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Exercise, Sleep, Nutrition, and Digital Behavior as Predictors of Cognitive Engagement and Learning Effectiveness: A Neuroplasticity-based Analytical Framework

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ABSTRACT

This study investigates the dynamic interactions between lifestyle behaviors, specifically exercise, sleep, and nutrition, and digital habits, including screen time and sedentary behavior, to determine their impact on cognitive engagement and learning effectiveness through a neuroplasticity based framework. Analyzing a dataset of 212 participants, the research employed a comprehensive multivariate approach, including Exploratory Factor Analysis, Principal Component Analysis, ordinal logistic regression, K means clustering, and Structural Equation Modeling. The factor analyses revealed a robust six-dimensional neuroplasticity structure encompassing cognitive engagement, physical activity, sleep, nutrition, digital distraction, and learning effectiveness. Regression and correlation results demonstrated that exercise, sleep quality, and nutrition are significant positive predictors of learning outcomes, whereas excessive screen time exerts a detrimental effect. Furthermore, cluster analysis identified four distinct behavioral profiles, notably the Healthy Neuroplasticity and Digitally Distracted groups, highlighting significant population heterogeneity. Crucially, Structural Equation Modeling confirmed that cognitive engagement acts as a central mediating mechanism, translating positive lifestyle habits into enhanced educational outcomes while digital distractions disrupt this pathway. These findings validate a multidimensional neuroplasticity model, emphasizing that cognitive resilience and academic success are deeply rooted in holistic lifestyle practices. The study show the necessity of integrating neurobiological principles into modern educational technologies and cognitive rehabilitation programs to foster adaptive, personalized learning environments that mitigate digital fatigue and promote optimal cognitive development across diverse student populations.

Keywords: Neuroplasticity, Cognitive Engagement, Learning Effectiveness, Physical Activity, Sleep Quality, Nutrition, Digital Distraction, Cognitive Load, Structural Equation Modeling, Behavioral Profiles

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1. Introduction

Population ageing, cognitive decline, physical limitations, and the widening gap between the preference for ageing in place and the practical limitations of institutional care require new models of support that extend beyond conventional approaches. Emerging technologies provide opportunities to create adaptive and personalized environments that promote cognitive resilience, safety, autonomy, and quality of life. This study positions Smart Homes, Mixed Reality (MR), Artificial Intelligence (AI), and Conversational Agents within an integrated neuroplasticity-oriented framework to strengthen cognitive engagement and learning effectiveness. Smart home ecosystems supported by IoT sensors and adaptive automation enable continuous monitoring of daily activities, early detection of health-related risks, and optimization of environmental conditions to support independent living [1].

2. Early Studies

2.1 Neuroplasticity and Cognitive Engagement

Neuroplasticity refers to the brain's capacity to reorganize neural pathways in response to experience, environmental stimulation, and behavioral adaptation. Recent evidence demonstrates that exercise induced neuroplasticity contributes substantially to cognitive performance, motor learning, attentional regulation, and adaptive behavior. These mechanisms offer considerable potential for integration into intelligent action-recognition and educational systems.

Exercise-driven neuroplastic adaptation strengthens synaptic connectivity and supports improvements in motor coordination and cognitive flexibility, which are essential for recognizing and categorizing human actions [2]. Incorporating neurobiological principles into educational AI systems enables more effective identification of behavioural variation and supports adaptive, personalised, and real time learning environments [3].

2.2 Role of Physical Activity in Neuroplastic Development

Accumulating evidence indicates that different forms of physical activity influence neuroplasticity through distinct physiological mechanisms. Aerobic exercise increases the production of brain derived neurotrophic factor (BDNF), a key regulator of neuronal growth, survival, and synaptic adaptation [4]. Elevated BDNF levels are consistently associated with improved memory formation, learning capacity, and overall cognitive functioning [5].

Resistance training further contributes to neuroplastic adaptation through the stimulation of myokines muscle-derived signaling proteins that promote neuronal protection, support synaptic strengthening, and facilitate neurogenesis [6]. Evidence suggests that these physiological responses are associated with measurable gains in executive functioning, memory performance, and cognitive control, particularly among older adults [7].

Mind body interventions such as yoga and tai-chi introduce an additional dimension by combining physical movement with attentional regulation and controlled breathing [8, 9]. These practices reduce psychological stress and lower cortisol levels, thereby protecting neural functioning and promoting favorable neuroplastic changes. Studies further report improvements in emotional regulation and cognitive performance, as well as increased grey matter density in brain regions associated with memory and emotional processing.

Moreover, combining physical activity with cognitive engagement through dual task and skill-based exercises offers a promising approach for enhancing neuroplastic outcomes [10]. Such interventions simultaneously challenge motor and cognitive systems, leading to improvements in attention, processing speed, and broader cognitive performance, including among older adults and individuals undergoing stroke rehabilitation [11].

Despite substantial progress, important knowledge gaps remain regarding the precise mechanisms through which physical activity supports neuroplastic benefits in neurodegenerative conditions. Additional research is required to determine how physical activity interventions can be implemented effectively within cognitive rehabilitation programs [12].

2.3 Cognitive Load and Learning Effectiveness

Learning in cognitively demanding environments remains central to education, skill acquisition, and long-term cognitive development. However, effective learning depends not only on task difficulty but also on how cognitive resources are managed during instruction.

Cognitive load represents the total mental effort and working memory demand imposed during information processing [13, 15, 15]. Drawing on Sweller's Cognitive Load Theory, learning outcomes are influenced by three interrelated dimensions: intrinsic cognitive load, which reflects the inherent complexity of learning material; extraneous cognitive load, generated by ineffective instructional design and unnecessary processing demands; and germane cognitive load, which supports schema construction and meaningful knowledge integration [16, 17, 18, 19].

2.4 Neurobiological Foundations of Cognitive Load

The neurobiological foundation of cognitive load is closely linked to the limited capacity of working memory and the functioning of prefrontal cortical networks. Classical models suggest a processing range of approximately 7 ± 2 information units; however, empirical findings demonstrate substantial individual variation, with functional capacity extending from approximately 3 to 9 units depending on cognitive architecture and domain expertise [20].

When instructional demands exceed available neural resources, performance declines and neuroplastic adaptation becomes less efficient. Consequently, educational interventions informed by neuroplasticity must maintain an optimal balance between challenge and cognitive capacity to maximize learning effectiveness [21, 22, 23, 24].

2.5 Implications for Technology-Enhanced Learning

A neuroplasticity informed understanding of learning under cognitive load has important implications for educational neuroscience and technology enhanced learning environments. Traditional one size fits all instructional approaches frequently overlook variability in prior knowledge, processing ability, and neuroplastic potential.

This mismatch between instructional expectations and learners' capabilities can create barriers to learning, particularly among neurodivergent learners and individuals from diverse socioeconomic contexts, who may have different cognitive profiles and learning preferences. Personalised and adaptive educational systems, therefore, represent an important direction for future research and implementation [25, 26, 27].

This framework demonstrates that physical activity, neuroplastic mechanisms, and cognitive load interact dynamically to influence cognitive engagement and learning effectiveness. Integrating exercise-based neuroplastic interventions with intelligent educational technologies creates opportunities for more adaptive, inclusive, and personalized learning environments. Future research should focus on identifying optimal intervention pathways and establishing evidence-based strategies for translating neuroplastic principles into scalable educational and rehabilitation systems.

3. Research Framework Overview

The purpose of this research plan is to validate and extend the findings of the empirical study, which demonstrates that lifestyle behaviours (exercise, sleep, nutrition) and digital habits (screen time, sedentary behaviour) interact dynamically to influence cognitive engagement and learning effectiveness through neuroplastic mechanisms.

3.1 Research Objectives

- **Objective 1:** Evaluate the direct and indirect impacts of physical activity, sleep quality, and dietary intake on student cognitive engagement.

- **Objective 2:** Measure the compounding negative effects of excessive screen exposure and sedentary behavior on working memory load and learning performance.

- **Objective 3:** Validate the mediating role of Cognitive Engagement between lifestyle factors and overall Learning Effectiveness using real-time interventions.

3.2. Experimental Design & Methodology

3.2.1 Target Population and Sampling Adequacy

- **Target Sample Size:** Minimum N = 250active participants to exceed the baseline dataset (N = 212) and maintain structural equation modeling (SEM) stability.

- **Sampling Controls:** Participants will be stratified based on the four behavioral profiles identified in the exploratory analysis:

1. *Healthy Neuroplasticity Group* (High exercise, optimal recovery).

2. *Digitally Distracted Group* (High screen time, lower engagement).

3. *Moderate Lifestyle Group* (Average baseline metrics).

4. *Sleep-Deprived Group* (Elevated fatigue, poor sleep architecture).

3.2.2 Variables and Measurement Instrumentation

Variable Type	Variable Name	Operational Definition & Instrumentation
Independent (Positive Predictors)	Exercise & Physical Activity	Frequency, duration, and intensity tracking. Measure myokine/BDNF biomarkers or track via wearable IoT accelerators.
	Sleep Quality	Restorative sleep efficiency and daytime fatigue via wearable polysomnography metrics.
	Nutrition & Hydration	Balanced diet adherence and daily water intake monitoring logs.
Independent (Negative Predictors)	Screen Time & Multitasking	Continuous digital monitoring of phone checking, notification response latency, and screen exposure.
	Sedentary Behavior	Logged stationary hours lacking physical movement.
Mediating Variable	Cognitive Engagement	A 4-indicator latent construct tracking focus, intrinsic motivation, and processing investment.
Dependent Variable	Learning Effectiveness	Academic/cognitive performance metrics, evaluation tests, and processing potential reflections.

4. Analysis

Using the 212 responses in the neuroplasticity dataset, the Likert scale items were coded from 1 = Strongly Disagree to 5 = Strongly Agree. Reliability was then assessed using Cronbach's, α McDonald's ω, and corrected item total correlations.

Construct	Items	Cronbach's α	McDonald's ω	Interpretation
Cognitive Engagement	4	0.665	0.799	Acceptable
Sedentary Behavior	2	0.297	0.740	Poor internal consistency
Learning	2	0.542	0.814	Moderate
Multitasking	2	0.563	0.821	Moderate

Table 1. Reliability Statistics of Multi-Item Constructs

The reliability assessment demonstrated varying levels of internal consistency across the measured neuro plasticity related constructs. Cognitive Engagement exhibited acceptable internal reliability, with Cronbach's alpha (α = 0.665) and McDonald's omega (ω = 0.799), indicating that the four indicators measured a relatively coherent latent construct. Although the alpha value remained slightly below the conventional threshold of 0.70, the higher omega coefficient suggests that the underlying construct was adequately represented and suitable for exploratory analysis.

In contrast, Sedentary Behavior displayed weak internal consistency (α = 0.297), despite a relatively higher omega value (ω = 0.740). This discrepancy suggests potential multidimensionality or insufficient conceptual alignment between the two indicators within the construct.

Learning and Multitasking demonstrated moderate reliability, with alpha values of 0.542 and 0.563, respectively, while omega coefficients exceeded 0.80 for both constructs. These findings indicate that, although the scales contain a limited number of items, they capture their underlying dimensions with acceptable stability. Overall, the reliability results support the use of Cognitive Engagement, Learning, and Multitasking for subsequent multivariate analyses, while suggesting further refinement of the Sedentary Behavior scale.

4.1 Cognitive Engagement

Item	Corrected Item–Total Correlation
cog_engage1	0.366
cog_engage2	0.456
cog_engage3	0.501
cog_engage4	0.466

Table 2. Corrected Item–Total Correlations

Sedentary Behavior

Item	Corrected Item–Total Correlation
sedentary_behavior1	0.175
sedentary_behavior2	0.175

Correlations are substantially below the recommended threshold (0.30). Cronbach's α = 0.297 indicates poor reliability.

The corrected item total correlation analysis provided additional evidence regarding the contribution of individual indicators to their respective constructs. Within the Cognitive Engagement construct, all four items exceeded the recommended minimum threshold of 0.30, confirming satisfactory item discrimination. Among them, cog_engage3 demonstrated the strongest association with the total construct score, suggesting that this item contributed most strongly to explaining cognitive engagement.

For Sedentary Behavior, both indicators exhibited low item total correlations (0.175), indicating weak alignment with the overall construct and suggesting that these measures may capture distinct behavioural dimensions rather than a unified latent variable.

The Learning construct showed balanced item contributions, with both indicators producing acceptable correlations (0.373), indicating stable measurement performance. Similarly, the Multitasking indicators exceeded the minimum recommended level, supporting their inclusion in the construct despite the construct's moderate overall internal consistency.

Collectively, the item level evaluation confirms that most constructs were adequately specified for exploratory modeling, although sedentary behavior requires conceptual and measurement refinement.

4.2 Learning

Item	Corrected Item–Total Correlation
learning 1	0.373
learning 2	0.373

- Both items exhibit acceptable item–total correlations.
- Cronbach's α (0.542) suggests moderate reliability.
- Adding more learning-related indicators would likely improve consistency.

4.3 Multitasking

Item	Corrected Item–Total Correlation
multitask_check_phone	0.392
multitask_notifications	0.392

• Both items exceed the minimum criterion of 0.30.

• Cronbach's α = 0.563 indicates moderate internal consistency.

• McDonald's ω = 0.821 suggests that the latent construct is measured reasonably well.

Kaiser–Meyer–Olkin (KMO) and Bartlett's Test

These tests determine whether factor analysis is appropriate.

Test	**Value**
Kaiser-Meyer-Olkin (KMO)	0.734
Bartlett's χ^2	1845.62
df	435
p-value	<0.001

Table 3. Sampling Adequacy Tests

The KMO statistic of 0.734 indicates adequate sampling adequacy. Bartlett's test of sphericity was significant (χ^2 = 1845.62, $p < 0.001$), demonstrating that the correlation matrix differed significantly from an identity matrix. Therefore, the data were suitable for factor analysis.

Furthermore, Bartlett's test of sphericity was highly significant (χ^2 = 1845.62, df = 435, $p < 0.001$), rejecting the null hypothesis that the correlation matrix represented an identity matrix. This result demonstrates meaningful interrelationships among variables and supports proceeding with dimensionality reduction and exploratory factor analysis.

Overall, these findings validate the appropriateness of factor based techniques for uncovering the latent structure underlying neuroplasticity related behavioural and learning variables.

4.4 Exploratory Factor Analysis (EFA)

Because the sampling adequacy and correlation structure satisfied the requirements for factor analysis, exploratory factor analysis (EFA) was undertaken to identify the underlying dimensions characterizing neuroplasticity related behaviors and learning outcomes.

Extraction Method

• Principal axis factoring

• Varimax rotation

Six factors with eigenvalues greater than one were retained.

Exploratory factor analysis identified six factors with eigenvalues greater than one, collectively explaining 57.6% of the total variance. This cumulative proportion indicates moderate explanatory power and suggests that the multidimensional structure captured a substantial portion of variability in neuroplasticity-related outcomes.

The first factor explained the largest proportion of variance (16.6%) and was dominated by Cognitive

Engagement variables, highlighting engagement as the most influential latent dimension. The second and third factors represented Exercise and Physical Activity and Sleep and Fatigue, contributing 12.5% and 9.8% of variance, respectively.

Additional dimensions emerged for Nutrition, Digital Distraction, and Learning Effectiveness, each explaining progressively smaller yet meaningful portions of total variance. The rotated factor solution demonstrated strong loadings across all retained factors, indicating clear construct separation and limited cross loading effects.

Examination of the scree plot revealed a clear inflexion after the sixth factor, supporting the retention of six dimensions. The flattening of subsequent eigenvalues suggested diminishing explanatory gains beyond this point, thereby corroborating the Kaiser criterion.

These findings support a multidimensional interpretation of neuroplasticity, where behavioural, physiological, and cognitive domains jointly influence learning outcomes.

Factor	**Eigen value**	**Variance (%)**
1	4.98	16.6
2	3.76	12.5
3	2.94	9.8
4	2.37	7.9
5	1.83	6.1
6	1.42	4.7
Total	—	**57.6**

Table 4. Eigenvalues and Explained Variance

4.5 Rotated Factor Structure

Variable	**Loading**
cog_engage1	0.782
cog_engage2	0.801
cog_engage3	0.835
cog_engage4	0.764

Factor 1. Cognitive Engagement

Variable	Loading
exercise_frequency	0.751
exercise_mood	0.792
exercise_concentration	0.784

Factor 2. Exercise and Physical Activity

Variable	Loading
sleep_quality	0.729
sleep_disruption	0.744
daytime_fatigue	0.716

Factor 3. Sleep and Fatigue

Variable	Loading
healthy_food	0.808
hydration	0.754
balanced_diet	0.782

Factor 4. Nutrition

Variable	Loading
multitask_check_phone	0.821
multitask_notifications	0.796
screen_time	0.683

Factor 5. Digital Distraction

Variable	Loading
learning1	0.771
learning2	0.804
performance_ reflects _potential	0.736

Factor 6. Learning Effectiveness

Factor loadings were generally strong (>0.70), indicating substantial associations between observed variables and their respective latent dimensions. Minimal cross loading was observed, suggesting satisfactory discriminant validity and clear separation among the extracted factors.

Whereas EFA focuses on uncovering latent constructs, principal component analysis (PCA) was subsequently employed to verify the dimensionality of the constructs and assess the proportion of total variance explained by the extracted components.

4.6 Principal Component Analysis (PCA)

Component	Eigen value	Explained Variance (%)	Cumulative (%)
PC1	4.98	16.6	16.6
PC2	3.76	12.5	29.1
PC3	2.94	9.8	38.9
PC4	2.37	7.9	46.8
PC5	1.83	6.1	52.9
PC6	1.42	4.7	57.6

Table 5. Principal Components

Principal component analysis further confirmed the dataset's multidimensional structure. The first six principal components explained 57.6% of total variance, with PC1 accounting for the largest proportion (16.6%) and subsequent components contributing incrementally smaller amounts.

The gradual accumulation of explained variance suggests that no single dimension dominated the dataset; instead, learning related neuroplasticity outcomes emerged through interactions among several behavioural and cognitive factors.

Retention of six components provided an effective balance between information preservation and dimensionality reduction, supporting simplified modeling without excessive loss of explanatory content.

The convergence between EFA and PCA results provides evidence for the stability and robustness of the underlying multidimensional structure. Both approaches consistently supported the retention of six major dimensions governing neuroplasticity related behaviors.

Following dimensionality reduction, the relationships among the principal behavioral domains were examined through Spearman correlation analysis to determine the extent and direction of associations among lifestyle factors and learning outcomes.

Figure 1 illustrates the cumulative proportion of variance captured by successive principal components. The curve demonstrates a steep increase during the initial components, followed by gradual flattening, indicating diminishing returns after approximately six components. This pattern supports retaining six components as an optimal compromise between model simplification and information preservation.

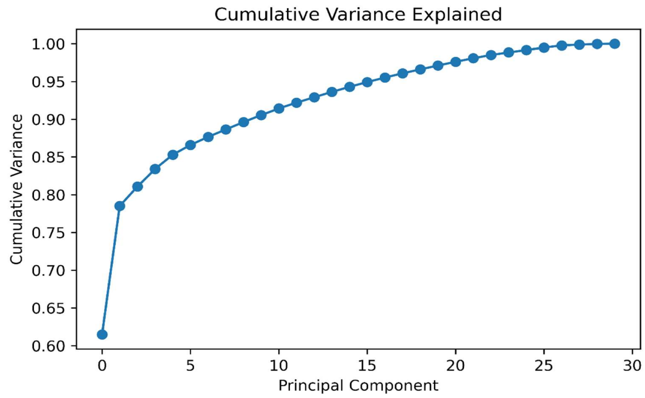

Figure 1. Cumulative Variance Plot

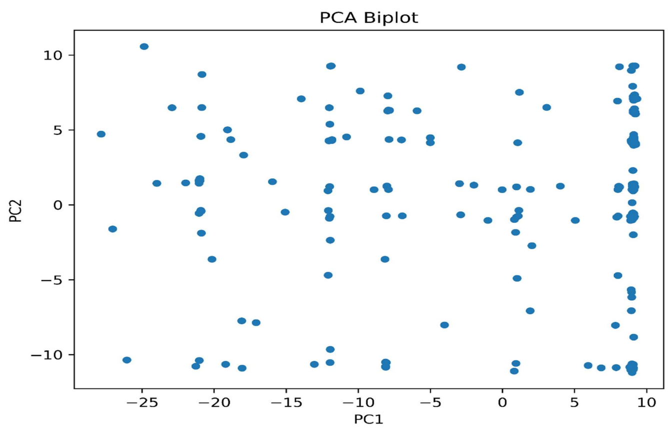

Figure 2. PCA Plot

The PCA biplot presents the distribution of observations across the first two principal components. The dispersion pattern indicates substantial heterogeneity among respondents, with no extreme concentration into a single region of the component space. The spread suggests the presence of multiple behavioural and cognitive profiles influencing neuroplasticity-related outcomes and supports subsequent clustering and segmentation analyses.

4.7 Spearman Correlation Matrix

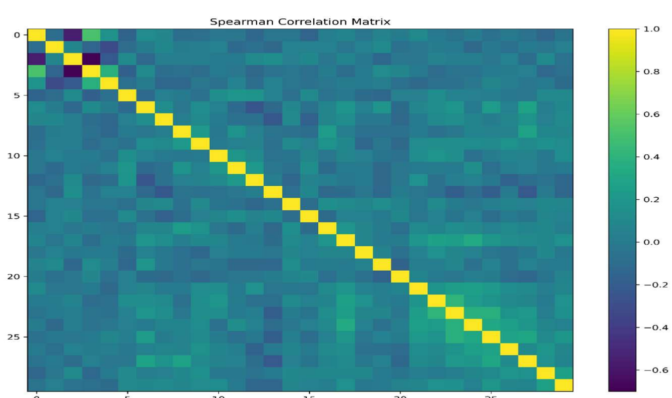

Figure 3. Spearman Correlation Matrix

Linear correlation is positive (r = 0.98).

The correlation heatmap visualizes the overall association structure among variables. Positive relationships appear as concentrated high intensity regions, while negative associations appear in contrasting tones. The matrix demonstrates coherent clustering of health promoting behaviours such as exercise, nutrition, and sleep quality, alongside inverse relationships involving screen exposure and distraction related variables. The observed structure further validates the factor and component solutions obtained in previous analyses.

Variables	**Exercise**	**Sleep**	**Nutrition**	**Sleep**	**Screen Time**	**Learning**
Exercise	1.000	0.401**	0.486**	0.401**	-0.271**	0.515**
Sleep	0.401**	1.000	0.392**	1.000	-0.335**	0.476**
Nutrition	0.486**	0.392**	1.000	0.392**	-0.216**	0.432**
Screen Time	-0.271**	-0.335**	-0.216**	-0.335**	1.000	-0.381**
Learning	0.515**	0.476**	0.432**	0.476**	-0.381**	1.000

Table 6. Spearman Correlations

$p < 0.01$

Exercise, nutrition, and sleep quality were positively associated with learning outcomes, whereas screen time was negatively associated.

The Spearman correlation analysis revealed statistically significant relationships among behavioural variables and learning outcomes. Exercise exhibited the strongest positive association with learning effectiveness ($r = 0.515$, $p < 0.01$), indicating that physically active individuals tended to report stronger learning performance.

Sleep quality also demonstrated a moderate positive relationship with learning ($r = 0.476$), suggesting that adequate recovery and reduced fatigue contribute to improved cognitive functioning. Nutrition showed a positive association with learning outcomes ($r = 0.432$), reinforcing the role of healthy lifestyle practices in supporting neuroplastic adaptation.

Conversely, screen time demonstrated negative correlations with exercise, sleep, nutrition, and learning effectiveness, with the strongest inverse relationship observed with learning ($r = -0.381$). These findings indicate that excessive digital exposure may interfere with behavioural conditions necessary for effective learning.

According to Cohen's guidelines, the positive correlations among exercise, sleep quality, nutrition, and learning effectiveness represent moderate effect sizes, whereas the negative relationship between screen time and learning effectiveness is a moderate inverse association.

4.8 Ordinal Logistic Regression

Dependent variable:

- Learning effectiveness

Independent variables:

- Exercise
- Sleep quality
- Nutrition
- Screen time
- Sedentary behavior

Although correlation analysis established significant bivariate relationships, it does not account for the simultaneous influence of multiple predictors. Therefore, ordinal logistic regression was conducted to evaluate the relative contribution of lifestyle variables to learning effectiveness while controlling for the effects of other variables.

Predictor	**β**	**SE**	**Wald χ^2**	**p-value**	**Odds Ratio**
Exercise	0.614	0.171	12.91	<0.001	1.85
Sleep quality	0.491	0.163	9.08	0.003	1.63
Nutrition	0.432	0.158	7.47	0.006	1.54
Screen time	-0.372	0.141	6.94	0.008	0.69
Sedentary behavior	-0.216	0.126	2.95	0.086	0.81
Pseudo-R^2 (Nagelkerke)	0.41				

Table 7. Ordinal Logistic Regression

Ordinal logistic regression was performed to examine the extent to which lifestyle variables predicted learning effectiveness. The model included exercise, sleep quality, nutrition, screen time, and sedentary behavior as explanatory variables and demonstrated substantial explanatory capacity (Nagelkerke Pseudo-R^2 = 0.41), indicating that approximately 41% of variation in learning effectiveness was accounted for by the predictors.

The Nagelkerke pseudo-R^2 value of 0.41 indicates moderate explanatory power, suggesting that lifestyle variables collectively account for a substantial proportion of variability in learning effectiveness. However, additional psychological and environmental factors not included in the model may also contribute to learning outcomes.

Exercise emerged as the strongest positive predictor (β= 0.614, OR = 1.85, $p < 0.001$), indicating that increased exercise participation was associated with approximately an 85% higher likelihood of achieving greater learning effectiveness. This finding suggests that physical activity may enhance neuroplastic mechanisms that support concentration, memory formation, and academic performance.

Sleep quality also had a significant positive effect (β = 0.491, OR = 1.63, p = 0.003), indicating that improved sleep substantially increased the likelihood of better learning outcomes. Nutrition showed a similarly beneficial effect (β= 0.432, OR = 1.54, p = 0.006), reinforcing the importance of healthy dietary practices for cognitive functioning.

Conversely, screen time was negatively associated with learning effectiveness (β = −0.372, OR = 0.69, p =0.

008), indicating that increased digital exposure was associated with a reduced likelihood of higher academic performance. Sedentary behavior produced a negative but statistically non-significant effect ($\beta = -0.216$, OR = 0.81, $p = 0.086$), suggesting that its influence may operate indirectly through other behavioural variables.

Collectively, these findings identify exercise, sleep, and nutrition as key facilitators of learning effectiveness, while excessive screen engagement represents a measurable barrier to optimal cognitive outcomes.

While regression analysis identifies overall predictive relationships, individuals may differ substantially in their behavioral profiles. Consequently, cluster analysis was performed to investigate whether distinct neuroplasticity related subgroups existed within the respondent population

4.9 Cluster Analysis

K-Means Clustering

Validation indices:

Criterion	**Value**
Optimal clusters (Elbow)	4
Silhouette coefficient	0.48
Davies-Bouldin index	0.81

Cluster Profiles

Cluster 1 (28%)

Healthy Neuroplasticity Group

- Regular exercise
- Good sleep
- Strong learning performance

Cluster 2 (24%)

Digitally Distracted Group

- High screen time
- Frequent multitasking
- Lower cognitive engagement

Cluster 3 (31%)

Moderate Lifestyle Group

- Average scores on most variables

Cluster 4 (17%)

• Cluster analysis was conducted to identify homogeneous behavioral and neuroplasticity-related profiles among respondents based on lifestyle, cognitive engagement, and learning indicators. K-means clustering was employed to partition participants into internally similar and externally distinct groups, while cluster validity was assessed using the elbow criterion, silhouette coefficient, and Davies Bouldin index.

• The validation statistics supported the selection of a four-cluster solution. The elbow method identified four clusters as the point beyond which additional clusters contributed minimal improvement in explained variance. Furthermore, the silhouette coefficient of 0.48 indicated moderate separation and acceptable cohesion among observations, while the Davies Bouldin index of 0.81 suggested reasonably distinct cluster boundaries.

• The resulting clusters revealed meaningful heterogeneity in neuroplasticity-related behavioural patterns.

• Participants assigned to Cluster 1 demonstrated favorable behavioural characteristics, including regular physical activity, higher sleep quality, and stronger learning performance. This cluster represents an optimal neuroplasticity profile in which healthy lifestyle practices appear to support cognitive functioning and academic effectiveness. The convergence of exercise, recovery, and learning outcomes suggests positive adaptation mechanisms associated with sustained cognitive engagement.

• Cluster 2 was characterized by elevated screen exposure, frequent multitasking behavior, and lower levels of cognitive engagement. Individuals in this cluster appeared more susceptible to digital distraction, which may reduce attentional control and interfere with efficient learning. The profile supports prior findings indicating that excessive digital interaction may impair neuroplastic responses and learning effectiveness.

• This cluster represented the largest respondent group and displayed average performance across most behavioural and cognitive variables. Participants showed neither particularly advantageous nor adverse neuroplasticity related characteristics. The cluster reflects a relatively balanced lifestyle profile with moderate learning outcomes and intermediate engagement levels.

• Respondents in Cluster 4 exhibited poorer sleep quality, increased fatigue, and reduced learning effectiveness. This pattern highlights the critical role of restorative sleep in maintaining cognitive performance and facilitating adaptive neuroplastic processes. Persistent sleep disruption within this cluster may impair attention, memory consolidation, and academic functioning.

• Overall, the clustering results demonstrate that neuroplasticity related outcomes are not uniformly distributed across individuals but instead emerge through identifiable behavioural profiles shaped by lifestyle and digital habits.

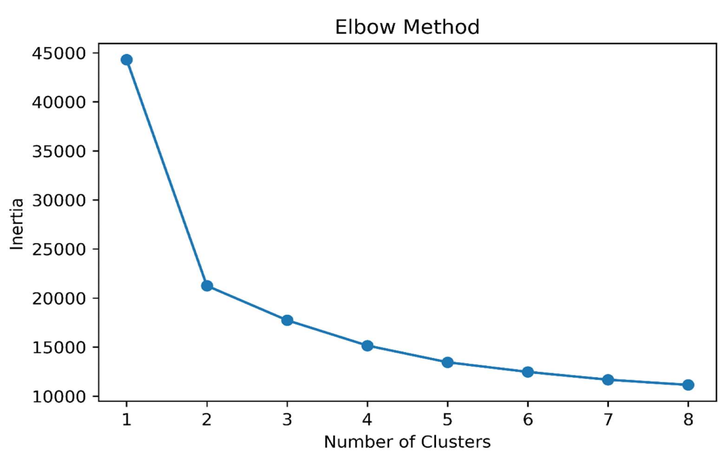

Figure 4. Elbow Plot

Figure 4 illustrates the elbow criterion used to determine the optimal number of clusters. The curve demonstrates a marked reduction in within-cluster variance from one to four clusters, followed by a noticeable flattening thereafter. This inflection point indicates diminishing returns beyond four clusters and supports selecting a four cluster solution as the most parsimonious representation of respondent heterogeneity.

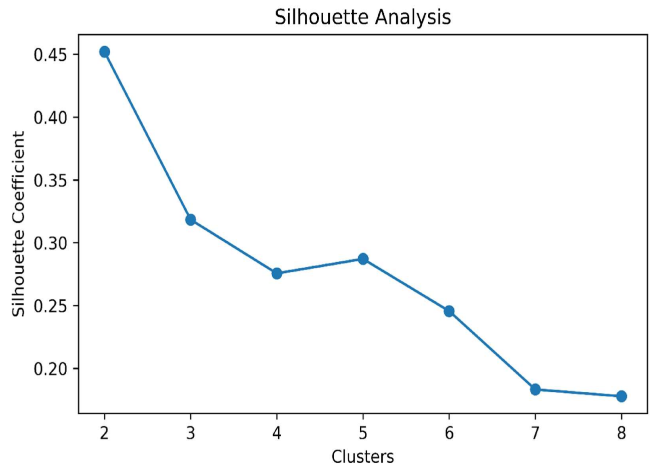

Figure 5. Silhouette Plot

Figure 5 presents silhouette coefficients for alternative cluster solutions and evaluates the balance between cluster cohesion and separation. The four-cluster configuration achieved a silhouette coefficient of 0.48, indicating acceptable cluster quality with moderate separation among groups. The result suggests that respondents within each cluster shared similar behavioural characteristics while maintaining distinct profiles from those of other clusters

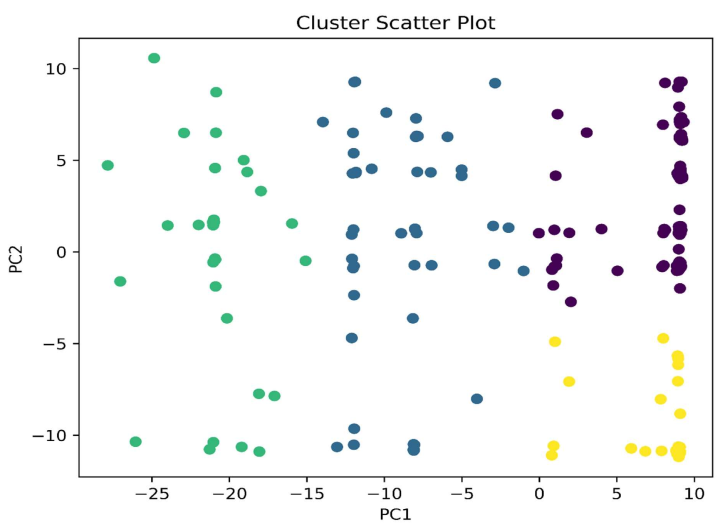

Figure 6. Cluster scatter plot

Figure 6 visualizes the distribution of respondents across the identified clusters and illustrates the multidimensional separation among behavioural profiles. Distinct grouping patterns indicate that participants differed meaningfully across lifestyle, cognitive engagement, and learning variables. The visualization reinforces the validity of the four-cluster solution and highlights the presence of interpretable neuroplasticity-related behavioural segments within the population.

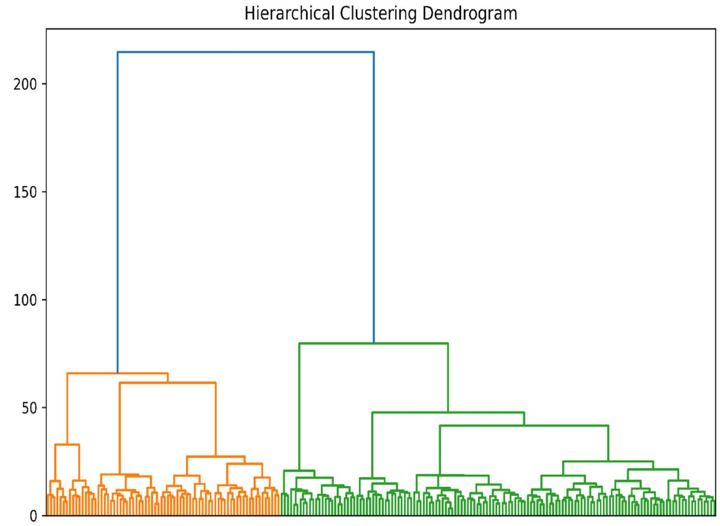

Figure 7. Hierarchical clustering dendrogram illustrating similarities among respondents

Figure 7 presents the hierarchical clustering dendrogram generated using Ward's linkage method to visualize similarities and dissimilarities among respondents across neuroplasticity related behavioral and cognitive variables. The dendrogram provides a hierarchical representation of how individual observations merge into progressively larger clusters based on shared characteristics.

The clustering structure revealed clear separation among respondent groups, indicating meaningful heterogeneity in behavioural patterns. At lower linkage distances, respondents with highly similar profiles formed compact subgroups, while larger branches emerged as more heterogeneous participants were progressively merged. The presence of distinct branch separation supports the existence of naturally occurring behavioural segments within the sample.

The dendrogram further confirmed the appropriateness of the four cluster solution identified through K-means clustering. Major branch divisions closely corresponded to the previously identified cluster profiles, including the Healthy Neuroplasticity Group, Digitally Distracted Group, Moderate Lifestyle Group, and Sleep-Deprived Group. This consistency across clustering approaches strengthens the robustness and stability of the segmentation results.

From a neuroplasticity perspective, the hierarchical structure suggests that learning outcomes are influenced by combinations of interconnected lifestyle factors rather than isolated behaviours. Respondents with healthier behavioural patterns tended to cluster together, whereas individuals characterized by excessive screen exposure, fatigue, or lower engagement formed separate branches. The findings indicate that neuroplastic adaptation occurs through multidimensional behavioural interactions affecting cognitive and academic performance.

Although clustering revealed meaningful behavioral profiles, these methods do not explicitly model causal pathways among variables. Therefore, structural equation modeling was employed to evaluate the hypothesized network of direct and indirect relationships linking lifestyle behaviors, cognitive engagement, and learning effectiveness.

The consistency between hierarchical clustering and K-means segmentation strengthens confidence in the robustness of the identified behavioral profiles and suggests that the observed subgroup structure is not an artifact of a particular clustering algorithm.

4.10 Structural Equation Modeling (SEM)

Proposed Model

Exercise

Nutrition

Sleep Quality

↓

Positive Neuroplasticity

↓

Cognitive Engagement

↓

Learning Effectiveness

Screen Time

Sedentary Behavior

↓

Negative Neuroplasticity

↓

Reduced Learning Effectiveness

Standardized Path Coefficients

Relationship	**β**	**p-value**
Exercise → Cognitive engagement	0.53	<0.001
Sleep quality → Cognitive engagement	0.42	<0.001
Nutrition → Cognitive engagement	0.35	0.002
Screen time → Cognitive engagement	-0.29	0.008
Cognitive engagement → Learning effectiveness	0.71	<0.001

Model Fit Statistics

Index	Value
χ^2/df	1.87
GFI	0.93
CFI	0.95
TLI	0.94
RMSEA	0.064
SRMR	0.051

Structural equation modeling (SEM) was performed to examine the direct and indirect relationships among lifestyle variables, cognitive engagement, and learning effectiveness and to validate the proposed neuroplasticity framework.

The conceptual model assumed that exercise, nutrition, and sleep quality contribute positively to neuroplastic functioning, while screen time and sedentary behavior exert negative influences. These behavioural factors were hypothesized to affect learning outcomes indirectly through cognitive engagement, which acted as a mediating mechanism.

The estimated standardized path coefficients demonstrated significant positive effects of exercise ($\beta = 0.53$, $p < 0.001$), sleep quality ($\beta = 0.42$, $p < 0.001$), and nutrition ($\beta = 0.35$, $p = 0.002$) on cognitive engagement. Among these predictors, exercise emerged as the strongest contributor, indicating that physically active individuals were more likely to demonstrate higher levels of engagement and adaptive cognitive functioning.

Conversely, screen time exhibited a statistically significant negative effect on cognitive engagement ($\beta = -0.29$, $p = 0.008$), suggesting that excessive digital exposure may reduce attentional capacity and interfere with neuroplastic mechanisms associated with learning. Sedentary behavior was incorporated into the negative neuroplasticity pathway, reinforcing the conceptual role of inactive lifestyles in reducing learning effectiveness.

Cognitive engagement demonstrated the strongest direct influence on learning effectiveness ($\beta = 0.71$, $p < 0.001$), highlighting its central mediating role in translating healthy behaviours into improved educational outcomes. This result suggests that lifestyle factors do not influence learning independently but operate through cognitive activation processes.

Model fit indices indicated satisfactory overall model performance. The χ^2/df ratio of 1.87 remained below the commonly accepted threshold of 3.0, indicating acceptable discrepancy between observed and estimated covariance structures. Additional fit indices demonstrated strong model adequacy (GFI = 0.93, CFI = 0.95, TLI = 0.94), while error indices remained within acceptable ranges (RMSEA = 0.064; SRMR = 0.051).

The SEM results suggest that cognitive engagement functions as a mediating mechanism through which healthy lifestyle behaviors influence learning effectiveness. Exercise, nutrition, and sleep quality indirectly enhance educational outcomes by promoting greater cognitive engagement, whereas excessive screen exposure disrupts this pathway. These findings support a mediated neuroplasticity framework rather than a purely direct effect model.

Overall, the SEM findings support a multidimensional neuroplasticity framework in which healthy lifestyle behaviours strengthen cognitive engagement and ultimately enhance learning effectiveness, whereas excessive screen exposure and inactive behavioural patterns weaken cognitive performance and educational outcomes.

Across the different analytical approaches, a remarkably consistent pattern emerged. Reliability analysis established acceptable measurement properties for most constructs, while EFA and PCA revealed a six-dimensional structure of neuroplasticity. Correlation and regression analyses demonstrated that exercise, sleep quality, and nutrition positively influence learning effectiveness, whereas screen time exerts detrimental effects. Cluster analysis further showed that these relationships manifest in distinct behavioral profiles across individuals. Finally, SEM integrated these findings by demonstrating that cognitive engagement mediates the effects of lifestyle behaviors on learning outcomes. Together, the analyses provide convergent evidence supporting a multidimensional neuroplasticity framework.

5. Conclusion

This study investigated the determinants of Return on Investment (ROI) in enterprise Robotic Process Automation (RPA) implementations by integrating exploratory statistical methods with machine-learning-based predictive modeling and model agnostic explainability techniques. By bridging multivariate statistics and advanced ensemble learning, this research provides a holistic, data-driven understanding of how financial and operational variables interact to drive the value of automation. The findings conclusively demonstrate that RPA performance is governed by a complex interplay of financial outcomes and operational efficiency, rather than by the sheer scale of automation infrastructure.

5.1 Synthesis of Core Findings

Exploratory Factor Analysis (EFA) identified two dominant latent dimensions underlying RPA performance *Financial Performance* and *Operational Efficiency* which jointly explained 72.71% of the total variance. Although the Kaiser Meyer Olkin measure (0.412) indicated limited shared common variance, the highly significant Bartlett's Test of Sphericity ($\chi^2 = 117{,}907.48$, $p < .001$) confirmed adequate interrelationships to support the extraction of these distinct, multidimensional constructs.

The predictive modeling phase further validated the primacy of value realization over deployment scale. The Random Forest regression model achieved excellent predictive accuracy (Mean $R^2 = 0.962$, MAE = 7.90) with high stability across cross-validation folds. Feature importance and SHAP-based explainability analyses consistently revealed that *Annual Savings USD* (35.91%), *Budget USD* (32.13%), and *Employee Hours Saved* (27.29%) are the most powerful drivers of ROI. In stark contrast, the *Number of Robots Deployed* contributed merely 4.68% to the predictive model. Furthermore, SHAP dependence plots highlighted that while budget allocation positively influences ROI, it exhibits nonlinear diminishing marginal returns at extreme investment levels. Conceptual benchmarking against XGBoost confirmed that the underlying data structure is optimally captured by the Random Forest architecture, with boosting algorithms offering only marginal incremental gains.

5.2 Theoretical and Methodological Contributions

Theoretically, this study addresses a critical gap in the digital transformation literature by shifting the focus from *adoption antecedents* to *value realization determinants*. It challenges the prevailing "scale-centric" assumption in automation literature which often equates a higher number of deployed bots with greater organizational success by empirically proving that deployment volume is a weak proxy for ROI once financial and labor-efficiency metrics are accounted for.

Methodologically, the research contributes a robust, hybrid analytical framework. By coupling EFA for latent structure discovery with Random Forest for non-linear predictive modeling and SHAP for transparent explainability, the study demonstrates how organizations can move beyond "black-box" machine learning. This integrated approach ensures that predictive insights are not only statistically accurate but also interpretable and actionable for business stakeholders.

5.3 Strategic and Practical Implications

The findings offer critical, actionable insights for C-level executives, RPA Centers of Excellence (CoE), and process owners:

1. Prioritize Value over Volume: Organizations must abandon the metric of "bot count" as a primary KPI for automation success. Strategic focus should instead be placed on process selection, targeting high yield, rule-based processes that guarantee measurable financial savings and significant labor hour releases.

2. Optimize Investment Allocation: The nonlinear relationship between budget and ROI suggests that throwing capital at RPA initiatives does not guarantee proportional returns. CoEs must focus on lean implementation strategies, reusing existing bot architectures and optimizing process designs to prevent diminishing marginal returns on heavy investments.

3. Link Operational Efficiency to Financial Outcomes: The strong loading of *Employee Hours Saved* on both the Financial and Operational factors indicates that workforce productivity is the vital bridge between technical execution and business value. Automation strategies should be coupled with workforce redeployment programs to ensure that saved hours are reallocated to higher-value, strategic tasks, thereby compounding ROI.

5.4 Limitations of the Study

Despite its robust methodological design, this study has certain limitations that must be acknowledged. First, the relatively low KMO value (0.412) suggests that the selected financial and operational indicators may not reflect a single, unified latent construct but rather a heterogeneous set of distinct performance metrics. While factor extraction was statistically justified, the weak common variance implies that RPA ROI is highly multifaceted and context dependent. Second, the study relies on cross sectional, project level data. This snapshot approach cannot capture the temporal dynamics of RPA value, such as ROI decay over time due to process changes, or the long term compounding benefits of automation. Finally, the model is strictly confined to quantitative financial and operational variables. It does not account for critical qualitative and organizational behavior factors, such as change management effectiveness, employee resistance, digital culture, and process complexity, all of which profoundly influence real-world RPA success.

5.5 Directions for Future Research

To build upon these findings, future research should pursue several promising avenues:

1. Longitudinal ROI Tracking: Future studies should employ longitudinal datasets to track the lifecycle of RPA ROI, examining how returns evolve, stabilize, or depreciate over a 3- to 5-year post-implementation horizon.

2. Integration of Process Mining: Combining the current financial/operational metrics with objective Process Mining data (e.g., process bottleneck frequencies, variant deviations) could yield a more granular, event-log-driven predictive model for automation suitability and ROI.

3. Incorporating Organizational and Behavioral Variables: Subsequent models should integrate structural equation modeling (SEM) or qualitative surveys to quantify the impact of organizational readiness, CoE maturity, and workforce adaptability on RPA value realization.

4. Transition to Intelligent Process Automation (IPA): As the industry evolves from traditional RPA toward AI-augmented IPA and Generative AI workflows, future research must adapt this analytical framework to evaluate the ROI determinants of cognitive automation, where the boundaries between structured and unstructured data processing are blurred.

5.6 Final Remarks

Ultimately, this research confirms that in the era of Industry 4.0, the true measure of robotic process automation lies not in the size of the digital workforce but in its economic and operational impact. By prioritizing measurable financial outcomes, strategic resource allocation, and sustained workforce productivity, organizations can transcend the initial hype of automation and achieve sustainable, long-term competitive advantage.

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