowest achievement, significantly lower than *Confident Striders* ($p < .05$).

Relationship Between Background Attributes and Academic Outcomes

Including background attributes facilitated an examination of their overall associations with the outcomes of enjoyment and achievement. Gender showed a significant association with achievement, indicating that girls performed less well than boys ($b = -.19$, $p < .01$). Older students reported lower levels of enjoyment ($b = -.22$, $p < .01$), whereas socioeconomic status did not show any significant associations with either enjoyment or achievement.

Table S1. *LPA Outcomes*

Profile Name	*Confident Striders* (#1)	*Ambivalents* (#2)	*Fearers* (#3)	*Confident Battlers* (#4)
Enjoyment	$^{*}0.38_{2,\,3}$	*-0.22_{1}	-0.18_{1}	0.17
Achievement	0.24_{3}	-0.06	-0.27	0.23

Note. Means for each profile against the outcomes. $^{*}p < .05$ indicates tests of significant difference from zero. Subscript indicates profile[s] (rows) significantly different ($p < .05$) from each other for that indicator. Background attributes were controlled for and the findings to the outcomes are purged of variance attributable to these background factors.

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