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Do Myers-Briggs Personality Dimensions Align with Neural Engagement Patterns During Formal Presentations?

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1. ABSTRACT

In classrooms and boardrooms alike, the moment of presentation often reveals unexpected contrasts: we assume that confident individuals falter and the reserved ones find composure, or vice versa. These observations invite a deeper question: Do personality classifications meaningfully align with measurable neural engagement patterns during formal presentations?

This project investigated whether Myers-Briggs Type Indicator (MBTI) dimensions and emotional intelligence correspond with neural engagement patterns, using anonymised electroencephalography (EEG) data from forty-two undergraduate students at Middlesex University. Alpha, beta, and theta band power signals were captured through the Muse 2 wearable device across each student's full presentation. Ten Tableau visualisations and a K-means clustering analysis were used to examine engagement trajectories, cognitive workload, flow states, and volatility across MBTI and Emotional Intelligence (EI) categories.

The findings showed that MBTI type, at the group level, does not reliably predict average neural engagement: 86% of students shared a broadly stable, flow-adjacent baseline regardless of personality. Differences were most evident in trajectory and volatility: Extraverts showed higher early-phase engagement, while Introverts engaged more consistently across the session. Feeling types appeared more frequently in the two outlier clusters, suggesting that emotional sensitivity may be associated with stronger neural responses in evaluative contexts. However, the small sample size limits how far this can be interpreted.

The most distinctive finding was a single ISFJ (Introverted-Sensing-Feeling-Judging) participant with self-awareness as their EI strength, who registered the highest engagement and volatility in the dataset, likely reflecting how strong internal monitoring and social sensitivity can amplify rather than regulate attentional focus under evaluation.

The study concludes that personality type alone is an insufficient lens for understanding neural engagement during presentations. The more meaningful signal lies in the interaction between personality and emotional intelligence, examined at the individual level rather than through group averages.

2. DESCRIPTION OF THE PROJECT

2.1 Problem Definition

Personality classifications derived from frameworks such as the Myers-Briggs Type Indicator (MBTI) are widely used to explain differences in confidence and performance during formal presentations in educational and professional contexts. The MBTI categorises individuals across four dimensions: Introversion-Extraversion, Sensing/Observant-Intuition, Thinking-Feeling, and Judging-Perceiving (Myers et al., 1985).

Table 1.1 The Four Dichotomies of the MBTI

Extraversion–Introversion Dichotomy (attitudes or orientations of energy)	
Extraversion (E)	Introversion (I)
Directing energy mainly toward the outer world of people and objects	Directing energy mainly toward the inner world of experiences and ideas
Sensing–Intuition Dichotomy (functions or processes of perception)	
Sensing (S)	Intuition (N)
Focusing mainly on what can be perceived by the five senses	Focusing mainly on perceiving patterns and interrelationships
Thinking–Feeling Dichotomy (functions or processes of judging)	
Thinking (T)	Feeling (F)
Basing conclusions on logical analysis with a focus on objectivity and detachment	Basing conclusions on personal or social values with a focus on understanding and harmony
Judging–Perceiving Dichotomy (attitudes or orientations toward dealing with the outside world)	
Judging (J)	Perceiving (P)
Preferring the decisiveness and closure that result from dealing with the outer world using one of the Judging processes (Thinking or Feeling)	Preferring the flexibility and spontaneity that results from dealing with the outer world using one of the Perceiving processes (Sensing or Intuition)

Figure 2.1. MBTI Four-Dimension Framework
Source: Adapted from Myers and McCaulley (1985, p. 6).

Despite their widespread use, MBTI classifications are predominantly derived from self-reported psychometric assessments rather than measurable physiological evidence. Studies identify observable differences in presentation behaviour across personality types, but these findings rely on external observation rather than physiological measurement (Fekry et al., 2019).

Similarly, emotional intelligence has been shown to influence performance through self-regulation and self-efficacy (Mayer et al., 2016; Kelly et al., 2020), yet it is rarely examined alongside personality and neural data within a single framework. This study addresses that gap directly, examining whether personality dimensions correspond to measurable neural engagement patterns during live presentations using EEG data.

2.2 Why It Is Important

This project is important because it reframes presentation performance as a measurable cognitive process rather than a fixed personality trait.

In educational and professional settings, high-stakes decisions are frequently informed by inferred confidence or personality classifications, despite limited evidence that these reliably predict real-time engagement. In information technology education specifically, communication and behavioural competencies have been shown to significantly influence outcomes beyond technical expertise alone (Rodríguez et al., 2012). By introducing physiological measurement through EEG, this study provides a more direct and objective account of how individuals respond during presentations.

Cognitive load theory further supports this approach, demonstrating that attention and mental effort are interdependent processes operating within limited working memory capacity (Sweller et al., 2019). This study captures both simultaneously using EEG-derived metrics, specifically neural engagement (β/α) and cognitive workload (θ/α), allowing their interaction to be examined over time.

The integration of personality (MBTI), emotional intelligence (EI), and neural engagement within a single analytical framework addresses a key limitation in existing research, which typically examines these factors in isolation. Advances in wearable EEG technology, such as the Muse 2 device, made this integration feasible in a real-world classroom setting (Krigolson et al., 2017).

2.3 Who Will Benefit

Students benefit from a clearer understanding of how engagement varies during presentations, shifting the focus from fixed personality traits to measurable and dynamic cognitive states. This supports more effective preparation, self-awareness, and interpretation of performance, particularly in high-stakes academic contexts where outcomes contribute to degree classification and future opportunities.

Educators and assessors benefit from a more evidence-based perspective on presentation evaluation. By incorporating insights into attentional stability and cognitive load, assessment practices can move beyond assumption-based interpretations of personality.

Researchers benefit from a methodological contribution that integrates psychometric data, emotional intelligence, and EEG within a naturalistic setting, responding to calls for more individual-level, data-driven approaches in personality research (Fisher et al., 2018).

Organisations that rely on personality frameworks for training and evaluation may benefit from a more nuanced understanding of engagement. Effective presentations shape decision-making, stakeholder confidence, and communication outcomes (Swathi et al. 2015), and this study provides a basis for training strategies grounded in physiological evidence rather than classification alone.

3. LITERATURE REVIEW

3.1 State of the Art

Research on personality, emotional intelligence, and neural engagement has developed largely in separate fields, each offering partial insight into presentation performance without connecting to the others.

Personality frameworks such as the MBTI classify individuals across four dimensions: Introversion-Extraversion, Sensing-Intuition, Thinking-Feeling, and Judging-Perceiving (Myers et al., 1985). (Fekry et al. 2019) identified meaningful differences in group presentation behaviour across MBTI types, but their analysis relied on external observation rather than physiological measurement.

Table 3.1.

Table of 16 MBTI personality types and roles

Result	Type	Role	Result	Type	Role
ENTJ	Commander		ENFJ	Protagonist	
ENTP	Debater	Analysts	ENFP	Campaigner	Diplomats
INTJ	Architect		INFJ	Advocate	
INTP	Logician		INFP	Mediator	
ISTJ	Logistician		ISFP	Adventurer	
ESFJ	Consul	Sentinels	ESTP	Entrepreneur	Explorers
ISFJ	Defender		ISTP	Virtuoso	
ESTJ	Executive		ESFP	Entertainer	

Source: Adapted from (Fekry et al. 2019).

Behavioural analytics research has examined presentations through structured observation and visualisation, capturing engagement patterns without incorporating direct physiological measurement (Dafoulas et al., 2020). Emotional intelligence, defined as the capacity to perceive, use, understand, and manage emotions (Mayer et al., 2016), has been shown to reduce public speaking anxiety through self-awareness and emotional regulation (Kelly et al., 2020). Communication competence and emotional regulation have also been identified as significant performance factors in educational and organisational contexts (Rodríguez et al., 2012; Swathi et al., 2015). Despite this, EI is rarely examined alongside personality and physiological data within a single framework.

At the neural level, the beta-to-alpha ratio (β/α) is a reliable index of cognitive engagement, and the theta-to-alpha ratio (θ/α) reflects cognitive workload, with frequency band ratios among the most interpretable features for EEG-based analysis (Singh et al., 2023). No existing study has brought these three dimensions together using physiological measurement during live presentations, which is the gap this project directly addresses.

3.2 Current Solutions

Current solutions for assessing and improving presentation performance fall across three areas: psychometric profiling, behavioural observation, and technological intervention.

Personality and presentation performance are most commonly studied through psychometric instruments such as MBTI, emotional intelligence assessments, and communication apprehension scales. These tools provide structured insight into individual differences but rely on self-report and produce static profiles, limiting their ability to capture how engagement fluctuates during a live presentation.

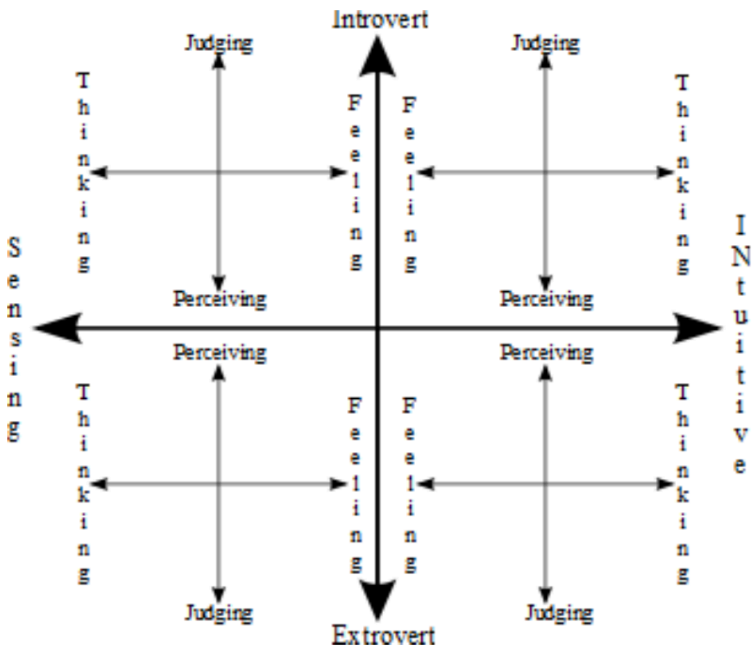


Figure 1. Structural representation of the Myers–Briggs Type Indicator (MBTI) four-dimension framework (Introversion–Extraversion, Sensing–Intuition, Thinking–Feeling, Judging–Perceiving).
Source: Adapted from (Rodríguez Montequín et al., 2012).

Behavioural and physiological observation systems offer more objective measurements. Engagement and interaction patterns have been captured through structured observation and visual analytics (Dafoulas et al., 2020), and gaze-monitoring systems have quantified attentional allocation during performance tasks (Du et al., 2013). While these approaches generate interpretable data, they remain limited to observable actions and do not capture underlying neural processes.

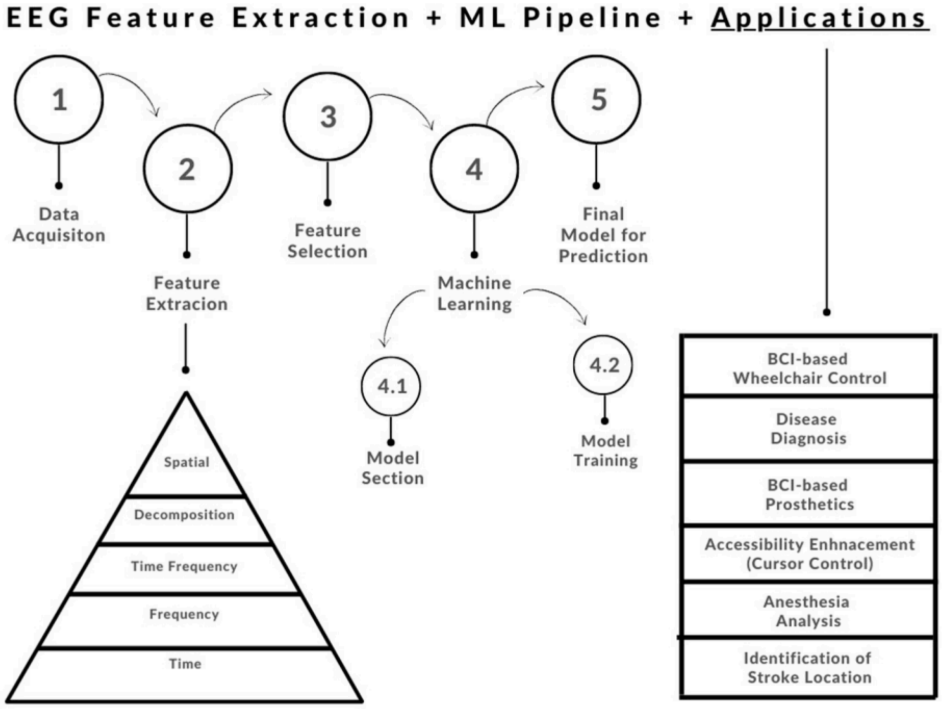


Figure 3. General EEG feature extraction and machine learning pipeline, illustrating stages from data acquisition to predictive modelling.
Source: Adapted from (Singh et al., 2023), based on (Subasi et al., 2019).

Virtual reality platforms have demonstrated improvements in presentation performance through simulated rehearsal environments (Bachmann et al., 2023), and AI-based feedback systems extract multimodal indicators such as vocal pacing and facial expressiveness for structured evaluation. However, these systems are designed to improve performance rather than to investigate the neural mechanisms underlying engagement during real presentations.

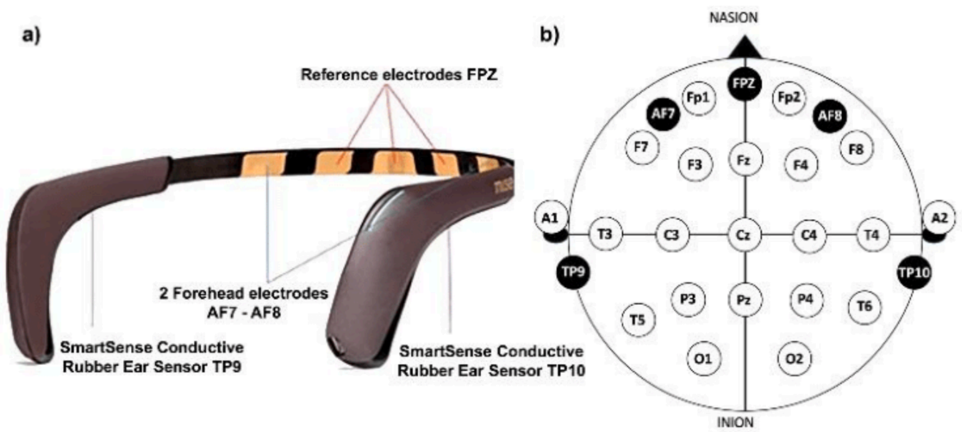


Figure 2. Electrode placement of the Muse 2 wearable Electroencephalography (EEG) device, illustrating frontal (AF7, AF8) and temporal reference (TP9, TP10) sensor positions within the international 10–20

system.
Source: Adapted from (InteraXon, 2022).

The Muse 2 wearable EEG device addresses this gap by enabling neural data collection in real-world classroom settings. With four electrodes (AF7, AF8, TP9, TP10) recording at 256 Hz via Bluetooth (InteraXon, 2022), and demonstrated reliability in detecting established neural signals (Krigolson et al., 2017), it provides an ecologically valid measurement that laboratory-grade systems cannot feasibly offer in naturalistic presentation contexts.

3.3 Why These Solutions Are Not Sufficient

The primary limitation of existing approaches is fragmentation. Personality frameworks, physiological measurement systems, and emotional intelligence models have developed independently and rarely operate within a unified analytical framework.

Psychometric tools capture personality traits but not real-time neural responses. Behavioural systems measure observable actions but not internal cognitive states. EEG research typically focuses on controlled cognitive tasks rather than socially complex environments such as presentations. Recent AI-driven feedback systems further illustrate this limitation, generating structured evaluations at scale but without incorporating validated personality constructs or physiological measurement (Gürtl et al., 2025).

As a result, a central question remains largely unanswered: do different personality types experience presentations differently at the neural level, or do they simply behave differently while sharing similar internal states? Addressing this requires integrating personality, emotional intelligence, and neural data within a single analytical framework, an approach not fully realised in existing research.

Cognitive load theory further underscores this gap, demonstrating that engagement and mental effort are interdependent processes (Sweller et al., 2019). Analysing engagement without considering workload provides an incomplete account of a participant's cognitive state during a presentation, which this study directly addresses.

3.4 Anticipated Challenges and Difficulties

Several methodological challenges were identified before analysis and shaped how findings are interpreted.

Consumer-grade EEG devices offer reduced signal fidelity compared to laboratory systems. (Mikhaylov et al. 2024) found that such devices are less sensitive to subtle cognitive differences, meaning derived engagement measures are directionally reliable but not precise indicators of specific neural processes. This study, therefore, prioritises ecological validity over measurement precision.

EEG frequency bands do not map to single cognitive states. As Cohen (2017) notes, similar patterns can reflect different processes depending on context, so engagement and workload metrics are interpreted as indicators of cognitive state rather than direct measurements.

The dataset includes 42 participants distributed across multiple MBTI types, with some types represented by very small numbers. Missing MBTI and EI data further reduces the sample for certain analyses. As (Fisher et al., 2018) highlight, variability within personality groups often exceeds differences between them, which limits generalisability. Findings are therefore interpreted as patterns rather than definitive conclusions.

Attention also naturally fluctuates over time during structured tasks, with mind-wandering rates varying independently of task conditions (Wammes et al., 2016). Some observed variation in engagement may therefore reflect natural cognitive dynamics rather than personality-driven effects.

Finally, this study is observational. Relationships between personality, EI, and neural engagement can be identified but not interpreted causally, and findings may be context-specific to this cohort and institutional setting.

4. AIMS & OBJECTIVE

4.1 Research Aim and Objectives

Research Aim

This study investigates how neural engagement during formal presentations relates to personality, as defined by the Myers-Briggs Type Indicator (MBTI), and emotional intelligence (EI). By combining EEG bandpower data from the Muse 2 wearable device with visual analytics and unsupervised clustering, the study explores whether personality and EI align with observable patterns in neural engagement, particularly in terms of timing, variability, and responsiveness.

Research Objectives

Objective 1: To preprocess and structure high-frequency EEG bandpower data through cleaning, participant-level integration with MBTI and EI datasets, and feature engineering, producing a reliable time-series dataset for analysis.

Objective 2: To derive neural and behavioural features capturing both the level and temporal dynamics of engagement during presentations, including neural engagement (β/α), cognitive workload (θ/α), divergence, and volatility.

Objective 3: To explore neural engagement patterns through Tableau visual analytics, examining how engagement evolves and varies across MBTI dimensions and EI categories at both group and individual levels.

Objective 4: To apply K-means clustering to participant-level features in Weka, identifying distinct neural engagement profiles without imposing predefined personality groupings.

Objective 5: To interpret the relationship between identified engagement profiles, MBTI dimensions, and EI, with particular focus on timing effects, interaction patterns, and individual variability.

4.2 Expected Contributions of the Study

This study contributes to three key areas.

First, theoretically, the study challenges the assumption that personality type directly determines engagement level. Findings suggest that personality influences the structure of engagement, including when it occurs, how stable it is, and how it responds to specific moments, rather than its overall magnitude.

Second, methodologically, the study integrates EEG-based feature engineering, visual analytics, and unsupervised clustering within a single analytical pipeline. By combining time-series analysis with participant-level modelling, it demonstrates how complex behavioural patterns can be identified without relying solely on predefined group comparisons.

Third, practically, the development of interactive Tableau visualisations provides an interpretable framework for analysing neural engagement in presentation settings. This has direct applications in educational assessment and organisational communication training, supporting more evidence-based approaches to understanding attention, performance, and individual differences.

5. METHODS AND METHODOLOGY

5.1 Project Context and Approach

This project sits at the intersection of data science, cognitive neuroscience, and visual analytics, examining neural engagement during formal presentations. It combines EEG signal analysis with personality theory (MBTI) and emotional intelligence (EI) to investigate individual differences.

A quantitative, exploratory, and data-driven approach was adopted. Python was used for data processing and feature engineering, Tableau for visual analytics, and Weka for unsupervised clustering, enabling patterns to emerge without predefined categories.

5.2 Data Collection and Preparation

The study uses anonymised EEG data collected during student presentations using the Muse 2 device. The dataset contains time-stamped bandpower values (delta, theta, alpha, beta) alongside participant identifiers.

MBTI and EI data were provided separately and merged using participant IDs. Preprocessing in Python included removing invalid rows, standardising the structure, and constructing a unified time-series dataset. Missing MBTI and EI values were retained and handled contextually during analysis.

5.3 Feature Engineering and Data Transformation

EEG signals were transformed into behavioural metrics, with engagement (β/α), workload (θ/α), and divergence computed. MBTI types were decomposed into four dimensions (IE, SN, TF, JP), and participant-level features were derived.

5.4 Visual Analytics and Exploratory Analysis

Tableau dashboards were developed to analyse neural engagement across time, personality, and emotional intelligence at both group and individual levels.

Research Question	Addressed By
How did brain activity change over the course of the presentation?	Visualisation 1
Did personality type affect when participants became most engaged?	Visualisation 2
Which personality types showed the highest overall engagement?	Visualisation 3
How differently did individuals within the same personality type respond?	Visualisation 4

Did some personality types experience flow more than cognitive strain?	Visualisation 5
Did personality dimensions produce different brainwave patterns?	Visualisation 6
Were participants with the same personality type consistent in their engagement?	Visualisation 7
How relaxed or alert were different personality types during the presentation?	Visualisation 8
Did emotional intelligence affect how strongly the brain engaged?	Visualisation 9
Did EI and personality together shape how stable engagement was over time?	Visualisation 10

5.5 Clustering and Integration of Results

Participant-level features were aggregated into a dataset of 42 participants and 17 variables, capturing engagement patterns, workload, neural activity, and variability.

K-means clustering was applied in Weka to identify natural groupings. As clustering requires numerical input, MBTI and EI variables were removed prior to analysis. Cluster labels were then merged back using Python to support interpretation.

5.6 Ethical Considerations and Reproducibility

All data were anonymised before analysis, and no additional data collection was conducted, ensuring compliance with ethical standards for secondary data use.

All scripts used for data processing, feature engineering, clustering, and integration are available in a public GitHub repository (see Appendix A), ensuring transparency and reproducibility.

6. WORK DONE – RESULTS

This section outlines the data processing and analysis pipeline, from raw EEG data to clustering and visualisation, using Python, Tableau, and Weka.

6.1 Raw Data Collection and Structure

The dataset consisted of raw EEG recordings from 42 anonymised participants, stored across approximately eleven CSV files. Each file contained time-series data collected during presentations, with participants identified using user IDs. Separate datasets containing MBTI types and Emotional Intelligence (EI) categories were later merged.

Each EEG file included multiple sensor readings, including neural signals (delta, theta, alpha, beta) and additional physiological and motion data (for example, accelerometer and PPG), which were not required for this analysis.

The original columns in the dataset were:

- session_id
- user
- sensor
- elapsed_sec
- sample_count
- delta
- theta
- alpha
- beta
- gamma_1
- gamma_2
- ppg_ir
- ppg_red
- ppg_ambient
- acc_x
- acc_y
- acc_z
- drl
- ref

To prepare the data, a Python script was used to combine and clean all files into a single structured dataset. The script filtered for EEG sensor data, standardised participant identifiers, selected relevant signal columns, and concatenated all files.

The dataset was then reduced to the following variables:

- participant
- elapsed_sec (renamed to time_seconds)
- delta
- theta
- alpha
- beta

Rows with missing values were removed, and entries where all EEG signals were zero were excluded, as they represent invalid readings. The data was then sorted by participant and time to preserve temporal structure.

The final output was a clean, unified time-series dataset of valid EEG signals for all participants, used for subsequent analysis. The full implementation is provided in *combine_and_clean_raw_eeg_01.py* (see Appendix A).

6.2 EEG Data Cleaning and Integration

Following initial cleaning, a second Python script was used to construct a structured time-series dataset and integrate personality data. The cleaned EEG dataset (*eeg_combined_clean_01.csv*) was loaded, containing delta, theta, alpha, and beta signals for 42 participants.

MBTI data were loaded separately, cleaned, and merged using participant IDs. Column names were standardised, and a left join was applied to retain all EEG records. MBTI data were available for 26 participants, with missing values for the remainder.

The Python script then performed feature engineering to derive behavioural metrics from the EEG signals. Two key measures were computed:

- Engagement: ratio of beta to alpha activity (β/α), represents attentional focus

- Cognitive workload: ratio of theta to alpha activity (θ/α), represents mental effort

These metrics transformed the raw EEG signals into interpretable behavioural indicators. In addition, the MBTI personality type was decomposed into its four constituent dimensions (by extracting each character from the MBTI string):

- Introversion/Extraversion (IE)
- Sensing/Intuition (SN)
- Thinking/Feeling (TF)
- Judging/Perceiving (JP)

Emotional Intelligence (EI) data were subsequently cleaned and merged using participant IDs, completing the integration of neural, behavioural, and personality variables.

The dataset was sorted by participant and time, and values were rounded for consistency before being saved as *eeg_timeseries_full_02.csv*.

The final dataset produced at this stage contained the following columns:

- participant
- time_seconds
- delta
- theta
- alpha
- beta
- MBTI
- engagement
- cognitive_workload
- IE
- SN
- TF
- JP
- EI

MBTI data were available for 26 participants and EI data for 19, resulting in missing values for these variables.

The full implementation is provided in *build_timeseries_dataset_02.py* and *integrate_ei_data_04.py* (see Appendix A).

6.3 Data Preparation for Visualization

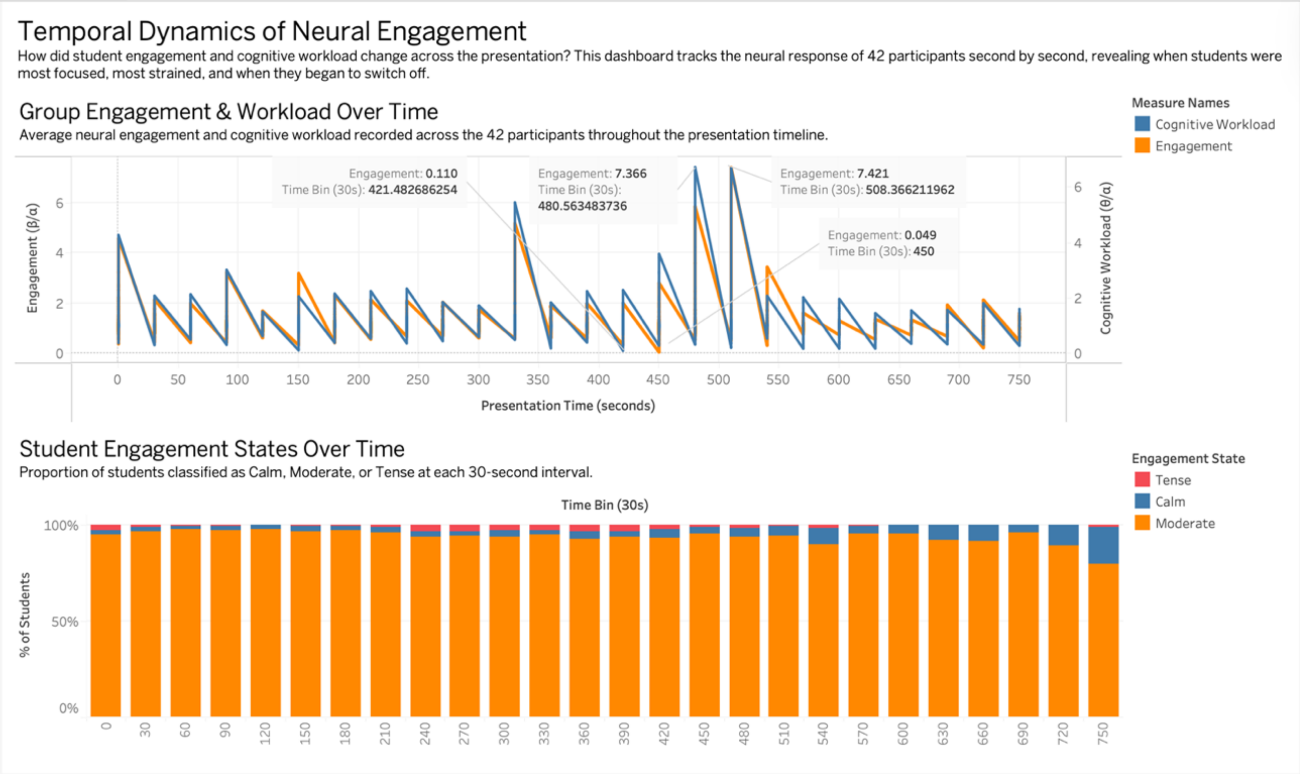
The final processed dataset (eeg_timeseries_final_version_04.csv) was exported and used in Tableau for exploratory data analysis and dashboard creation. It contained cleaned EEG signals, behavioural metrics, and personality features in a single structured dataset.

6.4 Data Visualizations

This section presents the visualisations developed to analyse neural engagement patterns, variability, and their relationship with personality traits across the dataset.

i. <u>How does Neural Engagement and Cognitive Load Evolve During a Presentation?</u>

This dashboard combines two visualisations to examine how students' neural engagement and cognitive workload change over the duration of a presentation.



Visualization 1. Neural Engagement and Workload Over Time

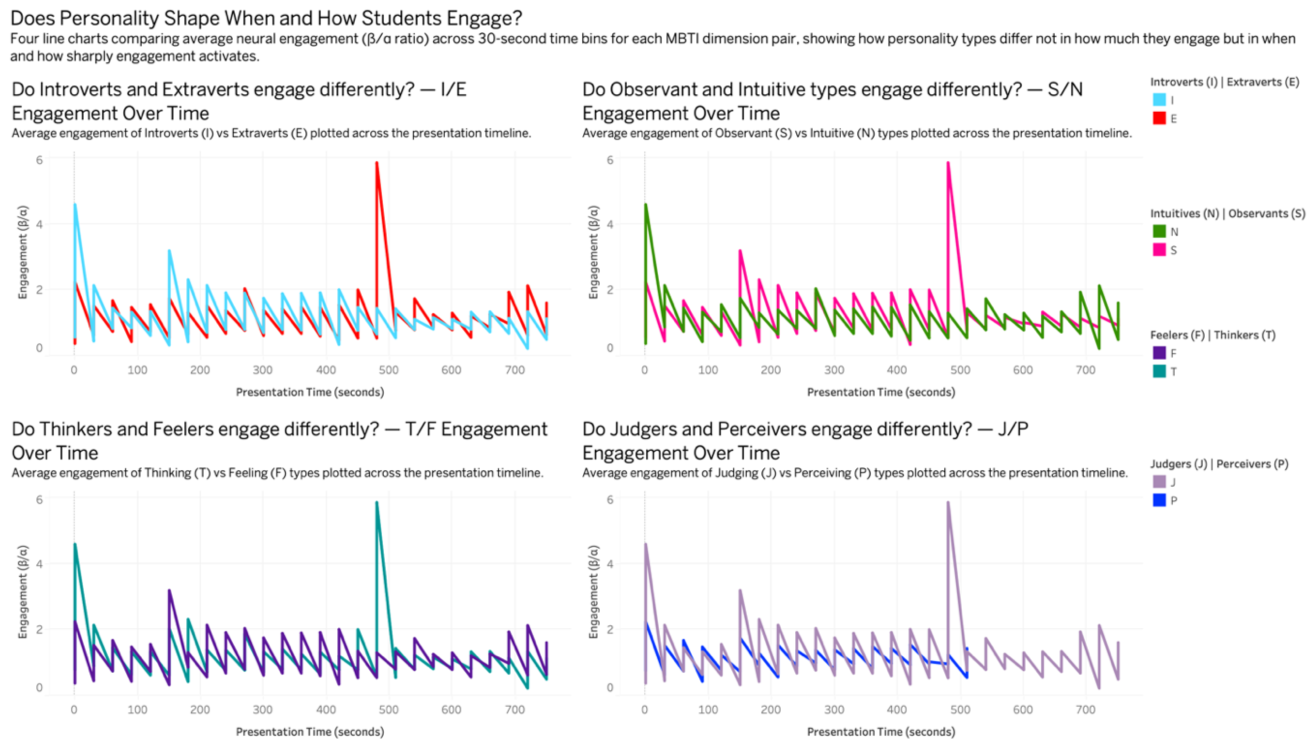
The first chart shows how engagement (β/α) and cognitive workload (θ/α) change over time, while the second shows the proportion of students in each state (Calm, Moderate, Tense) at 30-second intervals. The two lines closely track each other, indicating that attention and mental effort rise and fall together, consistent with cognitive load theory (Sweller et al., 2019). Peaks in engagement align with peaks in workload, suggesting active cognitive processing.

The pattern is highly variable rather than steady. Engagement peaks at approximately 7.421 around 8 minutes 30 seconds, with another peak shortly before, but also drops sharply to around 0.049 and 0.110 in the same period. These shifts suggest that engagement responds to specific presentation moments, such as transitions or complex tasks, aligning with research showing that attention fluctuates over time (Wammes et al., 2016).

Most students remain in a “Moderate” state (around 90–96%) throughout. This is stable in the early phase (0–4 minutes). In the middle phase (4–7 minutes), “Tense” states increase, aligning with engagement peaks and likely reflecting the question period following presentations at Middlesex University. In the later phase (after 7 minutes), “Tense” states decrease while “Calm” states increase, suggesting reduced engagement, consistent with attention decline over time (Wammes et al., 2016).

ii. <u>Do Personality Traits Influence When Neural Engagement Occurs?</u>

This dashboard examines whether MBTI personality dimensions influence when neural engagement occurs during a presentation, rather than how much engagement is observed overall.



Visualization 2. Neural Engagement Patterns by Personality Over Time

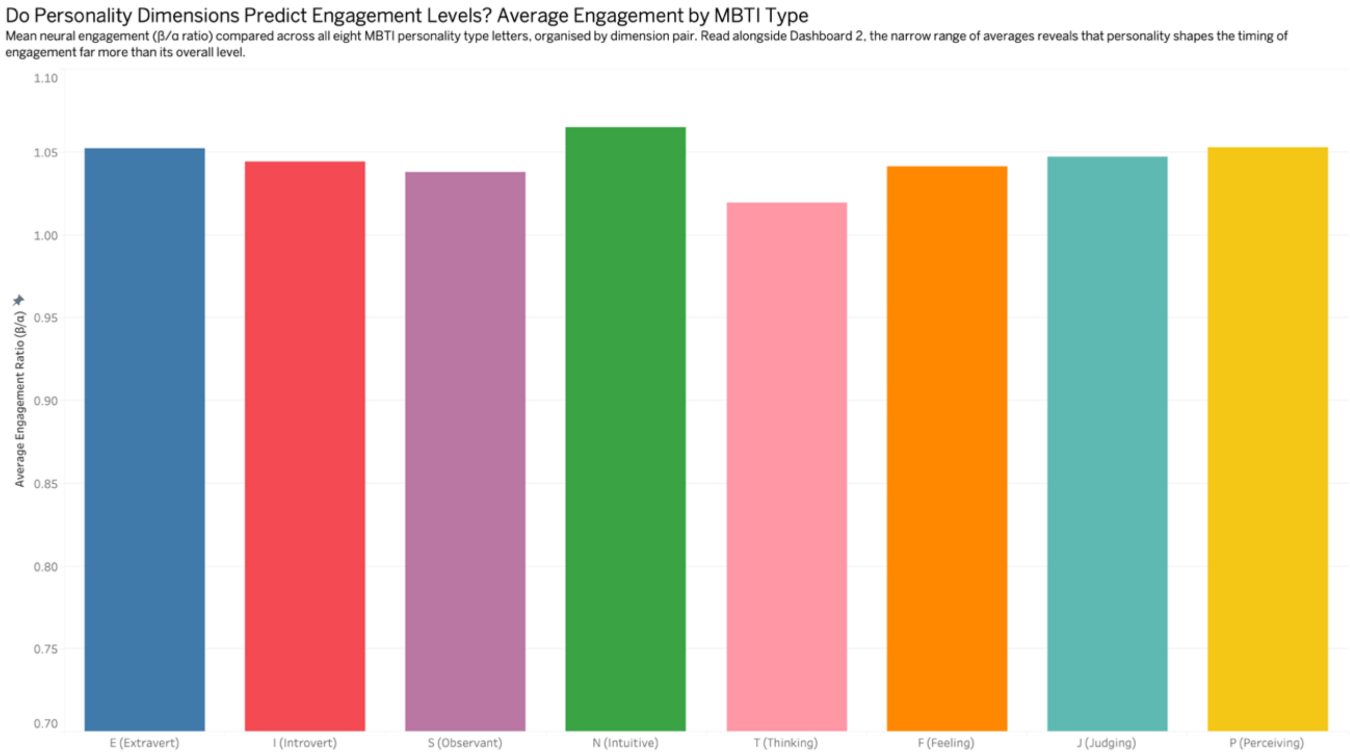
The four line charts show average β/α engagement across MBTI dimensions over time. A shared spike occurs at approximately 500 seconds, consistent with the previous dashboard, but its magnitude varies. Extraverts, Sensing (Observant) types, Thinkers, and Judgers show stronger increases (approximately 5.0–6.0), while Introverts, Intuitive types, Feelers, and Perceivers show smaller changes.

The I/E dimension highlights differences in timing: Introverts peak early (around 4.5) and decline, whereas Extraverts increase sharply at 500 seconds. Similar patterns appear in the S/N and T/F dimensions, where Sensing and Thinking types show clearer spikes, while Intuitive and Feeling types remain more stable. The J/P dimension shows the strongest contrast, with Judgers displaying multiple spikes and Perceivers remaining relatively flat.

These patterns suggest that MBTI dimensions influence engagement timing and responsiveness rather than sustained attention. However, results should be interpreted cautiously due to small subgroup sizes and the possibility that the 500-second spike reflects a small number of highly reactive individuals.

iii. <u>Does Personality Affect Average Neural Engagement?</u>

This bar chart compares average neural engagement (β/α) across all eight MBTI personality dimensions.



Visualization 3. Average Neural Engagement by Personality Type

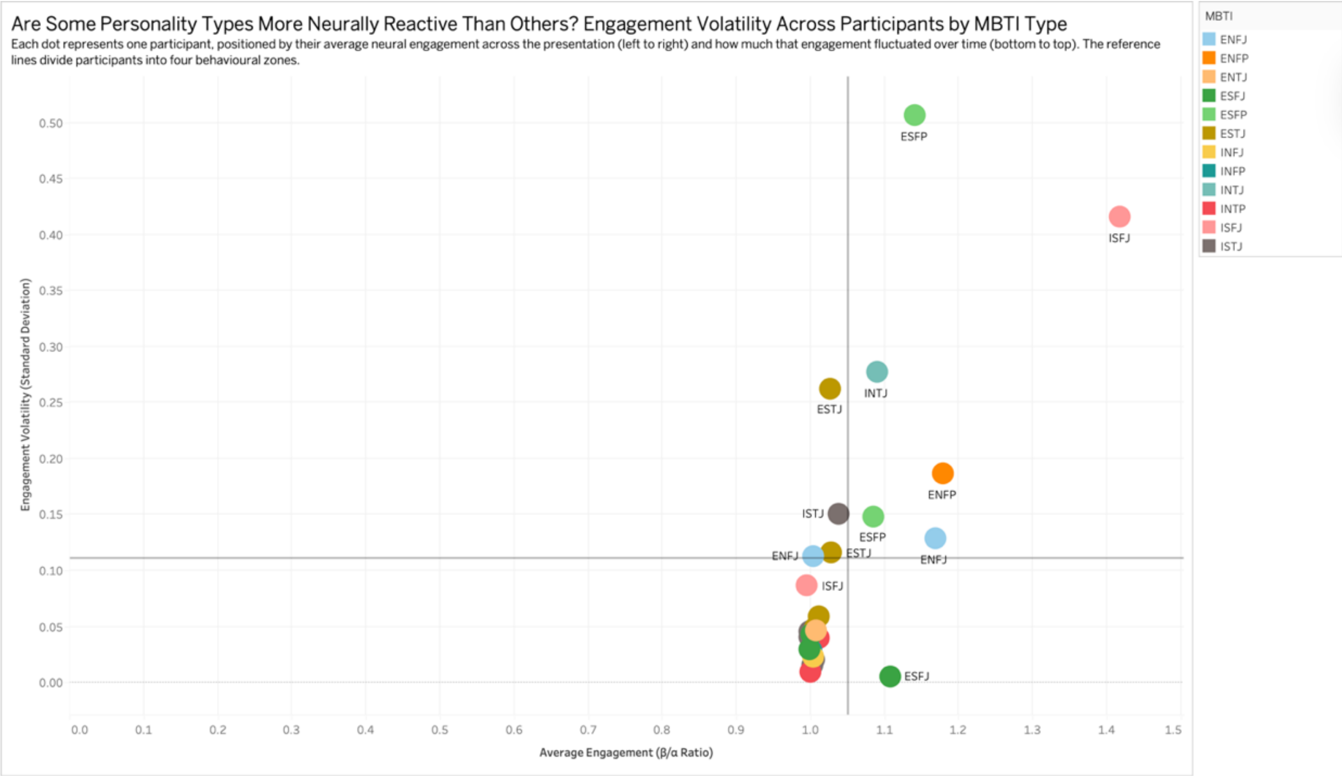
Values fall within a narrow range (approximately 1.01–1.07), indicating minimal variation in average engagement across personality groups. Intuitive types show the highest mean engagement (around 1.06–1.07), while Thinking types are the lowest (approximately 1.01–1.02), with all other dimensions clustering closely around the mean. This indicates that no personality dimension is associated with substantially different average engagement.

While personality groups differ in how engagement changes over time, they do not differ meaningfully in overall engagement. Personality is therefore associated with how engagement is distributed rather than its magnitude.

The similarity in averages also explains earlier temporal patterns: sharp spikes for certain groups are offset by lower values elsewhere, resulting in comparable means and indicating differences in responsiveness rather than sustained engagement.

iv. Do Personality Types Differ in Neural Engagement Variability?

This scatter plot shifts the analysis from group-level patterns to individual behaviour, representing each of the 26 participants with valid MBTI data as a single point.



Visualization 4. Neural Engagement Variability Across Participants

Each point represents average engagement (x-axis) and volatility (y-axis), allowing level and variability to be assessed together. Reference lines divide the chart into four zones. Most participants cluster around engagement values of 1.0–1.1 with low volatility, indicating stable, moderate engagement.

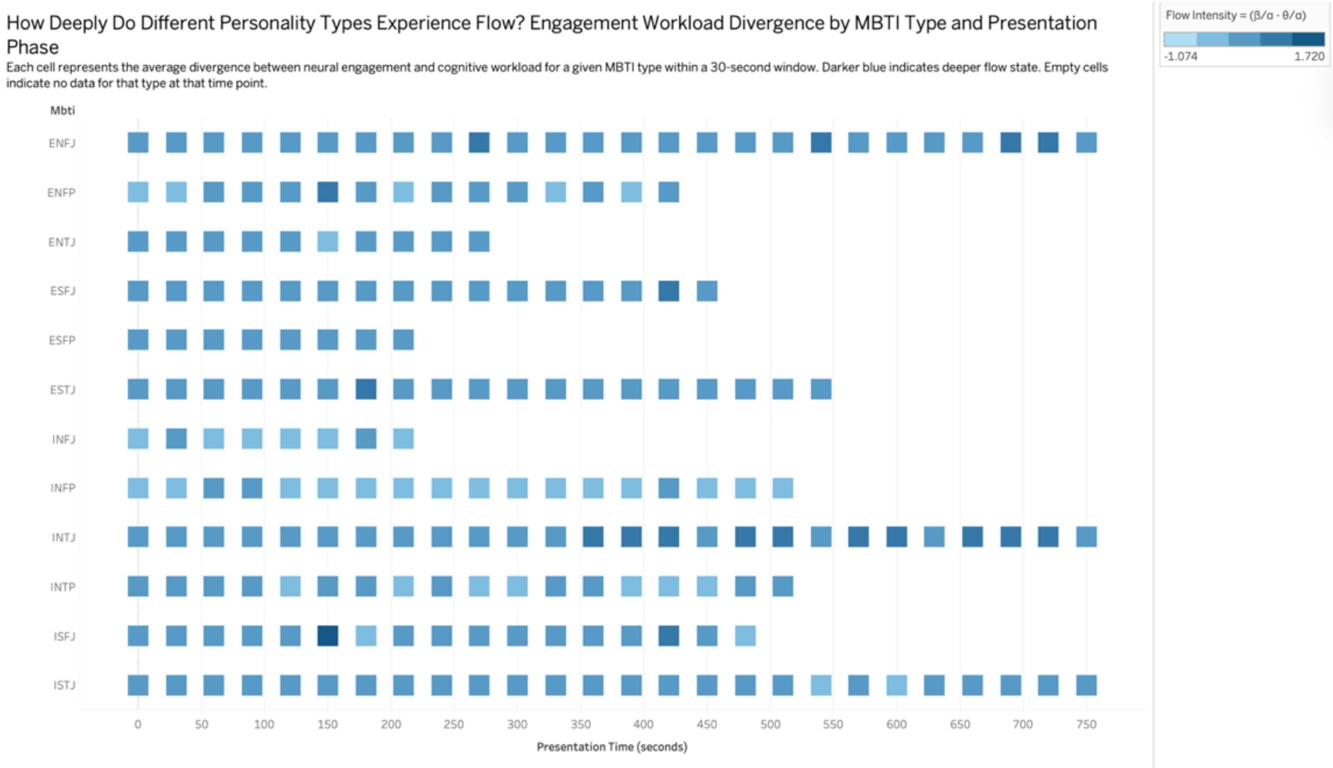
A small number of participants deviate from this cluster. One ESFP shows the highest volatility (approximately 0.50), while an ISFJ records the highest engagement (approximately 1.42) with relatively high volatility (around 0.41), indicating sustained but reactive engagement. Additional cases, including INTJ and ESTJ, show that higher variability is concentrated within a small subset of individuals.

This suggests that group-level trends do not apply uniformly within personality types. While Sensing and Judging types appeared reactive in earlier analysis, this is driven by a few individuals rather than the group. Similarly, although average engagement is similar across Thinking and Feeling types, Feeling types show a wider spread, while Thinking types are more tightly clustered.

Personality differences are therefore more evident in variability than in average engagement, and group-level summaries may obscure individual patterns (Fisher et al., 2018).

v. <u>Do Personality Types Differ in Neural Flow States?</u>

This heat map examines how neural engagement relates to cognitive workload across personality types over time, using divergence ($\beta/\alpha - \theta/\alpha$) as an indicator of flow intensity.



Visualization 5: Neural Flow Intensity Across Personality Types Over Time

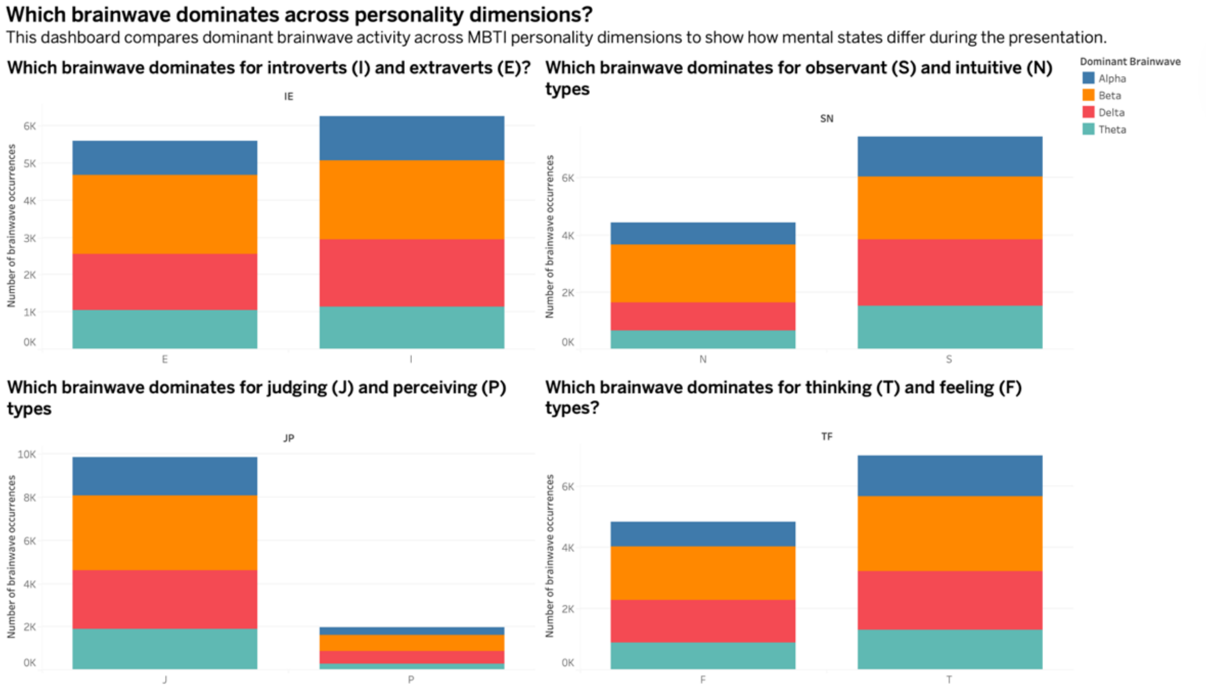
Each cell shows average divergence for a given MBTI type within a 30-second window. Darker shades indicate engagement exceeding workload, while lighter shades indicate a smaller difference. Positive divergence reflects a flow-like state, where engagement is maintained without proportional cognitive strain (Csikszentmihalyi, 1990; Huskey et al., 2018).

Across most types, engagement exceeds workload, indicating a generally flow-adjacent state. However, depth and consistency vary. INTJ types show stronger divergence, particularly in later phases, suggesting sustained flow, while ENFJ types also maintain relatively high and stable divergence. In contrast, INFP and INFJ types show lighter cells, indicating a more balanced relationship between engagement and workload.

Some types, such as ESFP and INFJ, have fewer observations, limiting reliability. Despite this, the chart shows that while average engagement is similar across types, the quality of engagement differs. Some types sustain stronger and more consistent flow-like states, while others remain closer to workload, suggesting personality relates to how efficiently engagement is maintained rather than its overall level.

vi. <u>Do Brainwave Patterns Differ Across Personality Dimensions?</u>

This visualisation compares the distribution of dominant brainwave activity across MBTI personality dimensions, showing how different frequency bands contribute to neural engagement during the presentation.



Visualization 6. Dominant Brainwave Activity Across Personality Dimensions

Across all dimensions, beta waves are most prominent, indicating active, task-focused processing. This aligns with EEG interpretations, where beta reflects alertness, while alpha and theta are associated with more relaxed or internally focused states (Cohen et al., 2017).

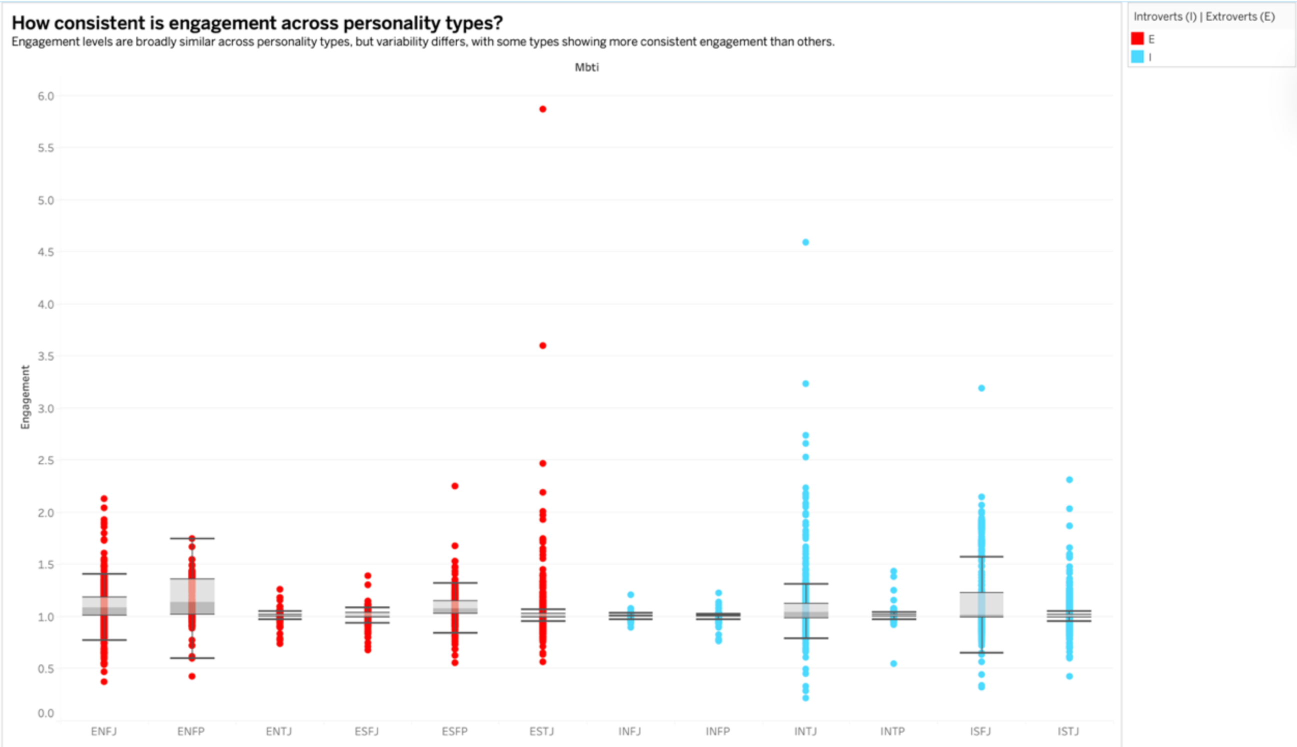
Differences emerge in the distribution of brainwave activity across personality dimensions. Extraverted and Sensing types show higher beta activity, suggesting more externally oriented engagement, while Introverted and Intuitive types show relatively higher alpha and theta activity, indicating more internally mediated processing.

Further variation appears in the Judging/Perceiving and Thinking/Feeling dimensions. Judging types show a more balanced distribution across bands, suggesting more consistent engagement, while Perceiving types are less consistent. Thinking types show stronger beta activity, indicating a more task-focused profile, whereas Feeling types show a broader distribution across non-beta states.

These patterns support earlier findings that personality differences lie in how engagement is expressed and distributed, rather than in overall levels.

vii. <u>How Consistent Is Neural Engagement Across Personality Types?</u>

This chart examines how neural engagement varies within each personality type by focusing on the distribution of values rather than the average.



Visualization 7. Distribution of Neural Engagement by Personality Type

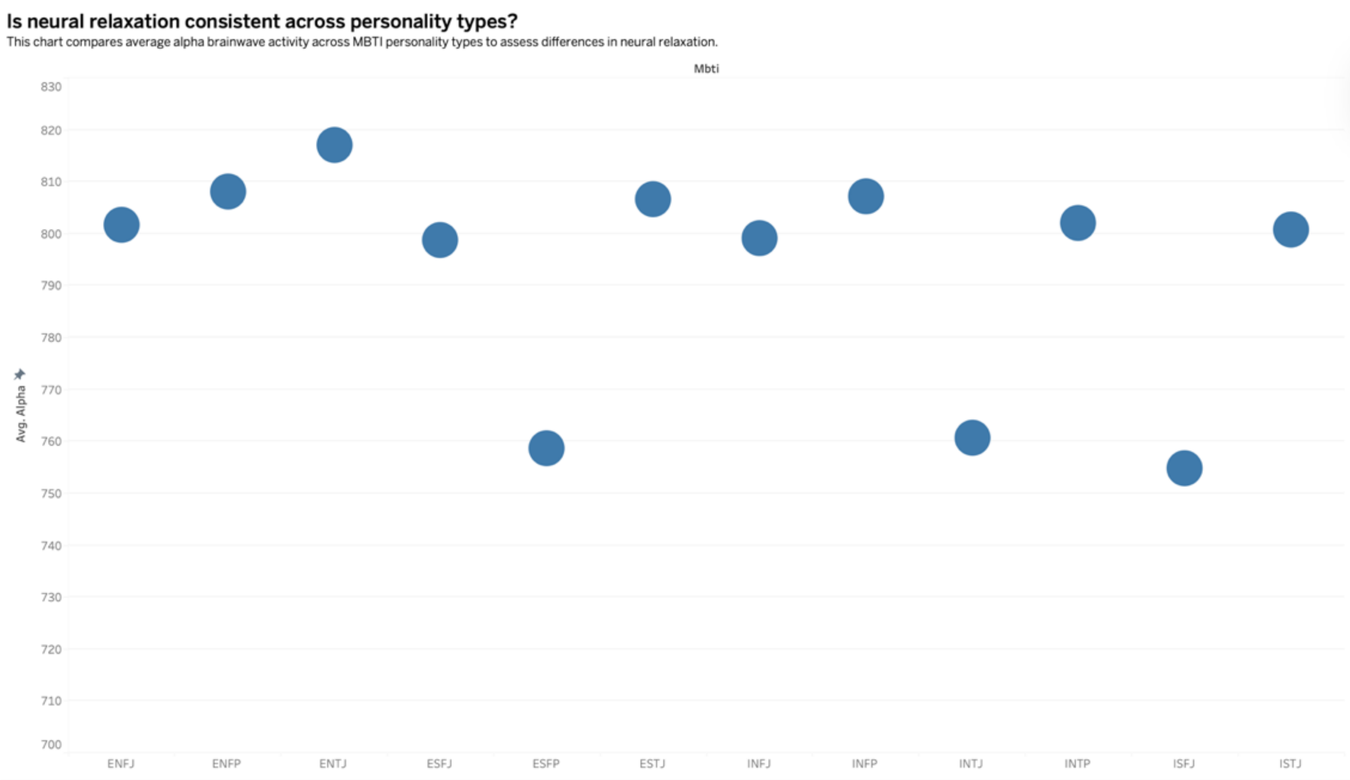
Median engagement levels are closely clustered across MBTI types, indicating no consistent difference in overall engagement. However, the spread reveals differences in consistency. Types such as ENTJ and ESFJ show tighter distributions, suggesting more stable engagement, while ESTJ and INTJ display wider spreads and more outliers, indicating greater fluctuation.

These patterns reinforce that personality does not significantly affect engagement level, but does influence its consistency over time. The presence of outliers shows that extreme engagement values are concentrated within specific individuals rather than evenly distributed across types.

This highlights a key methodological point. Focusing on averages alone would obscure these differences, while examining the full distribution reveals that personality-related effects are more visible in variability than in central tendency (Fisher et al., 2018).

viii. <u>Is Neural Relaxation Consistent Across Personality Types?</u>

This visualisation examines baseline neural relaxation across personality types using average alpha brainwave activity, a well-established indicator of relaxed and low-effort cognitive states.



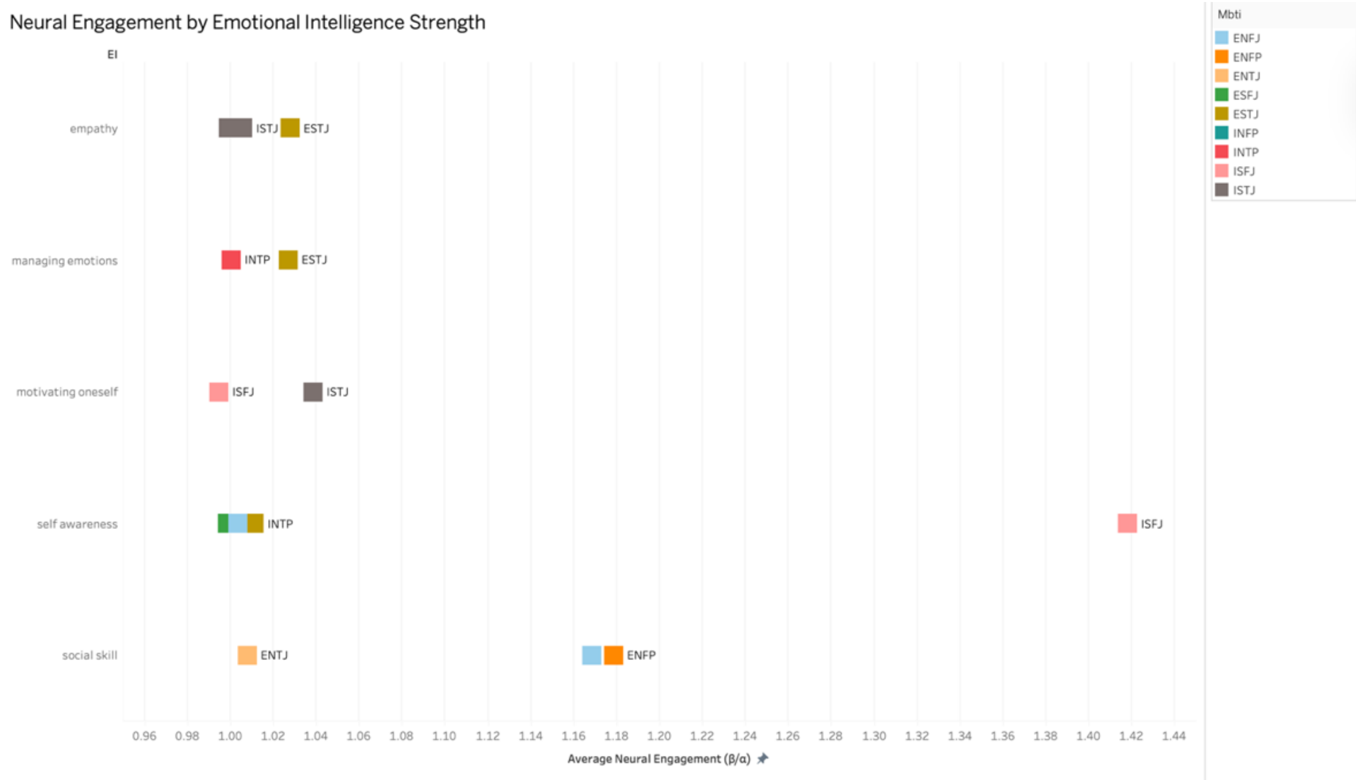
Visualization 8. Average Alpha Activity Across Personality Types

The distribution is tightly compressed, with all MBTI types falling within a narrow range and no clear outliers. This indicates that overall levels of neural relaxation are broadly consistent across personality groups, with no type showing a sustained difference in baseline calmness.

When considered alongside earlier findings, this suggests that while personality influences when and how engagement occurs, it does not affect overall relaxation levels. Differences, therefore, lie in how calmness is reached and maintained over time rather than in its average level.

This reinforces a central conclusion: personality differences are reflected in the structure and temporal dynamics of cognitive states, not in their magnitude. As with engagement, alpha activity remains similar across types in aggregate but differs in its underlying pattern.

ix. <u>Does Emotional Intelligence Influence Neural Engagement?</u>
This visualisation shows how neural engagement varies across Emotional Intelligence (EI) strengths.



Visualization 9. Neural Engagement by Emotional Intelligence Strength

Most categories display similar engagement levels, with Empathy, Managing Emotions, and Motivating Oneself clustering between 1.00 and 1.05, indicating minimal group-level influence.

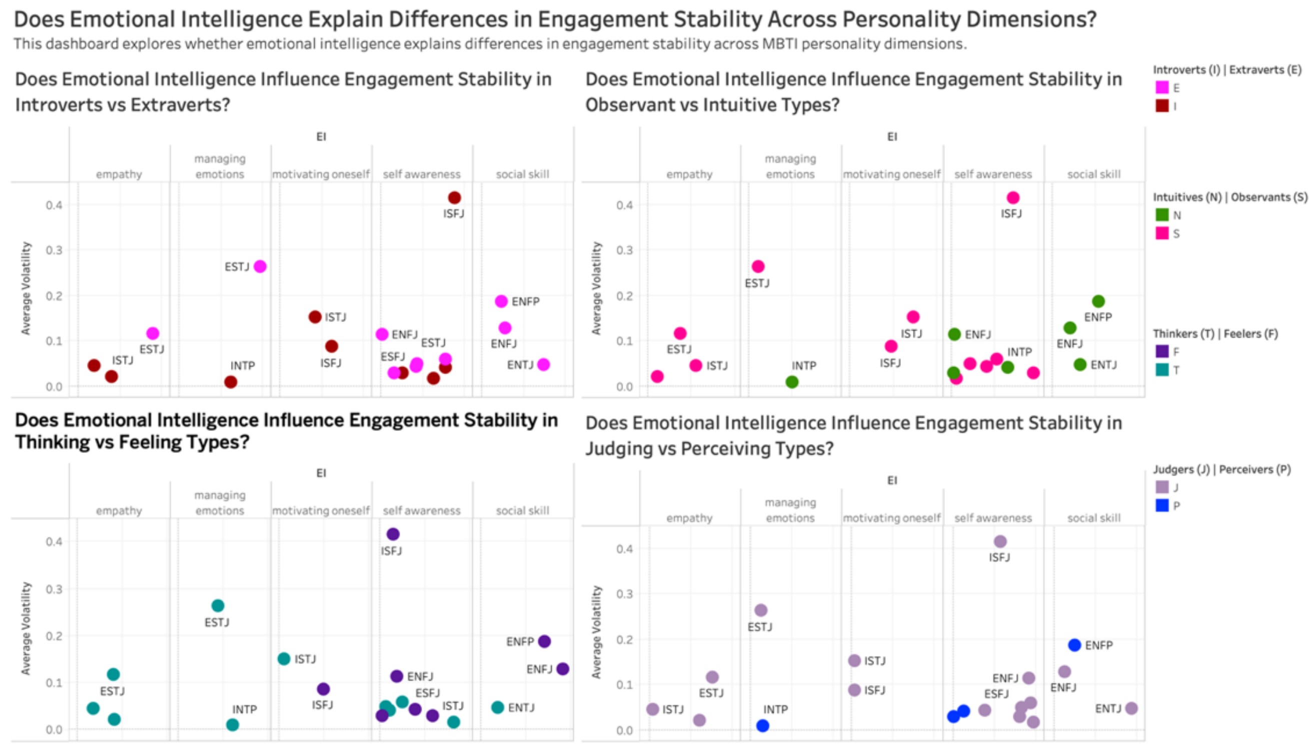
A clear exception appears in the Self-Awareness category, where one ISFJ participant shows the highest engagement (approximately 1.42). This suggests that when strong internal awareness aligns with personality, engagement may be amplified rather than stabilised, particularly in evaluative contexts (Kelly et al., 2020).

A similar but weaker pattern appears in the Social Skill category, where ENFJ and ENFP types show slightly elevated engagement (approximately 1.16–1.19), suggesting that alignment between EI and socially oriented traits may increase engagement.

These patterns indicate that engagement is shaped by the interaction between EI and personality rather than either alone (Mayer et al., 2016). However, small sample sizes limit reliability, so findings should be interpreted as indicative rather than definitive (Fisher et al., 2018).

x. <u>Does Emotional Intelligence Explain Differences in Engagement Stability Across Personality Dimensions?</u>

This visualisation uses a small multiples design to examine whether emotional intelligence (EI) explains differences in engagement stability across personality dimensions.



Visualization 10. EI and Personality Interaction in Engagement Stability

The most prominent pattern is the ISFJ participant in the self-awareness category, who shows both the highest volatility (approximately 0.42) and the highest engagement, indicating a highly active but unstable profile. This suggests that when strong self-awareness aligns with internally oriented personality traits, engagement may become more intense but less stable (Kelly et al., 2020; Mayer et al., 2016).

A smaller effect is observed for an ESTJ participant with elevated volatility, while most participants cluster near zero, indicating generally stable engagement. This suggests that variability is not explained by EI or personality alone, but by their interaction.

The ISFJ outlier also compresses the y-axis, reducing visibility of smaller differences, highlighting how outliers can both reveal patterns and distort interpretation (Fisher et al., 2018).

Across all visualisations, engagement levels remain broadly similar across personality types, while differences emerge in timing, stability, and form. The most meaningful variation is driven by the interaction between personality and emotional intelligence.

6.5 Preparing Participant Data for Clustering

The time-series dataset was transformed into a participant-level format for clustering by aggregating over 20,000 observations into summary features. A divergence metric ($\beta/\alpha - \theta/\alpha$) was computed to capture the balance between engagement and workload.

For clustering, presentations were segmented into early, middle, and late phases, with average engagement calculated for each. Additional features included mean engagement, workload, divergence, band activity, and engagement volatility.

All features were combined into a single dataset with one row per participant. Missing values were imputed using feature means, and MBTI and EI variables were reattached for interpretation but excluded from clustering.

The final dataset contained 42 participants and 17 features, structured as follows:

- participant
- early_engagement, mid_engagement, late_engagement
- mean_engagement, mean_workload, mean_divergence
- alpha, beta, theta
- engagement_volatility
- MBTI, IE, SN, TF, JP, EI

This dataset was exported as eeg_clustering_dataset_05.csv and used as the input for clustering analysis in Weka. The full implementation of this processing step is provided in the script clustering_dataset_05.py (see Appendix A).

6.6 Clustering Analysis Using Weka

Earlier visualisations showed clear variation in neural engagement between participants, while also indicating that group averages alone did not fully explain these differences. To explore this further, clustering was applied using Weka 3.8.6, allowing patterns to emerge directly from the data rather than from predefined personality categories.

Instead of comparing groups such as Introverts and Extraverts, clustering identifies distinct engagement profiles and groups participants based on similarity.

i. The dataset (eeg_clustering_dataset_05.csv) contained 42 participants and 17 attributes.

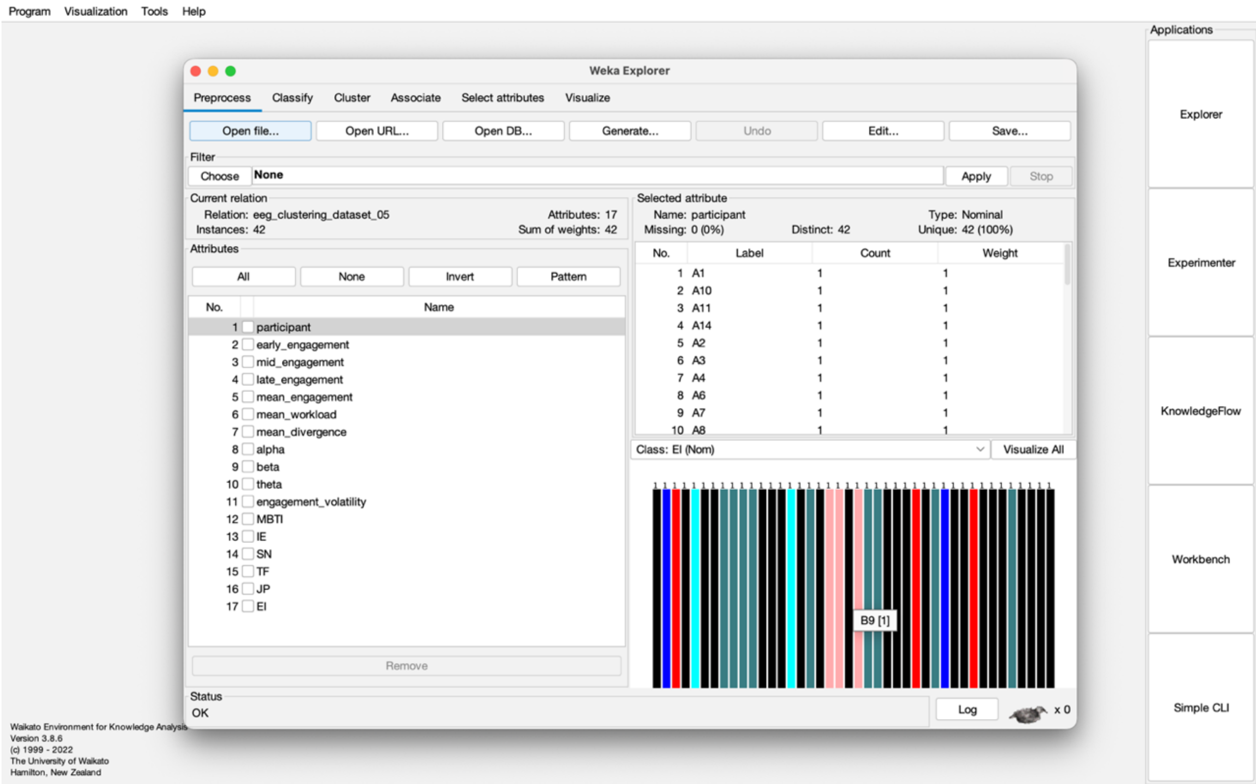


Figure 6.6.1. Dataset loaded in Weka Explorer

Non-numeric attributes (participant ID, MBTI, and EI) were removed, as K-means clustering operates only on numerical data.

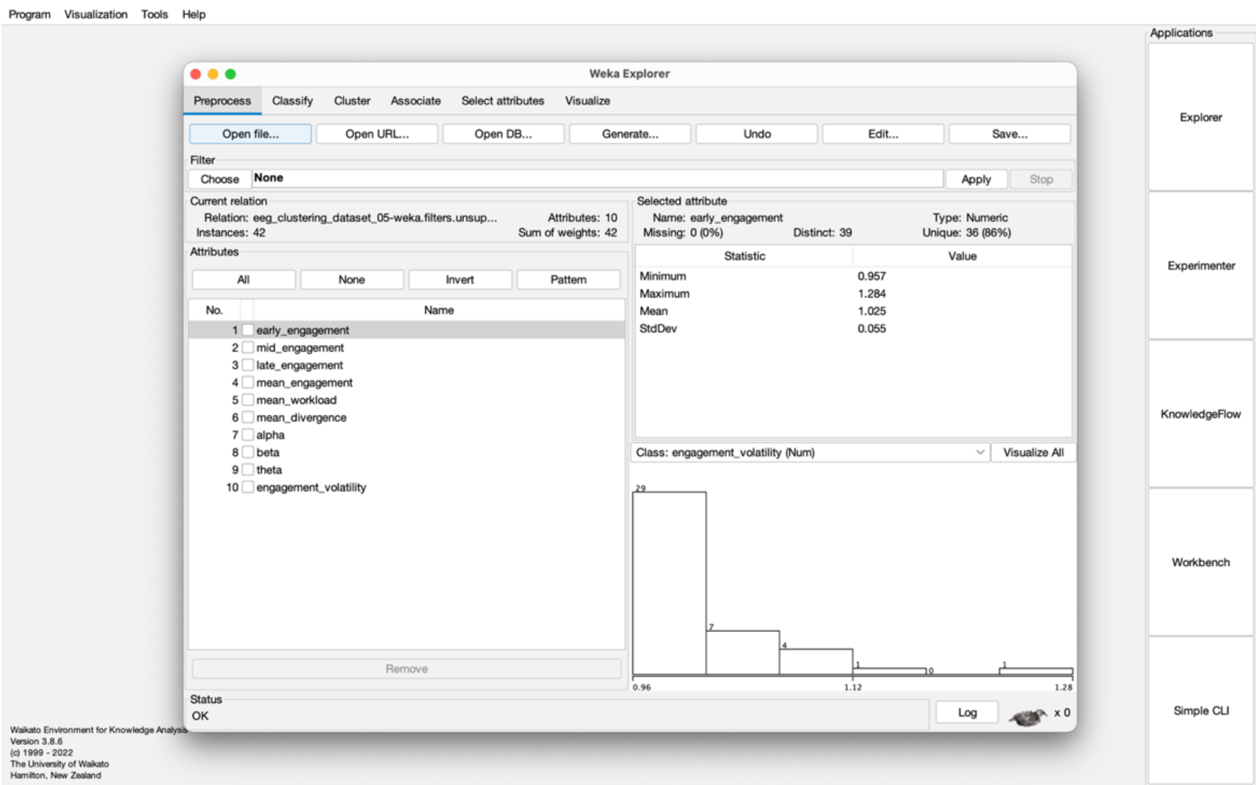


Figure 6.6.2. Selection of numerical features

The following features were used:

- early_engagement, mid_engagement, late_engagement
- mean_engagement, mean_workload, mean_divergence
- alpha, beta, theta
- engagement_volatility

These features capture engagement over time, cognitive effort, neural activity, and variability.

ii. Clustering was performed using SimpleKMeans with k = 3, based on earlier visual patterns suggesting one main group and smaller outliers.

The model used Euclidean distance, 500 iterations, and a fixed seed (10).

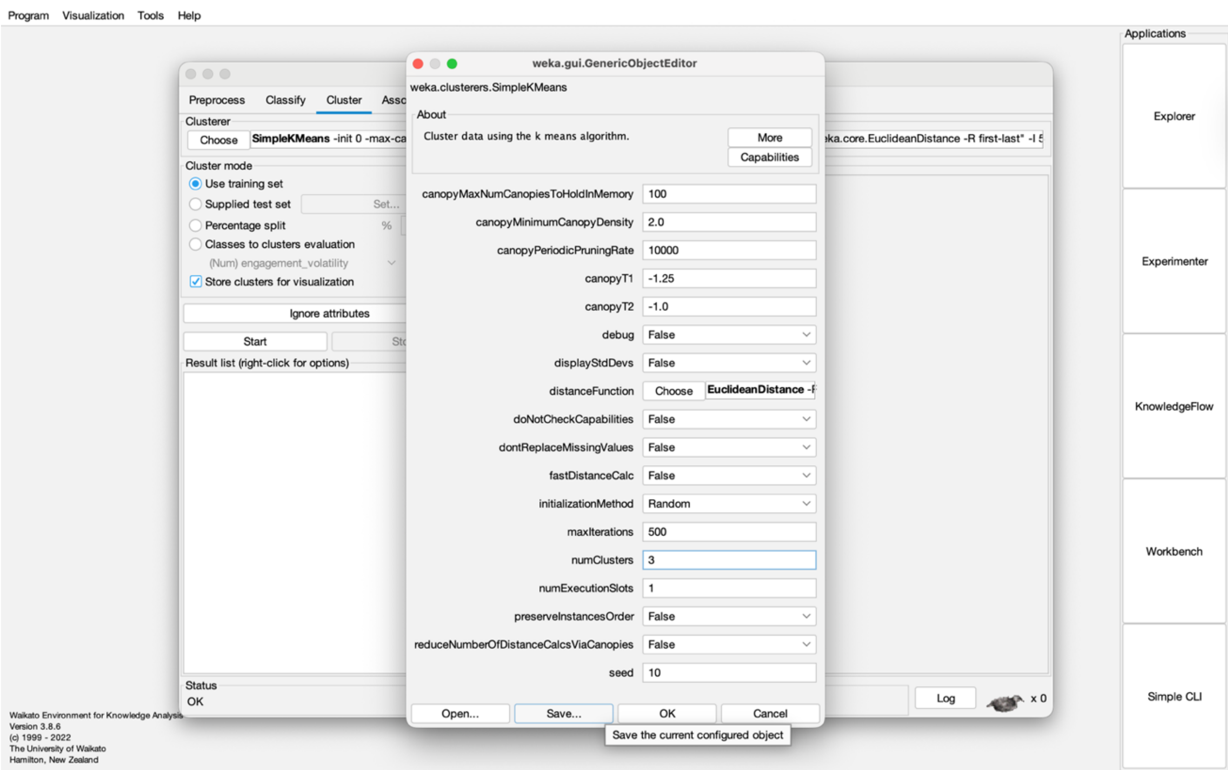


Figure 6.6.3. K-means configuration

The algorithm converged in 8 iterations with a WCSS of approximately 6.92.

iii. These are the clustering results:

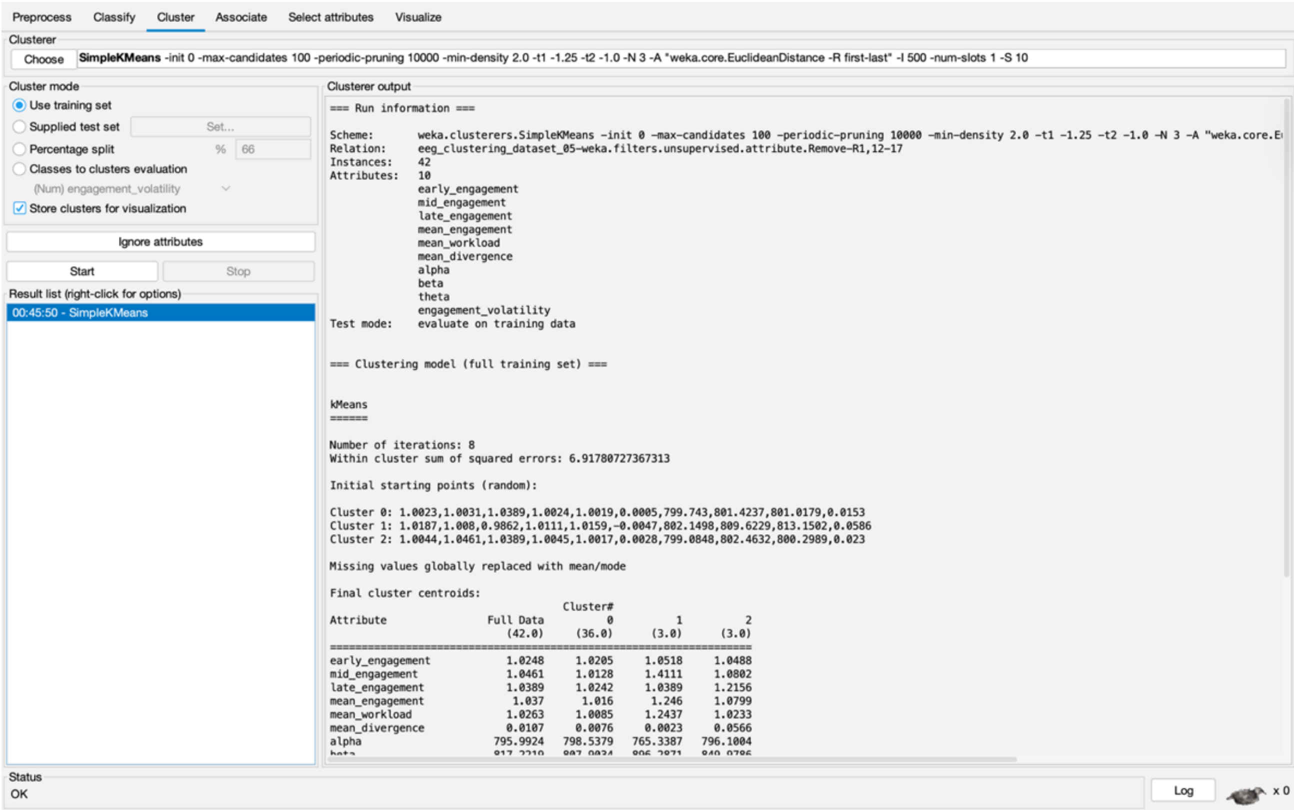


Figure 6.6.4. Cluster output

Three clusters were identified:

- Cluster 0: 36 participants (86%)
- Cluster 1: 3 participants (7%)
- Cluster 2: 3 participants (7%)

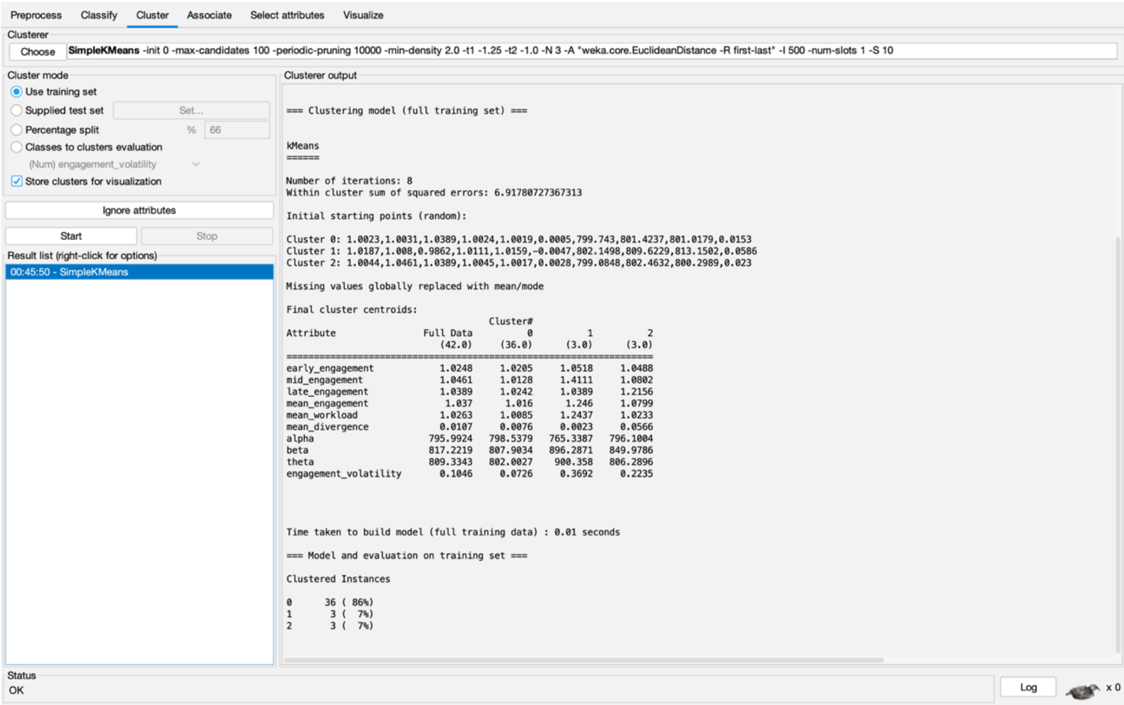


Figure 6.6.5. Cluster distribution

The three clusters represent different patterns of engagement behaviour across participants.

<u>Cluster 0 — Stable Moderate Engagers (86%)</u>

- Engagement: stable (≈1.02–1.04)
- Volatility: low (≈0.07)
- Divergence: minimal

Most participants fall into this group. Engagement is steady and moderate, with workload closely matching engagement. This reflects a consistent, balanced pattern seen across earlier visualisations.

<u>Cluster 1 — Reactive Mid-Session Engagers (7%)</u>

- Mid engagement: high (≈1.41)
- Workload: high (≈1.24)
- Volatility: very high (≈0.37)
- Divergence: near zero

These participants show a sharp spike in the middle of the presentation, followed by a drop. Engagement is intense but unstable, with high cognitive effort and little evidence of flow.

<u>Cluster 2 — Late-Building Flow Engagers (7%)</u>

- Engagement increases over time (late ≈1.22)
- Workload: moderate (≈1.02)
- Divergence: highest (≈0.057)

- Volatility: moderate

These participants gradually become more engaged, with engagement exceeding workload. This pattern aligns with a flow-like state (Csikszentmihalyi et al., 1990; Huskey et al., 2018).

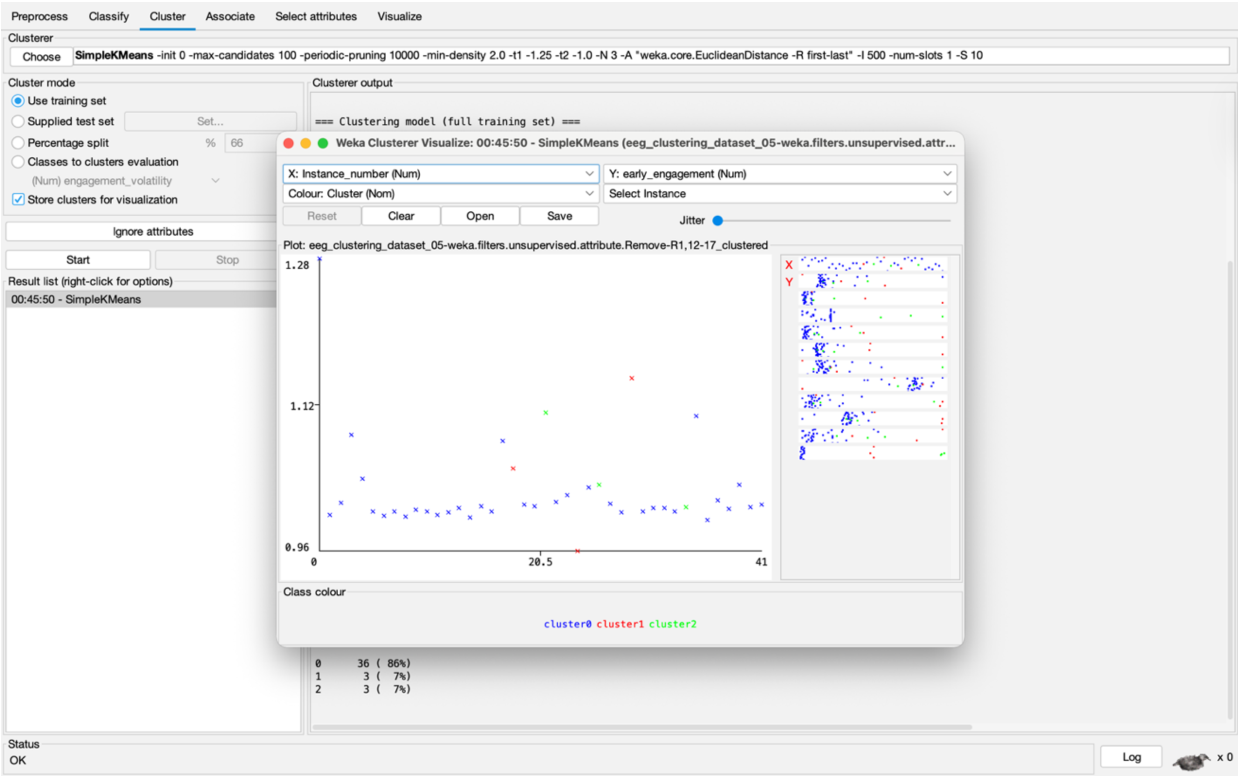


Figure 6.6.6. Cluster visualisation

Cluster 0 forms a dense central group, while Clusters 1 and 2 are more spread out, reflecting greater variability.

iv. Three key findings emerge.

- First, most participants (86%) show similar engagement patterns, stable and moderate, suggesting personality alone does not strongly determine engagement level.
- Second, the smaller clusters represent different engagement styles. Cluster 1 reflects reactive, high-effort engagement, while Cluster 2 reflects gradual, flow-like engagement.
- Third, differences between participants are driven more by variability and timing than by average engagement. This supports the idea that behavioural patterns over time are more informative than static measures (Fisher et al., 2018).

Although cluster membership cannot be directly linked to MBTI or EI due to small group sizes, the patterns align with earlier findings, suggesting these factors may interact to shape engagement behaviour.

6.7 Integration of Cluster Labels

Following clustering in Weka, the cluster assignments were exported as a CSV file. Since non-numerical attributes such as MBTI, EI, and participant identifiers had been removed prior to clustering for K-means compatibility, a Python script was used to map the resulting cluster labels back to the original participant-level dataset, where these variables were retained.

Alignment was achieved by row order, as both files preserved the same instance sequence. The final dataset contained behavioural features, cluster membership, and corresponding MBTI and EI variables, enabling interpretation of clustering results in relation to personality and emotional intelligence.

The final dataset structure was as follows:

- participant
- early_engagement, mid_engagement, late_engagement
- mean_engagement, mean_workload, mean_divergence
- alpha, beta, theta
- engagement_volatility
- MBTI, IE, SN, TF, JP, EI
- cluster

The full implementation of this processing step is provided in the script *merge_clusters_06.py* (see Appendix A).

6.8 Visualization of Cluster Labels

Following the integration of cluster labels, the final dataset was imported into Tableau for visual analysis. Participants with missing MBTI or EI data were excluded before visualisation, as incomplete records would distort cluster distributions across personality and EI categories.

The visualisations therefore reflect a reduced subset of the original 42 participants, and any interpretation of cluster membership in relation to personality and EI should be treated as indicative rather than definitive. To explore how clusters relate to personality type, a heatmap was created showing the distribution of participants across MBTI categories.

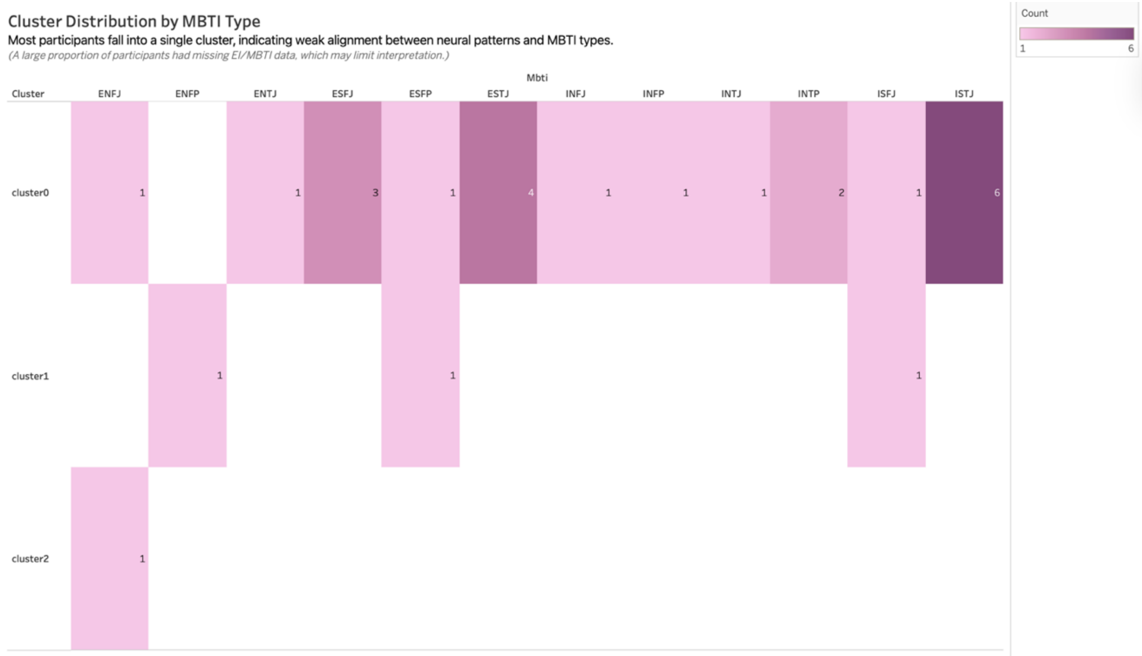


Figure 6.7.1. Cluster Distribution by MBTI Type

This visualisation shows that the majority of participants, across a wide range of MBTI types, are concentrated within Cluster 0, reinforcing earlier findings that most individuals exhibit a stable and moderate engagement profile regardless of personality type. In contrast, Clusters 1 and 2 contain only a small number of participants distributed across different types, with no single MBTI category clearly dominating these outlier groups.

A second heatmap was then developed to examine the distribution of cluster membership across Emotional Intelligence categories.

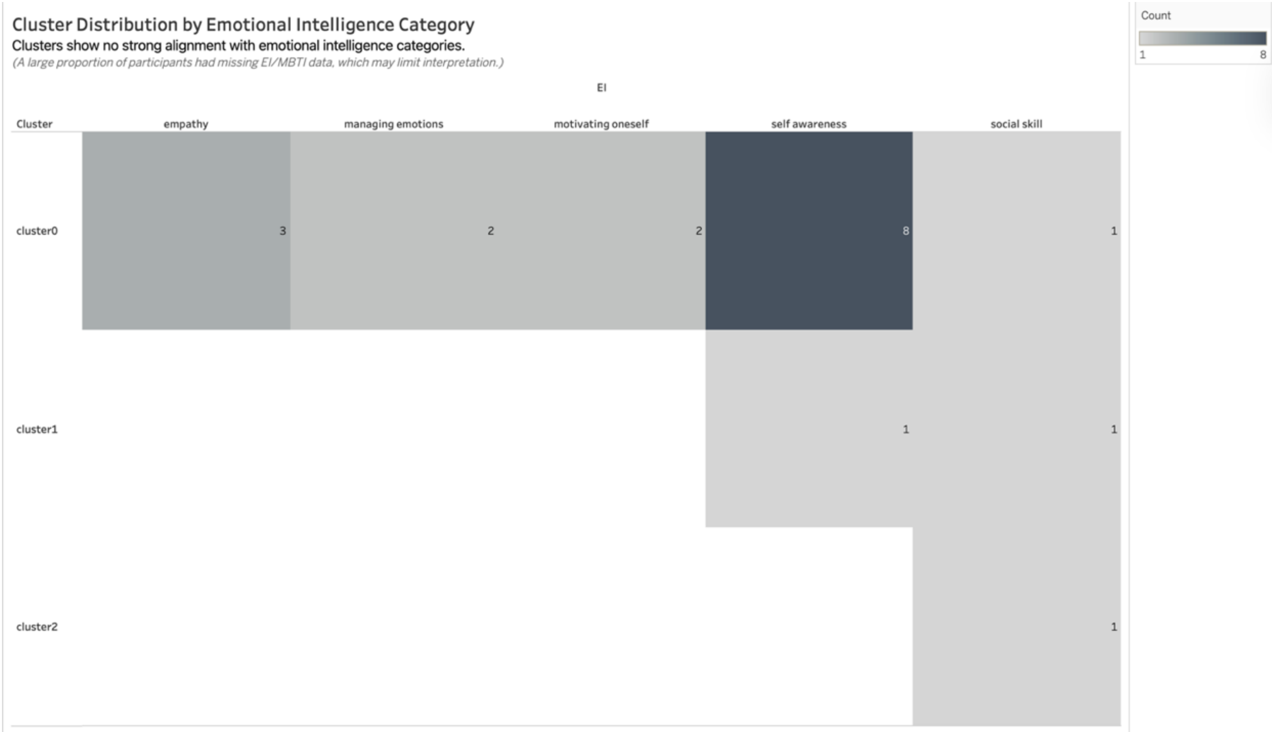


Figure 6.7.2. Cluster Distribution by Emotional Intelligence Category

A similar pattern is observed for Emotional Intelligence. Cluster 0 includes participants from all EI categories, indicating that stable engagement is not limited to a specific emotional strength. While Clusters 1 and 2 contain only a few participants, certain categories, such as self-awareness, appear to contribute to these outlier clusters, suggesting that specific EI–personality combinations may be associated with more extreme engagement patterns.

Together, these visualisations suggest that cluster membership is not strongly determined by MBTI type or EI category alone. Instead, personality and emotional intelligence appear to interact in more complex ways, with most participants following a common engagement pattern and only a small number exhibiting distinct behavioural profiles. These observations are explored in greater detail in the following section.

7. FINDINGS

The following findings draw on all ten Tableau visualisations and the K-means clustering analysis conducted in Weka.

7.1 MBTI Personality Type Does Not Meaningfully Predict Overall Engagement

Group-level averages show minimal separation between personality types, with engagement values consistently falling within a narrow β/α range of approximately 1.00–1.05. Within-type variation exceeds between-type differences, indicating that personality type alone is not a meaningful predictor of neural engagement. Differences emerge in how engagement evolves, not in its average level (Fisher et al., 2018).

7.2 The IE Dimension Shapes Engagement Timing

The path chart (Visualisation 2) shows that Extraverts exhibit sharper engagement increases during externally driven moments, while Introverts maintain more stable engagement throughout. Consistent with neurobiological accounts of extraversion, the IE dimension influences when engagement occurs rather than its magnitude.

7.3 Most Students Operate in a Flow-Adjacent State

The divergence heat map (Visualisation 5) shows engagement exceeding cognitive workload across most participants and time windows, indicating a flow-adjacent state (Csikszentmihalyi et al. 1990; Huskey et al., 2018). Flow depth varies by type, with INTJ participants showing stronger and more sustained divergence, suggesting personality is associated with how efficiently engagement is maintained rather than whether it occurs.

7.4 Engagement Stability Differentiates Individuals

Average engagement is broadly consistent, but volatility differs substantially across participants (Visualisation 4). Notably, an ESFP shows the highest volatility (~0.506), and an ISFJ shows both high engagement (~1.418) and high volatility (~0.415). Stability of engagement, rather than its level, is where meaningful individual differences emerge (Fisher et al., 2018).

7.5 A Distinct ISFJ Outlier Highlights Interaction Effects

Across Visualisation 9, Visualisation 10, and clustering, one ISFJ participant with self-awareness as their dominant EI trait consistently appears as an outlier with the highest engagement and volatility. This combination appears to amplify rather than stabilise attentional focus under evaluative pressure, producing a highly active but unstable neural profile (Kelly et al., 2020).

7.6 Emotional Intelligence Alone Has Limited Predictive Value

The EI dot plot (Visualisation 9) shows minimal variation in average engagement across EI categories, suggesting EI alone is not a strong predictor of engagement. However, Social Skill appears across all clusters while other EI categories concentrate in the baseline group, indicating that EI may operate as a moderating variable, influencing the intensity with which personality-driven engagement patterns are expressed (Mayer et al., 2016; MacCann et al., 2020).

7.7 Clustering Reveals Three Distinct Engagement Profiles

K-means clustering identifies three profiles not visible through averages. Cluster 0 (86%) describes stable moderate engagers with consistent engagement, low volatility, and minimal divergence. Cluster 1 (7%) captures reactive mid-session engagers showing a sharp mid-phase spike, elevated workload, and high volatility, indicative of cognitive strain. Cluster 2 (7%) describes late-building flow engagers with progressively increasing engagement and the highest divergence, consistent with a deepening flow state (Csikszentmihalyi et al., 1990). Engagement differences are defined by trajectory and stability, not magnitude.

7.8 Personality and EI Do Not Directly Determine Cluster Membership

The dominant cluster contains a wide range of MBTI types and EI categories, while smaller clusters show mixed profiles with no dominant type. Neither personality nor EI alone predicts cluster membership, though specific combinations appear more frequently among outliers, suggesting interaction effects may contribute to extreme engagement profiles.

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8. CONCLUSION

8.1 Main Restrictions and Problems

The primary limitation is sample size. With 42 participants across 13 MBTI types, many with only one or two individuals, findings cannot be generalised at the type level. Individual cases, such as the ISFJ self-awareness outlier, are meaningful but not representative.

Missing MBTI and EI data further reduced the sample for personality-level analysis, limiting interpretation. The use of consumer-grade EEG also introduces reduced signal fidelity (Mikhaylov et al., 2024), meaning results are directionally reliable but not highly precise.

Finally, the observational design limits conclusions to association rather than causation, with potential confounding factors such as presentation experience or topic familiarity.

8.2 Key Contributions

This study makes three key contributions.

First, it shows that MBTI does not reliably predict neural engagement. Personality influences how engagement unfolds over time rather than its overall level. Emotional intelligence similarly has limited predictive value in isolation, but in combination with personality can amplify engagement patterns, suggesting a moderating effect.

Second, it identifies three engagement profiles, stable, reactive, and late-building, demonstrating that differences emerge in temporal patterns and variability rather than average engagement (Fisher et al., 2018).

Third, it establishes a reproducible framework integrating wearable EEG, psychometric data, and visual analytics to study engagement in real-world presentation contexts.

8.3 Lessons Learnt

Meaningful differences do not appear in averages, but in temporal patterns and individual cases.

The study reinforced the need for cautious interpretation, distinguishing between observed patterns and generalisable conclusions.

Technically, transforming EEG data required substantial preprocessing and careful feature design, with methodological decisions directly shaping outcomes.

8.4 Future Work

Future research should use larger, more balanced samples to enable statistical validation.

Using continuous EI measures would allow for a more nuanced analysis of its interaction with personality. The ISFJ self-awareness profile warrants targeted investigation to assess reproducibility.

Further work should examine MBTI and EI as combined predictors and adopt longitudinal designs to determine whether engagement profiles remain stable over time.

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10. APPENDIX

Appendix A: Code Implementation

The full implementation of the data processing and analysis pipeline is available at:

https://github.com/itsjustchioma/mbti-neural-engagement-analysis

The repository includes:

Python scripts:

- combine_and_clean_raw_eeg_01.py: Combines and cleans raw EEG datasets
- build_timeseries_dataset_02.py: Constructs a time-series dataset with MBTI
- integrate_ei_data_04.py: Merges emotional intelligence data
- clustering_dataset_05.py: Builds participant-level dataset for clustering
- merge_clusters_06.py: Merges clustering results with MBTI and EI

Generated datasets:

- eeg_combined_clean_01.csv: Cleaned and combined EEG dataset from all participants
- eeg_timeseries_full_02.csv: Initial time-series dataset with MBTI integration
- eeg_timeseries_final_version_04.csv: Final structured dataset used for visualisation
- eeg_clustering_dataset_05.csv: Participant-level dataset prepared for clustering
- csv_result-clusters_output_001.csv: Raw clustering output exported from Weka
- eeg_clustering_with_labels_06.csv: Final dataset with cluster labels merged with MBTI and EI

Appendix B: Personality Dimension Reference Sources

(Referenced descriptively in Section 7.3)

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