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Much Ado About Nothing? An EEG Study of the Beer Game for Neurophysiological Insights on Supply Chain Decision-Making

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Abstract: Volatile demand and information delays in multi-tier supply chains give rise to the well-known bullwhip effect, yet the cognitive mechanisms that drive the inventory decisions behind this phenomenon remain poorly explored. To address this gap, a beer-game experiment that couples game performance with neurophysiological evidence. Electroencephalogram (EEG) signals were collected while participants, who observed downstream orders, placed replenishment orders for 50 periods. A three-stage analytics process, incorporating topographical visualisation, dynamic time warping, and hierarchical clustering, was applied to the EEG time-series data to uncover latent neural patterns. Comparing inconsistency values across linkage methods, Ward's linkage performs best, with the lowest inconsistency (0.5785)

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and a cophenetic correlation coefficient of 0.7827. Furthermore, Silhouette analysis suggests an optimal solution of two clusters, with an average silhouette score of 0.65. Two cognitive profiles emerged: (1) hypoactive decision makers exhibiting lower cortical activation and (2) hyperactive decision makers with sustained high activation. Linking these profiles to operational outcomes shows that the hypoactive group generated 48.33% lower average cumulative cost and 66.59% lower standard deviation, indicating superior mitigation of the bullwhip effect. The results resonate with the Yerkes-Dodson law such that excessive activation may trigger over-thinking and stress, degrading performance in uncertain environments, whereas moderate activation supports calmer and more consistent choices. By revealing how neuro-cognitive states shape operational effectiveness, this study contributes a novel measurement framework and offers actionable insights for designing decision-support tools and training programs in disruptive supply-chain contexts.

Keywords: Electroencephalogram (EEG); beer game; dynamic time warping; time-series clustering; supply chain; decision-making

Managerial Relevance Statement:

This study proposes a novel three-stage analytics framework for jointly analysing EEG data and cost-performance data to derive management insights. It offers actionable guidance for supply chain leaders by linking neurophysiological states to operational outcomes. In our beer-game experiment, teams sustaining “calm focus” (lower frontal beta and gamma activation) achieved higher performance quality and tighter variability than hyperactive peers, consistent with the Yerkes-Dodson law. Managers could redesign decision cycles for cognitive thrift by restricting non-essential data and insert brief reflective pauses at replenishment gates to reduce overload and sharpen ordering accuracy. Low-friction biofeedback, e.g. EEG, can flag elevated beta/alpha ratios and trigger micro-resets. Standard operating procedures should privilege satisficing over exhaustive optimization to dampen the bullwhip effect and improve resilience without major system overhauls. A noteworthy insight is that higher arousal level with higher performance expectation leads to poorer cost outcomes, reinforcing that the importance of emotional intelligence to drive the performance gain rather than exerting excessive effort. Based on the above achievements, this paper is regarded to contribute to the following SDGs: SDG 4 and SDG 9.

1. Introduction

In today's complex supply chain environment, the bullwhip effect is recognized as a key factor in understanding how order uncertainties are amplified along upstream channels. With increasing emphasis on supply chain resilience [1], comprehending the underlying dynamics is essential for devising effective strategies to tackle contemporary challenges. To offer hands-on insight into these dynamics, a simulated environment, known as the beer distribution game, was developed that engages learners in the interactions among various supply chain entities while underscoring the critical importance of managing uncertainty. The beer distribution game (also known as the beer game) is a widely adopted educational tool in higher education, designed to simulate supply chain dynamics and enable participants to experience the challenges of supply chain coordination [2]. In this simulation, fluctuating customer demand is introduced without transparent demand information among supply chain entities, such as suppliers, manufacturers, wholesalers, and retailers. Participants have to make inventory replenishment decisions while considering lead times to minimize costs related to holding and backlogs. This process effectively demonstrates the bullwhip effect, where order fluctuations caused by the uncertainties amplify upstream in the supply chain [3]. Figure 1 illustrates the overall beer game process, where participants play the roles of key supply chain entities to experience the bullwhip effect. As a serious game, the beer game not only engages participants but also imparts critical educational objectives related to system dynamics, interdependencies, and the bullwhip effect, thereby fostering a deeper understanding of supply chain management (SCM) principles [4].

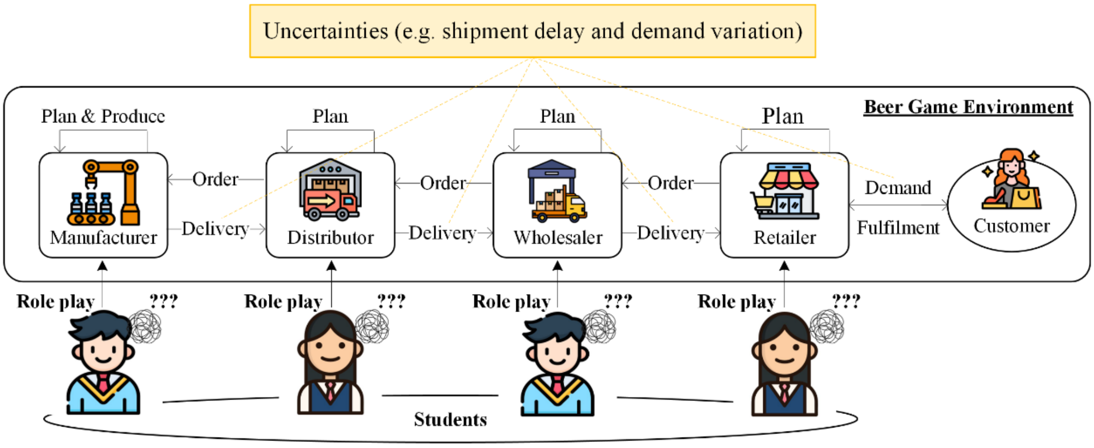


Figure 1. Beer game process to experience the bullwhip effect

Despite its successful implementation and significant attention within the SCM context, recent studies have predominantly focused on enhancing the game mechanics and integrating real-life supply chain elements. Dong and Boute [5] extended the conventional beer distribution game to the beer transportation game to introduce the metrics of carbon emissions, beyond the inventory management and shipping costs. Through the game, participants can experience the conflicting effect between decarbonisation and supply chain metrics. Roser et al. [6] introduced eight additional changes in the conventional beer game, covering the importance of communication, replenishment time, number of product variants, pull and levelling strategies. Therefore, participants can experience supply chain dynamics from a multitude of causes and effects. Additionally, efforts have been made to improve the learning experience through psychological and technological enhancements, such as incorporating 3D visuals, dialogue integration, and advanced data visualization tools [7][8]. However, the cognitive effort of participants, for example brain activities in the frontal lobe, during the game process remain underexplored. Understanding the correlation between cognitive effort and supply chain performance within the game could provide valuable insights into learning effectiveness and emotional preparedness for real-world supply chain challenges.

This study addresses this gap by conducting a series of experiments that utilize electroencephalogram (EEG) devices alongside performance metrics to analyse the psychological changes during the beer distribution game. The research aims to investigate the relationship between participants' emotional states and their in-game performance, offering a comprehensive evaluation of the learning experience. Furthermore, the findings may inform strategies for emotional preparation and decision-making under market uncertainties in real-life supply chain environments. By integrating neurophysiological data with educational outcomes, this study contributes to a deeper understanding of the interplay between cognitive and emotional factors in SCM education.

The rest of this paper is organised as follows. Section 2 reviews the preliminaries of EEG and its applications in educational research, summarizing the research gap of this study. Section 3 presents the research methodology, covering the beer game process, required instruments and data collection process. Section 4 details the case analysis conducted to implement EEG data monitoring during the beer game, followed by a discussion of the results in Section 5. Finally, conclusions and future directions are presented in Section 6.

2. Literature Review

In this section, we first review how the beer game has been used in contemporary supply chain research. EEG technology and its growing application in decision-making studies are then studied, positioning the present work to generate new insights for supply chain management.

2.1 Beer Game in Supply Chain Research

Originally devised as a pedagogical exercise [2], the beer game has matured into a versatile experimental environment that allows to probe questions which are prohibitively expensive to test in real-world supply chains. Recent studies elevate the beer game from a didactic tool to a serious scientific instrument. First, its controlled multi-echelon structure is effective to isolate behavioural drivers of order amplification. Under a risk-preference lens [4], the bullwhip effect is not merely an artefact of information delays but is shaped by prospect-theoretic biases. Their findings tested in the beer game environment suggest that pricing and contract incentives should be tailored to the dominant risk profile of decision makers. Second, the beer game provides a risk-free sandbox for rapid algorithmic experimentation [9]. A deep reinforcement learning agent is embedded in the classic four-stage setting and demonstrate that the agent can learn near-optimal replenishment rules even when upstream partners behave irrationally. Hence, firms can transfer the resulting policy to digital twins of real networks without disrupting ongoing operations, reducing inventory costs and order variance before code ever touches a production system. Further, the work [10] reveals that even partial deployment of reinforcement learning controllers cuts total system cost and suppresses bullwhip propagation in the beer game settings. Collectively, these contributions imply that the beer game is far more than a pedagogical illustration. It is a scalable and data-rich microcosm of real supply chains, where behavioural, technological and policy innovations can be stress-tested to obtain modern management insights [11].

2.2 Recent Advances of EEG Technology

EEG is a technology that measures the brain's electrical activity through electrodes, as brain cells communicate via electrical impulses [12]. With the rapid advancement of EEG technologies, increasingly wireless and portable EEG devices have been developed to serve not only clinical purposes but also industrial and commercial domains, such as ergonomic design and marketing [13][14]. Furthermore, the advancement of wet and dry electrodes has made these new EEG devices more accessible to researchers and users, moving beyond the limitations of traditional gel-based options electrodes. Although the collected signals may be susceptible to movement artifacts, the enhanced convenience for both researchers and participants significantly broadens the range of application scenarios. Regardless of advancements in EEG devices, five primary brain waves (i.e. alpha, beta, delta, theta, and gamma) are consistently collected for analysis [15]. Alpha waves (8 to 12 Hz) emerge during relaxed alertness and closed-eye meditation, indicating a calm yet wakeful mind. Beta waves (12 to 30 Hz) signal active, engaged thinking, problem-solving, and heightened alertness. Delta waves (0.5 to 4 Hz) are predominantly seen during deep, restorative sleep, playing a key role in healing and memory consolidation. Theta waves (4 to 8 Hz) are linked to relaxed states, daydreaming, creativity, and light meditation, often occurring during the transition from wakefulness to sleep. Lastly, gamma waves (30 to 100 Hz) are involved in the integration of complex information, higher cognitive functions, and conscious perception.

Grounded on EEG data acquisition, brainwave power analysis is increasingly used to quantify cognitive performance by linking specific brainwave ratios to observable mental states. In particular, the theta-beta ratio is a well-established metric where higher ratios typically indicate inattention, while lower ratios are associated with anxiety or focused engagement [16]. These quantitative measures transform raw power data into meaningful insights about attention and mental involvement. Similarly, the engagement index, derived from ratios like beta/(alpha+theta), provides a refined snapshot of cognitive engagement, reflecting the dynamic interplay of various brainwaves under different conditions [17]. Studies have further correlated distinct brainwave patterns with specific cognitive states; increased high beta and gamma activities, often in combination with varying levels of theta or alpha waves, have been linked to interest, stress, focus, and excitement. These metrics, while powerful, must be interpreted with caution as individual differences and contextual factors can influence brainwave patterns.

From the research perspective, Niso et al. [18] conducted a systematic literature review on the use of wireless EEG in academic research, selecting 110 highly relevant studies from an initial pool of 2,137 studies. They found that EEG technology has been utilized in academic research since 1975, with a steady increase in publication numbers over time. Additionally, the sample sizes in these studies ranged from 10 to 20 participants, with a median of 18 participants, and approximately 23% of the studies included fewer than 10 participants. Furthermore, the median number of channels used, which refers to effective electrodes of EEG devices to collect brainwave signals, was 14, with about 34% of the studies employing fewer than 8 channels. These findings on the development and usage patterns of EEG technology can effectively guide future research in selecting appropriate EEG devices and determining suitable sample sizes.

2.3 Use of EEG in Decision-Making Studies

Thanks to the recent advances on EEG technology, the related research can be further developed by considering more cognitive performance metrics. Xu and Zhong [19] reported that such wireless and portable EEG devices were helpful in obtaining students' cognitive performance in a real-time and quantitative manner. It is helpful for teachers to understand if students still remain attentive and meditative, maintaining the learning efficacy through some stimulation means. The suitability of EEG in serious games is underscored by its ability to provide real-time measurements of cognitive states, such as attention, engagement, stress, and cognitive load. For example, alpha and beta wave analyses are indicative of relaxation and focused attention, respectively, while theta waves are associated with memory consolidation and engagement [20]. EEG-derived metrics provide additional layers of analysis that enrich the evaluation of cognitive interventions [21]. These metrics facilitate the identification of optimal gameplay conditions that maximize cognitive engagement and minimize cognitive overload and confusion, thereby promoting a more effective learning environment. Another study has demonstrated that EEG metrics can effectively capture participants' levels of interest and stress during gameplay, offering a more comprehensive understanding of their learning experiences compared to traditional methods [22]. Furthermore, EEG enables the differentiation of subtle cognitive states that behavioural data alone cannot reveal, allowing for more precise tailoring of game-based interventions to enhance educational outcomes.

2.4 Summary of the Literature Review

In summary, EEG presents a highly suitable and valuable technology for analysing participants’ cognitive performance in serious games, for example beer game. By providing objective and real-time metrics on various cognitive states, EEG complements traditional assessment methods and offers deeper insights into the cognitive and emotional processes that drive effective learning. This enhanced understanding not only informs the design of more engaging and effective serious games but also extends to real-world applications by elucidating the mechanisms impacting cognitive development and decision-making behaviours.

3. Research Methodology

This section explains the core methodological components, including (i) selected EEG device and measures, (ii) process of beer game and data collection and (iii) data analysis methods. Our methodology follows the quasi-experimental design to analyse the cause-and-effect relationship because of its high practicality and light ethical considerations.

3.1 Selected EEG Device and Measures

According to Niso's survey [18], it is recommended for EEG studies to utilize a sampling rate of 250 Hz or higher to effectively capture signal presence and maintain high signal fidelity. 24.6% of the studies (i.e. the largest portion) included in this survey have employed the Emotiv EPOC system for research. In the context of the beer game process, gel-based electrodes are not recommended because of the associated discomfort which might introduce biases in data collection and complicate participant recruitment. Given these considerations, the Emotiv EPOC X headset was selected for this study, as shown in Figure 2. This device features 14 channels (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4) equipped with saline-based electrodes, eliminating participant discomfort. Each channel can collect the signal of alpha, beta-low, beta-high, theta and gamma waves.

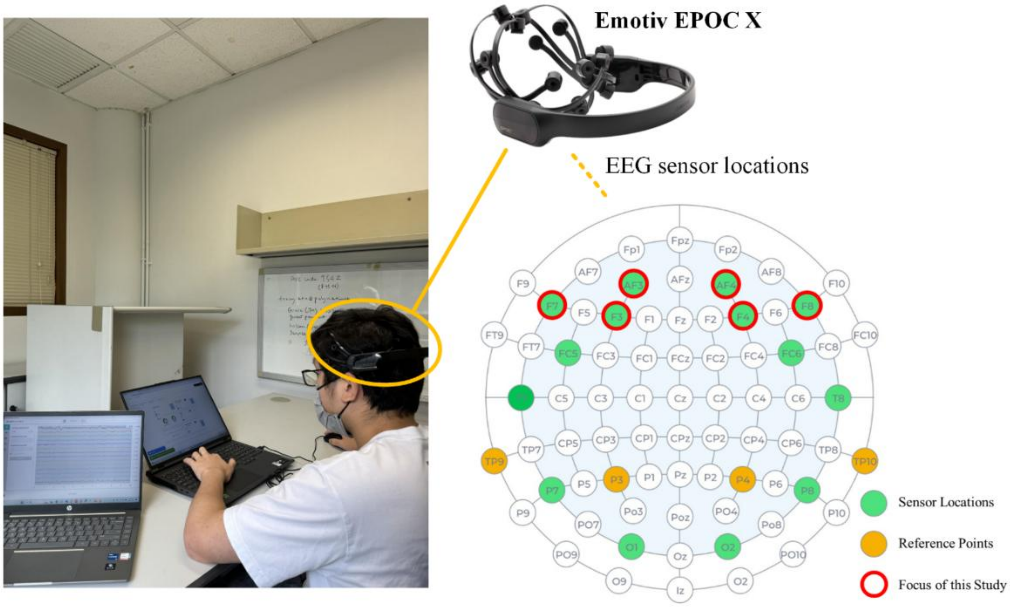


Figure 2. Selected hardware for EEG data collection

Using the Emotiv EPOC X, band power outputs are calculated as the average power across each frequency band from a 2-second trailing data sample at each electrode, expressed in microvolts squared per Hertz ($\mu V^2/Hz$). The Emotiv EPOC X supports a sampling rate of up to 256 Hz and facilitates wireless data transmission via Bluetooth Low Energy with a resolution of 14 bits. In addition to five primary brain waves, the beta wave collected from this device is further refined to two sub-bands, namely beta-low (betaL) and beta-high (betaH). Specifically, betaL is associated with the cognitive state of relaxed focus and light concentration, while betaH is associated with the high alertness, mental activity and potential stress. The power of the brainwaves can be further analysed to obtain high-level sights, like excitement, engagement, relaxation, interest, stress and focus, validated in multiple studies. Therefore, collecting data using Emotiv EPOC X devices can guarantee data reliability and accuracy.

3.2 Process of Beer Game and Data Collection

The core of the study involved participants engaging in the Beer Game, an online simulation provided by MA-system (accessible at https://beergame.masystem.se/). The Beer Game is a strategic SCM exercise where participants assume the role of a retailer within a four-tier supply chain consisting of manufacturer, distributor, wholesaler, and retailer. To streamline the focus on the retailer role, additional supply chain positions were occupied by ghost players, allowing each participant to concentrate solely on their responsibilities as a retailer.

Prior to commencing the Beer Game simulation, demographic data of each participant were meticulously collected to ensure a comprehensive understanding of the study sample. The demographic information included gender, age range, and education level. Additionally, participants were asked to complete a Likert-scale questionnaire assessing their knowledge level in the SCM domain, with responses ranging from 1 (strongly unconfident) to 5 (strongly confident). This measure aimed to gauge the participants' familiarity with supply chain concepts. Each participant was required to have 100% contact quality when wearing an Emotiv Epoc X headset. Participants were given a 30-second relaxation period while wearing the headset to collect baseline EEG data. This baseline measurement was essential for normalizing cognitive performance metrics during the game, thereby enhancing the accuracy of subsequent analyses.

Throughout the 50-week gameplay, participants continuously wore the Emotiv Epoc X headsets that capture real-time EEG data and derive cognitive performance metrics. These metrics provided valuable insights into the cognitive states of participants as they navigated the challenges of the supply chain environment.

Upon completion of the Beer Game simulation, game performance data were collected for each participant, with a particular focus on the total cost incurred over the 50-week period. By analysing the cost performance, patterns and potential cognitive factors influencing supply chain decision-making efficacy can be identified.

3.3 Three-Stage Data Analysis Process

The data analysis process consists of three stages to understand the influence of cognitive and control variables on total cost performance.

3.3.1 Stage 1: Exploratory Data Analysis of EEG Signals

In the first stage, the descriptive analysis and visualisation are applied to explore the collected EEG data so as to understand changes of cognitive performance over the game process. The band power outputs are taken from the 14 channels, with each channel covers five brain waves at different stages: the start, 25% of the process, middle, 75% of the process and the end of the game. The median values of output data are evaluated across all participants to create a brain activity heatmap for visualisation. The investigation of the decision-making process during the game focuses on the change in signals in the frontal lobe, which is responsible for problem-solving and reasoning [23]. In other words, the changes of power outputs in the channels of F3, F4, F7 and F8 (standard frontal electrodes) and AF3 and AF4 (anterior frontal electrodes) can be focused according to the above five defined time periods. Therefore, the cognitive load and effort made by the beer game can be fully understood.

3.3.2 Stage 2: DTW-based Signal Similarity Measurement

After exploring the overall change of EEG signals over the game process, the second stage aims to evaluate the similarity of participants' EEG signals which can be used to compare with the game performance. To do so, the dynamic time warping (DTW) is applied to investigate the similarity of the time-series band power data among participants [24][25]. For each participant, the power data of brainwaves, expressed as $X_i \in \mathbb{R}_{K \times M_i}$, are structured, where K and M_i denote the types of brainwaves considered and length (i.e. sample size) of the time-series data for the participant $i \in N$. To be specific, N represents the set of participants in the study. The extracted power data are smoothened by using the moving average so as to filter out noisy data, where the default smoothing factor of 0.25 is applied. Therefore, the smoothened power data are prepared for the DTW analysis.

In a pair of participants' brainwave power data, i.e. X_i and X_j where $i, j \in N$, the Euclidean distance is applied to evaluate the similarity. Thus, the distance value between m_i-th sample of X_i and m_j-th sample of X_j can be determined as in Equation (1).

$$d_{m_i m_j}(X_i, X_j) = \sqrt{\sum_{k \in K} (x_{k,m_i} - x_{k,m_j})^2} \tag{1}$$

The DTW algorithm aims to stretch datasets onto a common set of instants such that a global data-to-data distance measure is smallest as in Equation (2) [26].

$$\min.\mathcal{D} = \sum_{\substack{m_i \in M_i \\ m_j \in M_j}} d_{m_i m_j}(X_i, X_j) \tag{2}$$

The minimisation process is achieved through applying a combination of vertical, horizontal and diagonal moves in Equation (3) to (5), respectively:

$$(m_i, m_j) \rightarrow (m_i + 1, m_j) \tag{3}$$

$$(m_i, m_j) \rightarrow (m_i, m_j + 1) \tag{4}$$

$$(m_i, m_j) \rightarrow (m_i + 1, m_j + 1) \tag{5}$$

The resultant minimal distance value after the whole search process is referred to the similarity between two datasets. Thus, a similarity matrix based on the dynamic time warping analysis between participants' power signals, expressed as $S \in \mathbb{R}_{|N|\times|N|}$, is obtained.

3.3.3 Stage 3: Hierarchical Clustering for EEG Pattern Analysis

In the third stage, following the derivation of the similarity matrix $S \in \mathbb{R}_{|N|\times|N|}$ from the DTW analysis, hierarchical clustering is employed to group participants based on similarities in their brainwave band power data. Hierarchical clustering can provide deterministic clustering results, which allow exploration of the data structure at varying levels of detail [27][28]. The process begins by selecting an appropriate linkage algorithm, which defines how distances between clusters are calculated, influencing the resulting groupings. To identify the most suitable linkage algorithm, the degree of dissimilarity and consistency is evaluated [29]. Dissimilarity assesses how effectively clusters distinguish participant groups, measured by inspecting the cophenetic correlation coefficient. Consistency ensures the clustering structure is stable, verified through inconsistency values. These gauge how well the dendrogram reflects original pairwise distances. By comparing these metrics across linkage methods, the algorithm that optimally balances separation and reliability for the brainwave data can be chosen. Once the linkage algorithm is selected, a dendrogram is plotted to visualize the hierarchical clustering results. This tree-like diagram illustrates cluster mergers, with the vertical axis representing the dissimilarity (distance) at which clusters combine [30].

To determine the optimal number of clusters, we apply Silhouette analysis to the results of our hierarchical clustering. The Silhouette coefficient, ranging from –1 to +1, captures both cohesion and separation. Following the previous work [31], a mean Silhouette value above 0.5 indicates a reasonable cluster structure, meaning that observations lie close to their own cluster and far from neighbouring clusters. Subsequently, to effectively label each cluster, the time-series signals from 18 sources are visualised. Building on the length-normalisation procedure described in Stage 1 of the data-analysis approach, five key phases from each time series (at 0%, 25%, 50%, 75% and 100% of its length) are extracted and transformed by using Equation (6). This transformation emphasises temporal changes and facilitates direct comparison across signals.

$$\dot{x}_{k,m_i} = \mathrm{sign}\left(x_{k,m_i}\right) \cdot \ln\left(1 + \left|x_{k,m_i}\right|\right), \text{where } \mathrm{sign}\left(x_{k,m_i}\right) = \begin{cases} 1, x_{k,m_i} > 0 \\ 0, x_{k,m_i} = 0 \\ -1, x_{k,m_i} < 0 \end{cases} \tag{6}$$

These processed EEG profiles can then be compared alongside game-performance metrics and demographic variables. Grounded in cognitive-load theory and the Yerkes–Dodson law, this analysis seeks to uncover brainwave patterns that (i) inform post-game discussions in classroom settings and (ii) generate deeper insights into decision-making processes in real-world supply-chain contexts.

4. Experiments

Based on the proposed research methodology, 20 students were recruited to participate in the beer game, which exceeds the median sample size of existing EEG-based studies [18]. It provides a dataset that is typical for the field and sufficiently large for the exploratory analyses. An introduction session was provided for participants to understand the objectives and mechanics of the game, Participants were informed that their decisions were to be based on current inventory levels, on-order inventory, and consumer demand and their goal was to minimize total costs over a 50-week period, factoring in inventory carrying costs and backlog costs. Notably, the game incorporated an ordering lead time of at least three weeks, adding complexity to their decision-making process.

4.1 Demographic Summary of the Participants

Of the 20 participants, 11 were male and 9 were female. Most participants, 13 in total, were aged 25 to 30, with the remaining individuals in other age groups: one aged 15 to 20, five aged 20 to 25, and one aged 30 to 35. In terms of educational background, 16 of them held a master’s degree or higher, while the remaining 4 were undergraduates. Regarding SCM knowledge, participants reported an average rating of 3.5 with a median of 3.5 and minimal variability (standard deviation ≈ 0.27); the distribution also exhibited slight negative skewness (-0.31) and modest platy kurtosis (-0.67), indicating a fairly homogeneous level of familiarity with the subject. Consequently, the proposed three-stage methodology in Section 3.3 is appropriate to dig the patterns behind EEG data in this scenario.

4.2 Results in Stage 1 (Exploratory Data Analysis of EEG Signals)

According to the data pre-processing steps mentioned in Section 3.3, five 80-row data segments are made. To have an overview of the EEG signal changes over the beer game process, the median values of the signal power are considered and plotted by using EEGLAB [32]. Figure 3 shows the dorsal view of human brain topography with the intensity of EEG signals over the five stages, namely start, 25%, 50%, 75% and end of the beer game process. From the dorsal view, the brain activities in the frontal, parietal and occipital lobes are visualised, representing reasoning, sensation and perception functions [23]. As stated in Section 3.1, five types of brainwave, i.e. alpha, beta low, beta high, gamma and theta, can be collected from each of the 14 channels. The neural patterns of varying signal intensity indicate a dynamic shift in brain activity as participants progress through the task. In the early stage, there is an elevated level of brain activity across certain frequency bands, suggesting that participants are engaging deeply and focusing intently as they familiarize themselves with the game. This period is characterized by strong power values that imply heightened attention and cognitive effort during the initial learning and strategy-formulation phase.

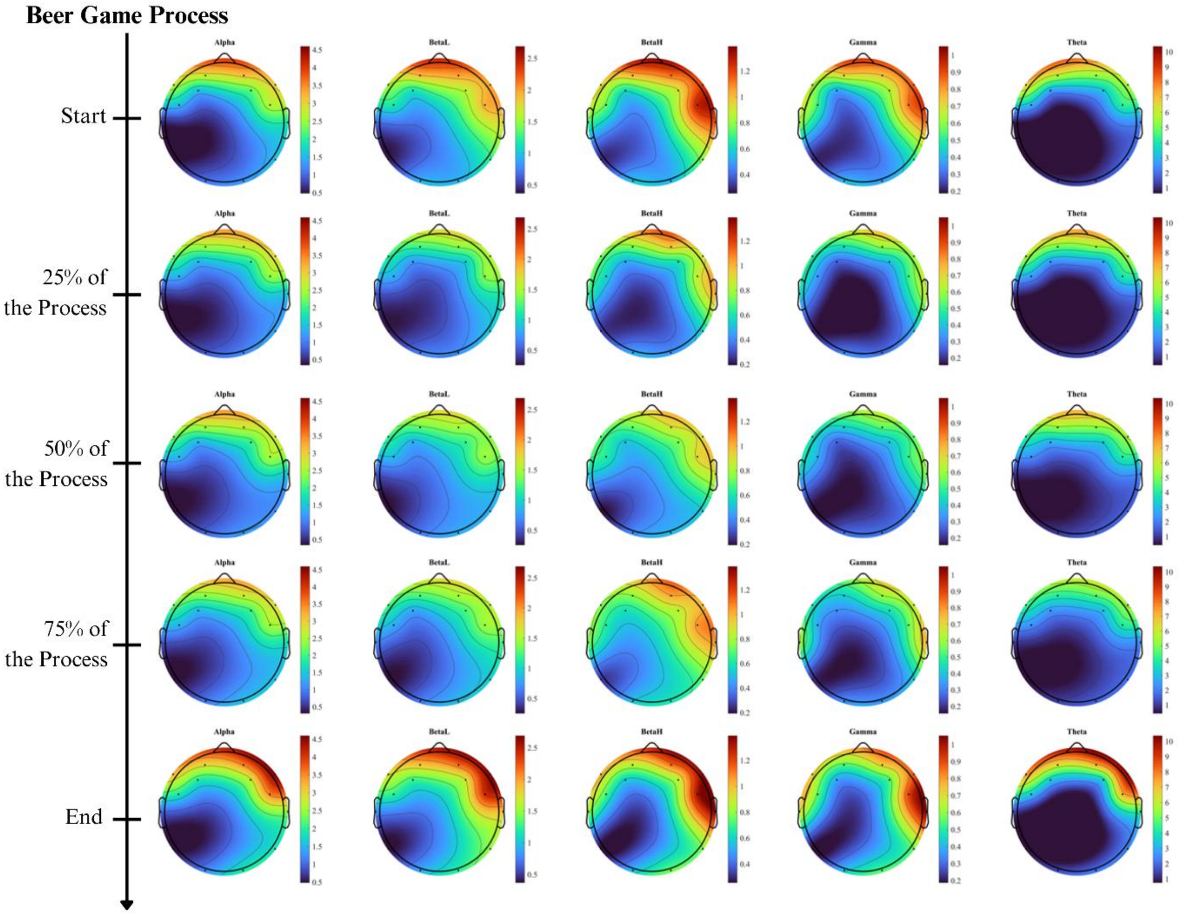


Figure 3. EEG topography plot over the beer game process

From the perspective of brainwaves, our results show that theta activity was predominant, indicating substantial internal cognitive processing such as working memory activation and error monitoring. Alpha waves, coming in as the second highest in power, suggest that while participants are cognitively engaged, they maintain a state of relaxed alertness, filtering sensory distractions effectively. In contrast, beta waves showed relatively low power throughout the process, which may imply that the game did not demand excessive externally focused attention or rapid sensorimotor responses. Notably, during the later stage, when more effects of uncertainties were cumulated leading to a high total cost, the surge in gamma activity points to an increase in high-level cognitive functions, such as advanced problem-solving and decision-making, in response to mitigating the high cost accumulation.

In addition to the shifts in brainwave patterns, the frontal lobe demonstrated consistent and significant activity throughout the game. This region's engagement supports its well-established role in higher-order cognitive processes including planning, strategic decision-making, and working memory. The continuous activation of the frontal lobe underscores how participants are not merely reacting to game stimuli but are dynamically adapting to evolving challenges by monitoring, evaluating, and adjusting their strategies in real time.

Overall, the interplay between brainwave activity and the frontal lobe's involvement paints a picture of cognitive adaptability throughout the beer game. Early high engagement gradually gives way to moderate states as the task becomes routine, only to escalate once more when uncertainty disrupts the established rhythm. This coordinated neural response reflects a balance between the internal processing required for strategic decision-making and the constant need for adaptation during complex and dynamic tasks.

4.3 Results in Stage 2 (DTW-based Signal Similarity Measurement)

Based on the aforementioned descriptive analysis on EEG signals, it is found that the participants' frontal lobes are relatively active during the beer game process. In view of this phenomenon, the channels from standard frontal electrodes (F3, F4, F7, F8) and anterior frontal electrodes (AF3 and AF4) are focused.

On the other hand, beta waves (including BetaL and BetaH) are linked to active thinking, focus, and problem-solving, while Gamma waves are involved in higher-level cognitive functions, including perception, learning, memory and consciousness. From the EEG topography plot shown in Figure 3, the changes of beta and gamma waves are observed, and thus they are selected to formulate 18 features, i.e. the multiplication of six channels and three brainwaves, per participant. Since the time spent on the beer game is varying among the participants, the number of signal strengths based on the selected 18 signal features are also varying. As shown in Figure 4, the number of EEG signals collected ranges from 2845 to 8308 with the average of 4417 records approximately. The interval between the signal collection is 0.125 seconds such that the beer game is completed in around 10 minutes. The larger value of the number of EEG signals collected refers to a longer time spent on the beer game process. In other words, Participant 13 spent the longest time among other participants in playing the beer game with around 17.3 minutes.

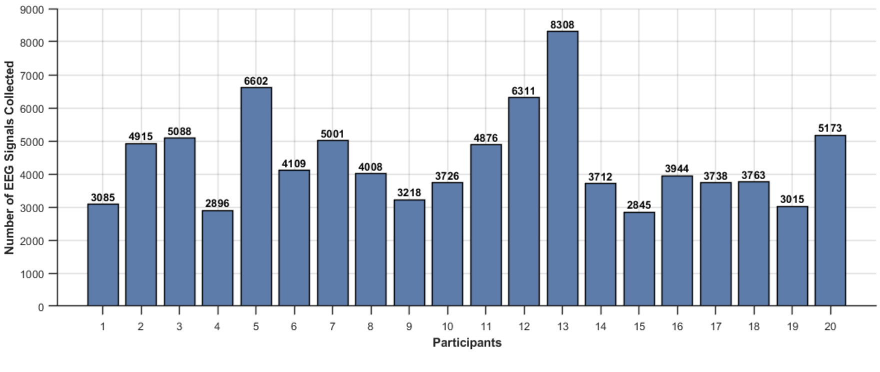
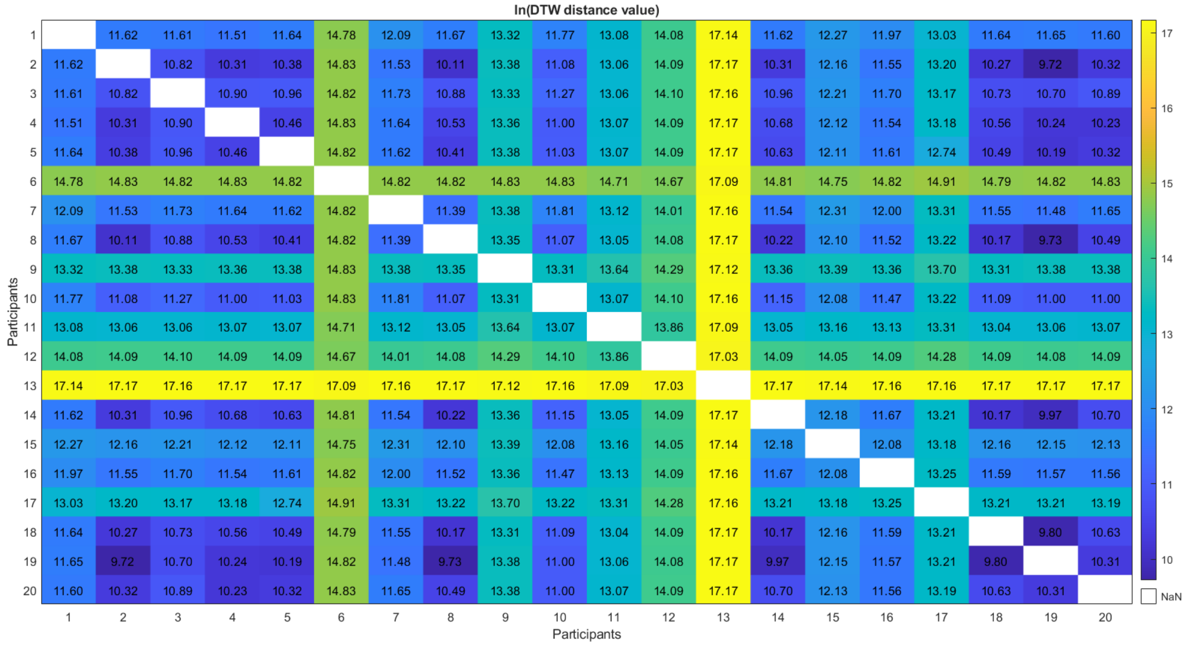


Figure 4. Number of EEG signals collected per participant

Through applying the DTW algorithm, the similarity of the selected EEG signal features among participants was determined. Figure 5 illustrates the heatmap of the dissimilarity value, namely the DTW distance value in the logarithmic scale, for stabilising the variance and improving the interpretability. A larger dissimilarity value implies a greater difference in EEG signal patterns between any two participants. From the heatmap, it is obvious that the EEG signal behaviour of participant 6 and 13 deviates from other participants.



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1		11.62	11.61	11.51	11.64	14.78	12.09	11.67	13.32	11.77	13.08	14.08	17.14	11.62	12.27	11.97	13.03	11.64	11.65	11.60
2	11.62		10.82	10.31	10.38	14.83	11.53	10.11	13.38	11.08	13.06	14.09	17.17	10.31	12.16	11.55	13.20	10.27	9.72	10.32
3	11.61	10.82		10.90	10.96	14.82	11.73	10.88	13.33	11.27	13.06	14.10	17.16	10.96	12.21	11.70	13.17	10.73	10.70	10.89
4	11.51	10.31	10.90		10.46	14.83	11.64	10.53	13.36	11.00	13.07	14.09	17.17	10.68	12.12	11.54	13.18	10.56	10.24	10.23
5	11.64	10.38	10.96	10.46		14.82	11.62	10.41	13.38	11.03	13.07	14.09	17.17	10.63	12.11	11.61	12.74	10.49	10.19	10.32
6	14.78	14.83	14.82	14.83	14.82		14.82	14.82	14.83	14.83	14.71	14.67	17.09	14.81	14.75	14.82	14.91	14.79	14.82	14.83
7	12.09	11.53	11.73	11.64	11.62	14.82		11.39	13.38	11.81	13.12	14.01	17.16	11.54	12.31	12.00	13.31	11.55	11.48	11.65
8	11.67	10.11	10.88	10.53	10.41	14.82	11.39		13.35	11.07	13.05	14.08	17.17	10.22	12.10	11.52	13.22	10.17	9.73	10.49
9	13.32	13.38	13.33	13.36	13.38	14.83	13.38	13.35		13.31	13.64	14.29	17.12	13.36	13.39	13.36	13.70	13.31	13.38	13.38
10	11.77	11.08	11.27	11.00	11.03	14.83	11.81	11.07	13.31		13.07	14.10	17.16	11.15	12.08	11.47	13.22	11.09	11.00	11.00
11	13.08	13.06	13.06	13.07	13.07	14.71	13.12	13.05	13.64	13.07		13.86	17.09	13.05	13.16	13.13	13.31	13.04	13.06	13.07
12	14.08	14.09	14.10	14.09	14.09	14.67	14.01	14.08	14.29	14.10	13.86		17.03	14.09	14.05	14.09	14.28	14.09	14.08	14.09
13	17.14	17.17	17.16	17.17	17.17	17.09	17.16	17.17	17.12	17.16	17.09	17.03		17.17	17.14	17.16	17.16	17.17	17.17	17.17
14	11.62	10.31	10.96	10.68	10.63	14.81	11.54	10.22	13.36	11.15	13.05	14.09	17.17		12.18	11.67	13.21	10.17	9.97	10.70
15	12.27	12.16	12.21	12.12	12.11	14.75	12.31	12.10	13.39	12.08	13.16	14.05	17.14	12.18		12.08	13.18	12.16	12.15	12.13
16	11.97	11.55	11.70	11.54	11.61	14.82	12.00	11.52	13.36	11.47	13.13	14.09	17.16	11.67	12.08		13.25	11.59	11.57	11.56
17	13.03	13.20	13.17	13.18	12.74	14.91	13.31	13.22	13.70	13.22	13.31	14.28	17.16	13.21	13.18	13.25		13.21	13.21	13.19
18	11.64	10.27	10.73	10.56	10.49	14.79	11.55	10.17	13.31	11.09	13.04	14.09	17.17	10.17	12.16	11.59	13.21		9.80	10.63
19	11.65	9.72	10.70	10.24	10.19	14.82	11.48	9.73	13.38	11.00	13.06	14.08	17.17	9.97	12.15	11.57	13.21	9.80		10.31
20	11.60	10.32	10.89	10.23	10.32	14.83	11.65	10.49	13.38	11.00	13.07	14.09	17.17	10.70	12.13	11.56	13.19	10.63	10.31	

Figure 5. Heatmap of the DTW distances in a logarithmic scale among participants

4.4 Results in Stage 3 (Hierarchical Clustering for EEG Pattern Analysis)

Hierarchical clustering was applied to analyse the similarity between participants, formulating a dendrogram. When formulating clusters in hierarchical clustering, the linkage algorithm plays a crucial role in sequentially connecting newly formed clusters and individual objects until all data are linked in a complete hierarchical tree. To determine the most appropriate linkage algorithm, various algorithms for computing distances between clusters are examined using inconsistency coefficients as evaluation metrics. Table 1 shows the comparison of the statistical measures of the inconsistency values among various linkage algorithms. In the comparison, the UPGMC and WPGMC are disregarded due to negative inconsistency values indicating inappropriate clustering. The ISD method (also known as Ward's linkage) exhibits the lowest average inconsistency value of 0.5785, compared to values such as 0.6362 for UPGMA, 0.6352 for FD, 0.6380 for SD, and 0.6456 for WPGMA. It suggests the formation of uniform and internally consistent clusters given that homogeneity within clusters is paramount. Furthermore, by using the ISD method, the cophenetic correlation coefficient of 0.7827 supports the reliability of the dendrogram in reflecting the intrinsic distance structure of the data, while the ISD method minimizes the increase in within-cluster variance at each merging step, producing clusters that are compact and homogeneous. Consequently, the dendrogram of the cluster tree formulated by using the ISD method can be constructed as shown in Figure 6.

Based on the dendrogram generated by hierarchical clustering, Silhouette analysis was conducted for cluster counts ranging from two to ten. In Figure 7, the mean Silhouette coefficient is plotted against the number of clusters. The highest coefficient (0.65) was observed when the number of clusters is two, indicating the most cohesive and well-separated clustering structure. Consequently, a two-cluster solution was adopted to characterize participants' neural dynamics during the beer game. Participants 6, 9, 11, 12, 13 and 17 were assigned to Cluster I, while participants 1, 2, 3, 4, 5, 7, 8, 10, 14, 15, 16, 18, 19 and 20 were assigned to Cluster II. For cluster labelling and interpretation, the time-series data from the 18 most decision-related signal sources (i.e. BetaL, BetaH and Gamma bands recorded at F3, F4, F7, F8, AF3 and AF4) were first normalised and then logarithmically transformed to accentuate inter-cluster differences. The transformed profiles were subsequently segmented into five game stages (start, 25 %, 50 %, 75 % and end) that together span 400 time units: the start and end stages comprise the initial and final 80 signal values, respectively, while each intermediate stage contains the 40 values immediately preceding and following the nominal quarter, midpoint and three-quarter time points. Figure 8 depicts, for each stage, the average signal strength of the two resulting clusters together with the associated 95 % confidence intervals, thereby highlighting how neural activity evolves throughout gameplay.

Table 1. Comparison of inconsistency values in terms of mean, median, minimum and maximum values among various linkage algorithms in hierarchical clustering

Linkage algorithm between clusters	Inconsistency values			
	Mean	Median	Min	Max
UPGMA	0.6362	0.7071	0	0.7745
UPGMC	0.0744	0.7071	-0.7071	0.7071
FD	0.6352	0.7071	0	1.1005
WPGMC	0.2233	0.7071	-0.7071	0.7071
SD	0.6380	0.7071	0	0.8079
ISD	0.5785	0.7071	0	1.1416
WPGMA	0.6456	0.7071	0	0.9524

Remarks: Unweighted average distance (UPGMA); Centroid distance (UPGMC); Farthest distance (FD); Weighted centre of mass distance (WPGMC); Shortest distance (SD); Inner squared distance (ISD); Weighted average distance (WPGMA)

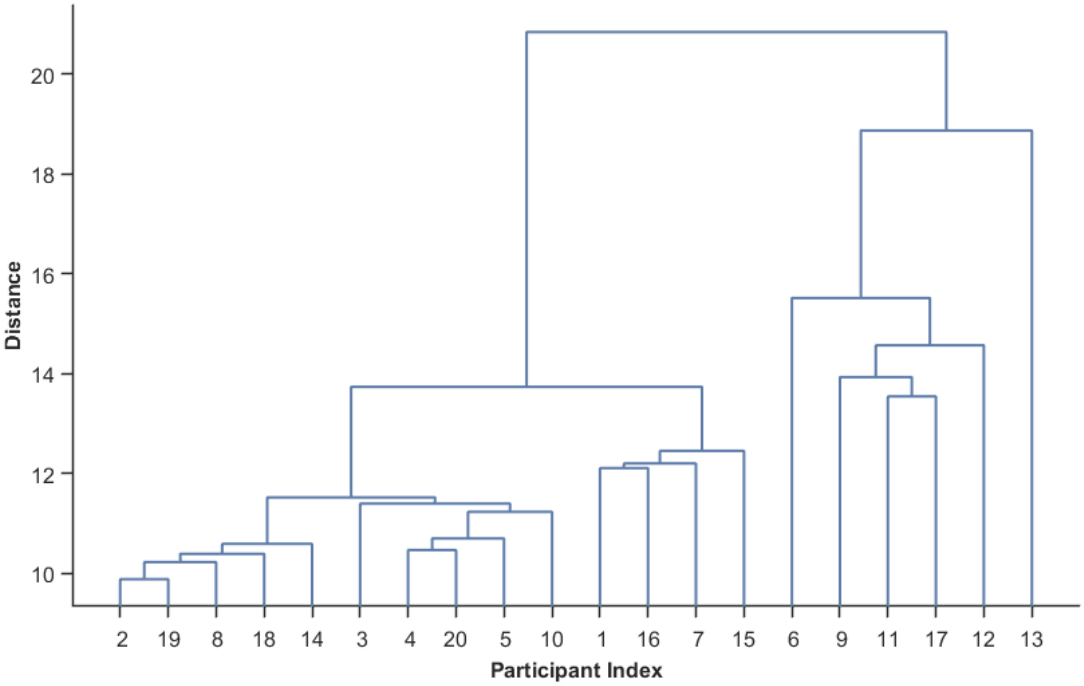

Figure 6. Dendrogram of the hierarchical clustering analysis

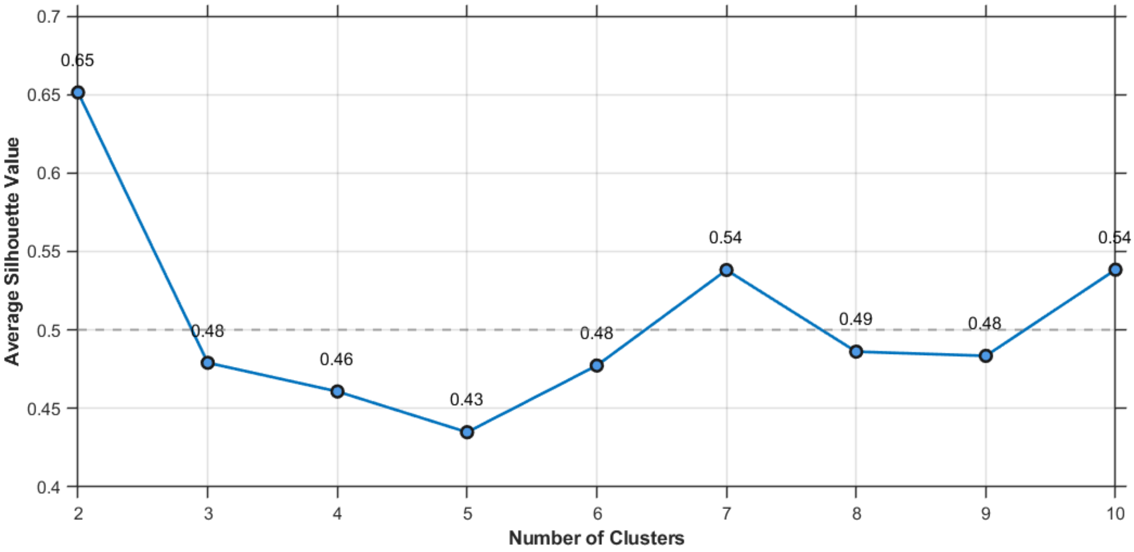

Figure 7. Silhouette analysis across different numbers of clusters

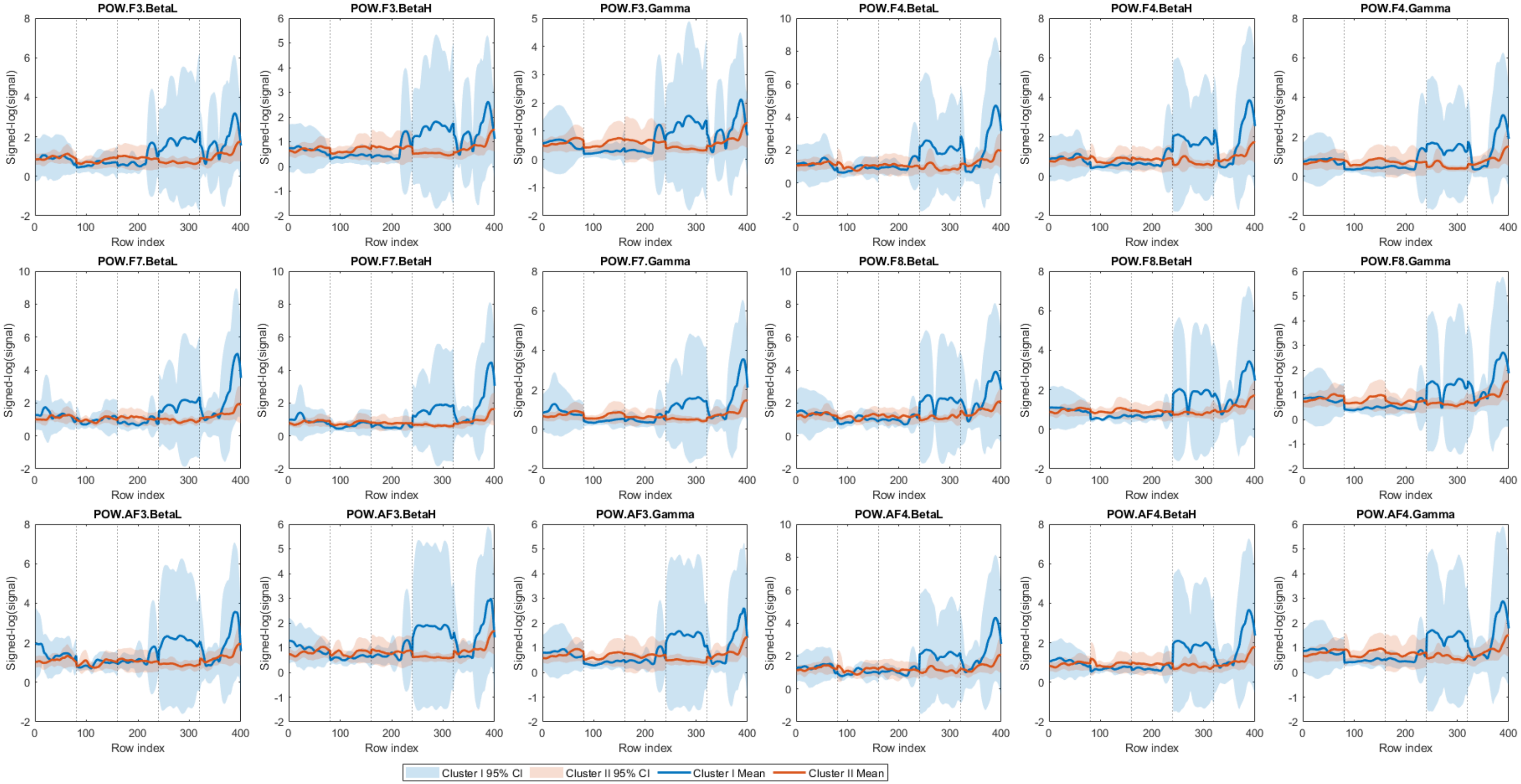

Figure 8. Mean and 95% confidence interval of EEG signal strengths in Clusters I and II

For each cluster, the mean signal values and their 95 % confidence intervals over 400 data points were plotted. It was observed that cognitive activity in Cluster I participants was elevated during the initial (0 %), 75 %, and final (100 %) phases of the game. In the initial phase, active exploration of the game environment was inferred, presumably to minimise total supply-chain cost. During the intermediate phases (25 % and 50 %), cognitive effort was comparatively attenuated. By contrast, slightly higher levels of sustained attention were recorded for Cluster II participants in these middle phases, suggesting focused problem comprehension and strategy formulation. As uncertainty peaked at the 75 % and final phases, Cluster I cognitive signals exhibited increased volatility, indicating frustration with uncontrollable cost fluctuations and intensified efforts to identify mitigation strategies. Overall, cognitive-load variability was markedly greater in Cluster I than in Cluster II, whose activity remained comparatively stable throughout the simulation. Accordingly, Cluster I and Cluster II were designated the Hyperactive EEG Group and Hypoactive EEG Group, respectively.

5. Discussion and Implications

According to the clustering results, further investigation with the game performance and other demographic information is conducted. In addition, the corresponding lesson learnt and implications are summarised in this section.

5.1 Analysis with the Game Performance and Demographic Variables

When the participants are classified into two different groups, namely hypoactive and hyperactive EEG groups, further investigation with the game performance and their demographic data can be conducted. Referring to the game performance in terms of the total retailer cost (i.e. the role that the participant played in the beer game), the cost performance in two different groups is summarised in Table 2. It is found that the hypoactive group (n = 14) exhibited a mean cost of 3180.3 and a median of 2352.5, with relatively modest variability (IQR = 3108.6; MAD = 1104.3; SD = 2061.3). In contrast, the hyperactive group (n = 6) incurred substantially higher average costs (mean = 6155.1; median = 4363.6) accompanied by markedly greater dispersion (IQR = 4699.3; MAD = 2349.6; SD = 6170.4), reflecting less predictable and more extreme cost outcomes. To better understand the differences between two groups, Figure 9 shows the corresponding box plot and violin plot to describe the distribution of the game performance among two groups. Especially, the violin plot of ln-transformed costs reinforces this finding, displaying a wider, flatter density for hyperactive behaviour, indicating greater variability, versus a narrower and more peaked distribution for the hypoactive group. Furthermore, the Cohen's *d* value is 0.8053, which represents a large effect size [33], indicating a practically meaningful difference in cost performance between the hypoactive and hyperactive groups. However, an individual in the hypoactive cluster poorly performed in the beer game with the result of high total retailer cost, like the outlier of the hypoactive cluster. If this individual is removed from the evaluation of Cohen’s d, the value is decreased to 0.2762. These results indicate that hypoactive behaviour in the beer game yields more cost-effective and stable performance than hyperactive strategies.

Table 2. Summary of sample size, mean, median, inter-quartile range, median absolute deviation and standard deviation of the total cost over the beer game among two groups of participants

Group	**n**	**Mean**	**Median**	**IQR**	**MAD**	**S.D.**
Hypoactive	14	3180.3	2352.5	3108.6	1104.3	2061.3
Hyperactive	6	6155.1	4363.6	4699.3	2349.6	6170.4
Remark: Inter-quartile range (IQR), median absolute deviation (MAD), standard deviation (S.D.)						

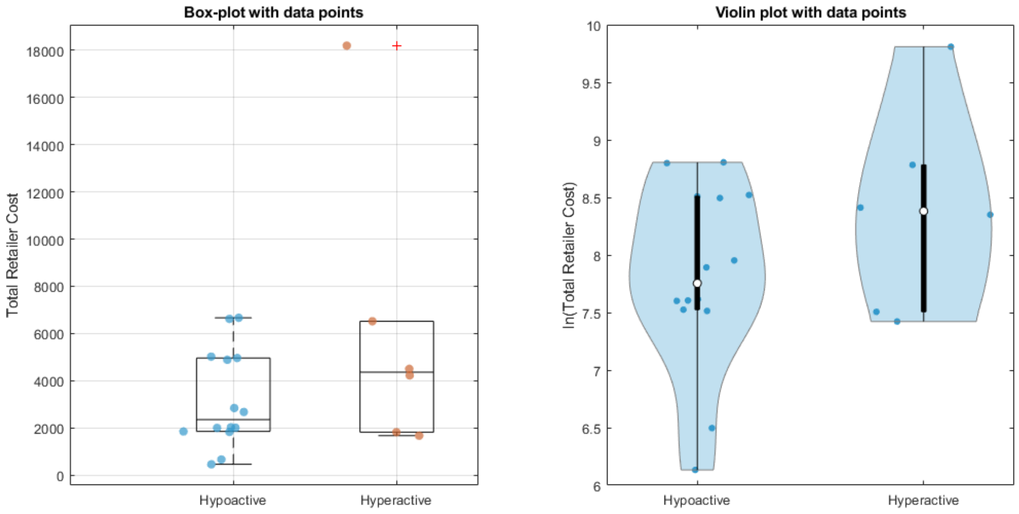

Figure 9. Box plot and violin plot for the game performance among two groups

Moreover, the demographic breakdown shows that the hyperactive group reported relatively higher SCM knowledge, with the average of 4.0 out of 5.0 (with the standard deviation of 0.8944) versus 3.3 (with the standard deviation of 1.2666) in the hypoactive group. Regarding the gender distribution among two clusters, the Fisher’s Exact test was performed, where p-value is 0.000 and Cramér’s V is 0.154. It shows the statistically significant, but relatively weak, association with gender among the clusters. In other words, the male proportion in the hyperactive cluster is significantly higher than in the hypoactive cluster. During the experiment, the hyperactive cluster reported higher SCM knowledge and higher performance expectations, which appears to have translated into performance pressure. The resulting anxiety is consistent with the elevated beta-band power from EEG signal observations and high arousal to over-reactive inventory decisions. In the hypoactive cluster, a “keep calm, monitor, and adjust sparingly” mindset reduced the bullwhip effect, leading to lower total cost despite lower declarative knowledge.

5.2 Lesson Learnt from the Analysis

From the findings of electrophysiological patterns, parietal alpha-suppression increased monotonically over the course of the game, consistent with sustained visual attention and vigilance. Frontal beta and gamma band power rose sharply only after the midpoint, signalling progressive recruitment of executive control, error monitoring and the rapid integration of multiple information streams. By contrast, frontal theta power showed a delayed rise that classically denotes compensatory effort once working-memory capacity is approached.

Hierarchical clustering separated the cohort into a hyper-active group (Cluster I) and a hypo-active group (Cluster II). Participants in Cluster I exhibited pronounced surges in betaH and gamma activity during the 75% of the game process and the final phase. The accompanying confidence intervals widened substantially, pointing to marked inter-individual variability and possible neural disorganisation. Cluster II displayed comparatively flat beta/gamma trajectories with consistently narrow confidence bands. Behaviourally, Cluster II achieved lower cumulative inventory costs and attenuated bullwhip amplification. These findings support a central postulate of cognitive-load theory [34]: learning efficiency is determined not by the absolute amount of mental effort but by how that effort is allocated. High performers (Cluster II) invested neural resources economically, channelling activity towards germane processing, whereas low performers (Cluster I) bore electrophysiological hallmarks of overload, suggesting that working memory was saturated by extraneous demands. Introducing reflective pauses may therefore help novices redistribute cognitive load, emulate the neural economy of experts and dampen, rather than amplify, the bullwhip effect.

On the other hand, the findings also resonate with the Yerkes-Dodson law as shown in Figure 10. An analysis of beer-game performance and participants' arousal levels revealed a quadratic relationship typical of the Yerkes-Dodson curve as in Equation (7), with $R^2 = 0.3686$ and adjusted $R^2 = 0.2897$ referring to the moderate effect in behavioural data. The inverted-U curve shows that a higher frontal beta/alpha ratio (an index of increased arousal) did not predict better outcomes; in fact, participants with moderate arousal levels were more likely to achieve top performance. Excessive activation can trigger over-analysis or stress, diminishing performance under uncertainty [32]. Thus, the present findings offer empirical support for the Yerkes-Dodson law in decision-making tasks. In dynamic tasks such as the beer game, decision quality hinges on the precision of cognitive engagement and the capacity to remain composed, rather than on the sheer volume of neural activity expended.

$$Performance = -1053.39 \cdot Arousal^2 + 368.86 \cdot Arousal + 4335.02 \tag{7}$$

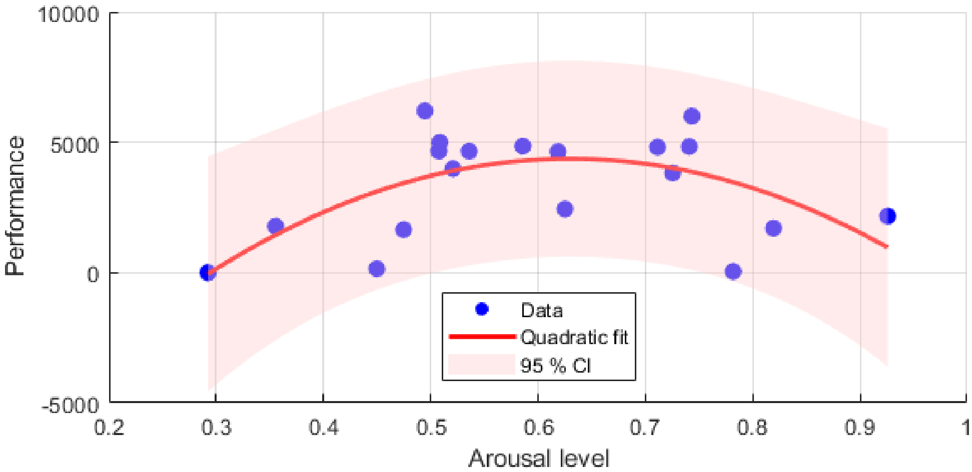

Figure 10. Quadratic fit between arousal level and performance from the participants (Remark: One outlier was detected and removed using the Mahalanobis distance (χ^2 test) at the 97.5th percentile; Performance was quantified as the maximum cost across all participants minus each participant's cost; Arousal level was calculated as the mean of the BetaL/Alpha and BetaH/Alpha ratios recorded at the F3, F4, F7, and F8 electrodes.

5.3 Implications to Supply Chain Management and Education

In today's global environment, where supply chains are constantly challenged by unforeseen disruptions [36], from political and economic shocks to natural disasters and technological failures, a key takeaway from this research is the importance of managing one's cognitive state during critical decision-making processes resonating the work [37].

The results reported are bounded by the default configuration of the chosen beer game. Exogenous customer demand was held at 4 units per week for Week 1 to 4 and then doubled to 8 units per week for Week 5 to 50. Each retailer started with 12 units of on-hand inventory and two inbound deliveries of 4 units scheduled to arrive in Week 1 and 2. The replenishment lead time was fixed at three weeks. Inventory holding and backlog penalty costs were set at $5 and $25 per unit per week, respectively. All human participants played the retailer position, while the wholesaler tier was represented by a computer agent (i.e. the ghost player function provided by the game). This computer agent may respond to orders in ways that differ from human behaviour, introducing additional uncertainty.

The findings, derived from analysing EEG beta and gamma power levels in frontal lobe channels during a simulated beer game, reveal that participants with lower cognitive activation, indicating a more relaxed and less overburdened mental state, consistently achieved better outcomes, particularly in terms of cost efficiency. This evidence supports the idea "*keep calm*." In the context of SCM, this principle encourages managers and decision-makers to approach challenges with composure and a readiness to embrace risk, rather than succumbing to the paralysis of over-analysis. When crises strike or uncertainties proliferate, a calm mental state can foster more intuitive and agile responses. It helps in filtering out the "noise" of excessive data and the tendency to micromanage, enabling leaders to focus on core priorities and strategic pivots for enhanced resilience.

At the same time, the research underscores that higher cognitive effort which might be equated with an intensive focus on minute details is not always beneficial. Instead, the concept of "*much ado about nothing*" warns against the pitfalls of overcomplicating decision processes. In practical terms, this means that meticulous efforts to control every variable or to anticipate every possible contingency can lead to cognitive overload, ultimately slowing down response times and inhibiting innovative, flexible problem-solving. For supply-chain decision-making, this finding suggests that decision-making frameworks for a range of engineering management applications [38] should incorporate deliberate simplification, which may prove more effective than complex, data-saturated strategies.

Last but not least, managing how people think is as crucial as teaching what to think. When using the beer game in teaching and learning activities, a calm launch with a short breathing exercise or mindfulness video at the beginning can relax participants to prevent the cognitive overload during the game. Moreover, the biofeedback, i.e. EEG signal monitoring, can be equipped to visualise the real-time cognitive states, such as stress and excitement, turning cognitive-state management into emotional intelligence tactics. By embedding the above tactics into both day-to-day operations and experiential learning tools, educators and managers can materially improve cost, agility, and resilience, turning '*keep calm*' from a slogan into an operating policy.

6. Conclusion

This study presents a systematic EEG analysis methodology applied during the beer game, a representative simulation of SCM. The proposed three-stage EEG data analysis process enabled a detailed exploration of the intricate relationship between cognitive load and operational performance. By clustering participants based on neurophysiological metrics, it is revealed that a calm, measured cognitive state, evidenced by lower beta and gamma activity, correlates with improved cost performance, whereas heightened cognitive activation does not yield a corresponding advantage. The results were visualized and validated, yielding a Cohen's d of 0.8053. Additionally, a Fisher's exact test indicated that the proportion of males in the hyperactive cluster is significantly higher than in the hypoactive cluster. The empirical evidence supports a “keep calm” approach and cautions against over-analysis (“much ado about nothing”), highlighting the pitfalls of overcomplicating decision-making processes. Prior beer-game and SCM literature emphasize information sharing, forecasting accuracy, and analytical processing as levers to reduce the bullwhip effect and costs. The above findings add a neurophysiological dimension, i.e. managerial cognitive state itself is a performance lever.

While the EEG-based evidence deepens our understanding of cognitive influences in supply chain decision-making, several limitations are acknowledged. First, the evidence is confined to a single beer game configuration in which all human subjects played the retailer role and interacted with aa computer agent. Second, the laboratory environment cannot capture time pressure and political constraints that shape real operational decisions. Addressing these constraints, by varying game parameters, recruiting larger heterogeneous cohorts, and integrating additional bio-signals, could provide more practical operations insights, and accelerate the design of effective pedagogies for supply chain professionals operating under uncertainty.

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