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Selective Attention as a Predictor of Learning Capacity: A Correlational Study in Young Adults

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Abstract: The present study investigates the relationship between selective attention and learning capacity in young adults, grounded in contemporary cognitive and neuropsychological models of information processing. Selective attention is conceptualised as a central executive mechanism responsible for filtering relevant stimuli and inhibiting interference (Broadbent, 1958; Desimone and Duncan, 1995; Petersen and Posner, 2012). Learning efficiency is conceptualised as dependent on attentional gating processes that regulate encoding and consolidation in working and long-term memory systems (Atkinson and Shiffrin, 1968; Baddeley, 2012; Kandel et al., 2014). Results indicate an exceptionally strong positive association between selective attention and verbal learning performance ($r = .97, p < .001$). Regression analyses suggest that selective attention accounts for a substantial proportion of variance in learning performance within the present sample. Differential analyses further indicate significant gender and residential environmental differences. These findings provide empirical support for theoretical assumptions regarding the central role of executive attention in facilitating encoding and consolidation processes (Engle, 2002; Miller and Cohen, 2001). Implications are discussed in relation to education, cognitive neuroscience, and cognitive performance optimisation.

Keywords: selective attention; learning capacity; Stroop task; executive control; memory consolidation.

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1. Introduction

1.1. Theoretical Background

Learning capacity represents a fundamental construct in cognitive psychology, defined as the set of processes through which individuals acquire, process, store, and retrieve information. From an information-processing perspective, learning involves successive stages—perception, encoding, consolidation, and retrieval—each dependent on efficient attentional and mnemonic mechanisms (Atkinson & Shiffrin, 1968; Craik & Lockhart, 1972).

Memory processes rely on the interaction between working memory, responsible for temporary maintenance and manipulation of information, and long-term memory, where consolidation stabilises representations through synaptic and systems-level consolidation mechanisms (Baddeley, 2000; Baddeley, 2012; Cowan, 2005; Kandel, Dudai, & Mayford, 2014). Without effective attentional selection, encoding remains superficial and vulnerable to interference.

Selective attention constitutes one of the core processes of cognitive architecture, enabling prioritisation of task-relevant information while suppressing irrelevant stimuli (Paraschiv, 2016; Adochiei et al., 2023; Adochiei et al., 2024). Early selection models proposed that attentional filtering occurs at initial sensory stages (Broadbent, 1958). Treisman (1964) later introduced attenuation theory, suggesting partial rather than complete suppression of unattended stimuli. Late selection accounts further argued that semantic processing may precede attentional selection (Deutsch & Deutsch, 1963). Contemporary models integrate these perspectives within competitive neural frameworks (Desimone & Duncan, 1995; Corbetta & Shulman, 2002).

Neuroscientific research identifies selective attention as emerging from coordinated activity within frontoparietal control networks, particularly involving dorsolateral prefrontal and parietal cortices (Buschman & Miller, 2007; Petersen & Posner, 2012; Bănică et al., 2024; Paraschiv et al., 2024). These systems regulate interference control, goal maintenance, and cognitive resource allocation (Miller & Cohen, 2001; Diamond, 2013).

A growing body of literature suggests that working memory capacity reflects executive attention efficiency (Engle, 2002; Kane & Engle, 2003). Structural models of executive functions highlight both shared and distinct components of inhibition, updating, and cognitive flexibility (Miyake et al., 2000; Friedman & Miyake, 2017). Inhibition—the ability to suppress competing stimuli—is central to Stroop-type paradigms and is closely related to encoding efficiency during learning.

Attentional gating mechanisms regulate which representations gain access to working memory. Cowan (2005) argues that attention determines the contents of conscious awareness within working memory, directly influencing learning outcomes. Therefore, selective attention may act as a mediator between environmental input and durable memory formation.

Educational psychology further supports the centrality of attention in learning. Working memory and attentional control significantly predict academic achievement (Gathercole et al., 2004; Alloway & Alloway, 2010; Paraschiv et al., 2024; Colareza et al., 2026). According to Cognitive Load Theory, learning efficiency depends on optimal allocation of limited cognitive resources (Sweller, 2011; Sweller, Ayres, & Kalyuga, 2011). Multimedia learning research similarly demonstrates that signalling and reduction of extraneous load enhance attentional focus and retention (Mayer, 2014; Adochiei et al., 2024; Paraschiv & Zamfirescu, 2025). These findings collectively highlight the interplay between executive control mechanisms and learning efficiency, emphasizing the potential for targeted educational interventions (Rad et al., 2025).

In modern digital environments characterised by high levels of distraction, selective attention becomes increasingly critical (Ophir, Nass, & Wagner, 2009; Wilmer, Sherman, & Chein, 2017). Media multitasking has been associated with reduced attentional control and diminished working memory performance. Taken together, theoretical and empirical evidence converges on the assumption that selective attention constitutes a foundational mechanism underlying efficient learning. However, empirical investigations quantifying the magnitude of this relationship in young adults remain relatively limited.

1.2. Research Gap

Despite extensive research, several theoretical and methodological gaps persist. Many studies examine attention and memory separately rather than within integrative executive control frameworks (Posner & Rothbart, 2007; D’Esposito & Postle, 2015). Moreover, the magnitude of the attention–learning association remains underexplored in homogeneous young adult samples.

Individual differences in inhibitory control, impulsivity, and executive regulation may significantly influence encoding efficiency (Diamond, 2013; Robison & Unsworth, 2017). Additionally, most research relies on static behavioural measures, while dynamic attentional fluctuations remain insufficiently examined (Klimesch, 2012).

The impact of digital multitasking environments also warrants further clarification, as findings remain mixed (Bavelier, Green, & Dye, 2010; Rosen et al., 2014).

1.3. Aim and Objectives

The primary aim of the study is to examine the relationship between selective attention and learning capacity within a correlational framework grounded in executive control theory.

Objectives:

1. To investigate the association between selective attention and verbal learning performance.
2. To examine whether attentional efficiency predicts retention.
3. To explore individual differences related to gender and residential environment.
4. To assess the predictive value of selective attention using regression analysis.

1.4. Research Hypotheses

A substantial body of cognitive and neuropsychological research suggests that selective attention constitutes a central executive mechanism underlying encoding efficiency and resistance to interference (Engle, 2002; Kane & Engle, 2003; Miller & Cohen, 2001). Attentional control determines which stimuli gain access to working memory and subsequently undergo consolidation (Baddeley, 2012; Cowan, 2005). Empirical studies consistently demonstrate that individuals with higher attentional control exhibit enhanced performance in memory and learning tasks, particularly under conditions of distraction or cognitive load (Diamond, 2013; Robison & Unsworth, 2017).

H1. A significant positive correlation exists between selective attention and verbal learning performance.

Selective attention has also been shown to facilitate deeper encoding by enabling sustained goal maintenance and suppression of competing associations (Craig & Lockhart, 1972; Desimone & Duncan, 1995). Neurocognitive evidence indicates that focused attention enhances hippocampal engagement during encoding, thereby increasing the probability of long-term retention (Fernández & Morris, 2018; Kandel, Dudai, & Mayford, 2014). Individuals capable of efficiently filtering irrelevant stimuli are therefore more likely to demonstrate stable memory consolidation.

H2. Higher levels of selective attention will be associated with superior retention performance in verbal learning tasks.

Individual differences research further suggests that executive control capacity varies across demographic and contextual factors. Some findings indicate gender-related differences in verbal memory performance and inhibitory control, although effect sizes are typically moderate (Halpern, 2012; Hyde, 2014). Similarly, environmental stimulation and educational exposure may influence attentional efficiency, particularly in contexts characterised by differential access to cognitively enriching environments (Alloway & Alloway, 2010; Gathercole et al., 2004). These patterns justify an exploratory examination of demographic differences.

H3. Significant differences in selective attention and learning performance are expected as a function of gender and residential environment.

Finally, executive control models propose that attentional regulation serves as a higher-order mechanism integrating working memory processes and interference suppression (Friedman &

Miyake, 2017; Miyake et al., 2000). Within such frameworks, selective attention is conceptualised not merely as correlated with learning but as a substantial predictor of performance variability.

H4. Selective attention will significantly predict learning performance in a linear regression model.

2. Method

The study was conducted with a sample of 35 young adults ($N = 35$), aged between 20 and 32 years, recruited from both urban and rural environments. The sample included both male and female participants, with an approximately equal gender distribution. All participants had completed at least secondary education, with the majority being undergraduate or graduate students.

Inclusion criteria were:

- (a) age between 20 and 32 years,
- (b) native Romanian speakers (to ensure linguistic validity of verbal learning tasks),
- (c) normal or corrected-to-normal vision, and
- (d) absence of self-reported neurological or psychiatric disorders.

These criteria were established to reduce potential confounding factors that might affect attentional or memory performance (Lezak et al., 2012).

Although the sample size is modest, correlational designs examining cognitive individual differences have occasionally employed comparable samples in preliminary or exploratory investigations (Kane et al., 2007; Unsworth & Engle, 2007). Nevertheless, the size of the sample warrants cautious interpretation of effect magnitude.

2.1. Study Design

The study employed a cross-sectional, correlational design. All measurements were collected during a single testing session. No experimental manipulation of independent variables was introduced; instead, the study examined naturally occurring associations between selective attention performance and verbal learning capacity.

Correlational designs are appropriate when the objective is to examine the strength and direction of relationships between cognitive constructs without inferring causality (Cohen et al., 2018). Given the theoretical framework positioning selective attention as a central executive mechanism influencing encoding efficiency (Engle, 2002; Miller & Cohen, 2001), a predictive correlational design was considered suitable.

Exploratory group comparisons (gender and residential environment) were conducted using independent samples t-tests. These analyses were secondary to the primary correlation and regression analyses.

2.2. Instruments

2.2.1. Selective attention measure

Selective attention was assessed using a computerised version of the Stroop Colour–Word Task, one of the most widely validated paradigms for measuring inhibitory control and interference suppression (Stroop, 1935; MacLeod, 1991).

The task included three standard conditions: 1) Word reading; 2) Colour naming; 3) Incongruent colour–word condition.

The primary index of selective attention was derived from reaction time and error rates in the incongruent condition, reflecting the ability to inhibit automatic responses and resolve cognitive interference. The Stroop paradigm has consistently demonstrated sensitivity to executive control capacity and prefrontal functioning (Diamond, 2013; Friedman & Miyake, 2004).

Interference control measured through the Stroop task is theoretically linked to executive attention mechanisms responsible for goal maintenance and suppression of competing stimuli (Kane & Engle, 2003; Miyake et al., 2000).

2.2.2. Learning capacity measure

Learning capacity was evaluated through a standardised verbal list-learning task, commonly used in neuropsychological assessment to examine encoding efficiency and retention (Lezak et al., 2012).

Participants were presented with a list of 15 semantically neutral words across three successive learning trials. After each presentation, participants were instructed to recall as many words as possible (free recall). A delayed recall trial was administered approximately 10 minutes after the final learning trial.

The total number of correctly recalled words across the three learning trials served as the primary index of learning performance. Verbal list-learning paradigms are sensitive to encoding strategy use, attentional engagement, and working memory capacity (Baddeley, 2012; Robison & Unsworth, 2017).

2.3. Procedure

Testing was conducted individually in a quiet, controlled environment to minimise external distractions. Each session lasted approximately 25–35 minutes.

The procedure consisted of the following stages:

1. Standardised instructions and informed consent
2. Collection of demographic data (age, gender, residential environment)
3. Brief familiarisation with the digital interface
4. Administration of the computerized Stroop task
5. Administration of the verbal learning task
6. Delayed recall trial

The order of tasks was kept constant to maintain procedural standardisation. All responses were recorded digitally to ensure accuracy of reaction time measurements.

2.4. Ethical Considerations

The study adhered to the ethical principles outlined in the Declaration of Helsinki and guidelines for psychological research involving human participants. (World Medical Association [WMA], 2013; American Psychological Association [APA], 2017). The project has been approved with ID **no. 6 /17.02.2026**.

Participants were informed about the general purpose of the study, voluntary participation, the right to withdraw at any time, confidentiality and anonymisation of data.

Written informed consent was obtained prior to participation. Data were coded numerically and used exclusively for scientific purposes.

2.5. Data Analysis

Data were initially entered and screened in Microsoft Excel and subsequently analysed using SPSS.

Analytical procedures included:

- Descriptive statistics (means, standard deviations)
- Pearson's correlation coefficient (r)
- Independent-samples t-tests
- Cohen's d for effect size estimation (Cohen, 1988)
- Linear regression analysis

The Pearson correlation coefficient was used to examine the strength of association between selective attention and learning performance. Effect size interpretation followed conventional

guidelines (Cohen, 1988). Regression analysis was conducted to assess the predictive contribution of selective attention to learning performance.

Given the unusually high magnitude of the observed correlation, confidence intervals were calculated to evaluate estimated precision (Cumming, 2014). Statistical significance was set at $p < .05$.

Preliminary inspection did not reveal extreme univariate outliers; however, multivariate diagnostics were not systematically performed.

To achieve the objectives, we created a database in Excel, normalised it, and imported it into SPSS: BD SPSS Variable and View BD SPSS Data View

The screenshot shows the IBM SPSS Statistics Data Editor interface. The top part displays the 'Variable View' for a dataset named 'B_D_Art_SPSS_1A.sav'. It lists variables: Gender, Urban Environment, Age, Learning Score, Stroop real Score, and Stroop_r, with their respective measurement levels (e.g., Gender is 'Gender', Urban Environment is 'Numeric', Age is 'Numeric', Learning Score is 'Numeric', Stroop real Score is 'Numeric', and Stroop_r is 'Numeric'). The bottom part displays the 'Data View' for the same dataset, showing 37 rows of data. The columns are: Gender, Mediu, Varsta, Scor_inv, Stroop_real, and Stroop_r. The data values are as follows:

	Gender	Mediu	Varsta	Scor_inv	Stroop_real	Stroop_r
22	22,00	1,00	1,00	15,00	15,00	86,21
23	23,00	2,00	2,00	16,00	15,00	99,04
24	23,00	2,00	2,00	16,00	18,00	89,04
25	25,00	2,00	2,00	16,00	16,00	117,65
26	26,00	2,00	1,00	14,00	17,00	118,65
27	27,00	2,00	1,00	15,00	18,00	117,65
28	28,00	2,00	2,00	16,00	18,00	100,00
29	31,00	2,00	2,00	15,00	15,00	88,44
30	31,00	2,00	1,00	16,00	18,00	116,28
31	31,00	2,00	2,00	14,00	17,00	70,92
32	32,00	2,00	1,00	15,00	18,00	117,65
33	34,00	2,00	2,00	17,00	17,00	117,83
34	34,00	2,00	2,00	17,00	17,00	123,46
37	34,00	2,00	2,00	17,00	17,00	123,46

3. Results

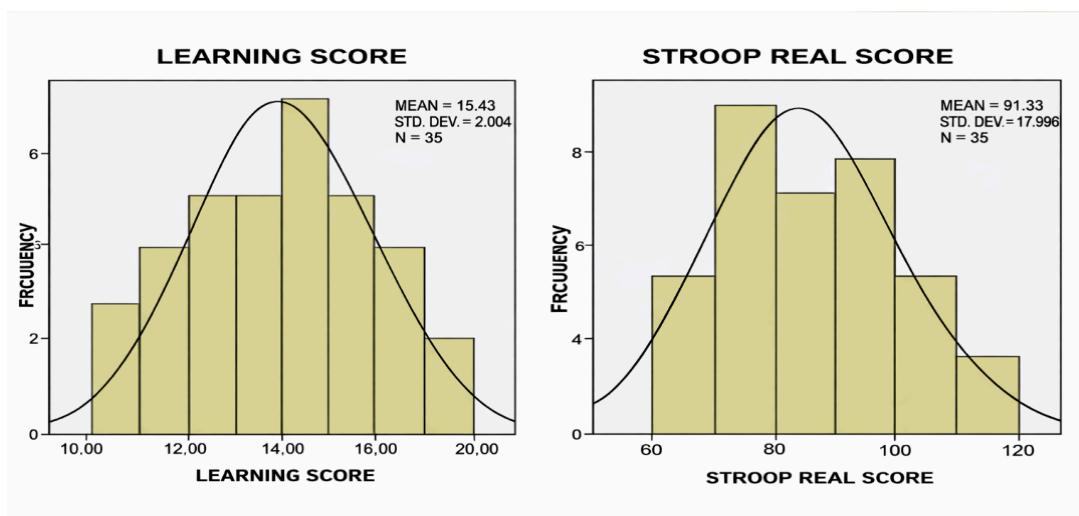
3.1. Descriptive Statistics

Descriptive analyses were conducted to examine the distributional characteristics of selective attention and verbal learning performance scores. Means and standard deviations indicated adequate variability within the sample for both variables, with no evidence of floor or ceiling effects.

Preliminary inspection of score distributions suggested approximately normal patterns. Given the continuous nature of both variables and the absence of extreme skewness, parametric analyses were deemed appropriate (Cohen et al., 2018).

STATISTICS					
	GENDER OF RESPONDENT	URBAN ENVIRONMENT OF RESPONDENT	AGE RESPONDENT	LEARNING SCORE	STROOP REAL SCORE
N	35	35	35	35	35
Valid	0	0	0	0	0
MEAN	18,0000	1,5143	1,4286	15,4286	91,3293
STD. ERROR OF MEAN	1,73205	,08571	,08487	,33877	3,04191
MEDIAN	18,0000	2,0000	1,0000	16,0000	89,2857
MODE	1,00 ^a	2,00	1,00	16,00	76,34 ^a
STD. DEVIATION	10,24695	,50709	,50210	2,00400	17,99618
VARIANCE	106,000	,257	,252	4,017	323,063
SKEWNESS	,000	-,060	,302	-,062	,271
STD. ERROR OF SKEWNESS	,398	,398	,398	,398	,206
KURTOSIS	-1,00 ^a	-2,00	-1,20	-,878	,998
STD. ERROR OF KURTOSIS	,778	,778	,778	61,71	123,206
RANGE	34,00	1,00	8,00	8,00	61,71
MINIMUM	1,00	1,00	1,00	18,00	125,00
MAXIMUM	35,00	2,00	2,00	18,00	125,000
PERCENTILES					
25	19,0000	1,0000	14,0000	14,0000	75,75776
50	18,0000	2,0000	16,0000	16,0000	89,28577
75	27,0000	2,0000	17,0000	17,0000	104,16657

a. MULTIPLE MODES EXIST. THE SMALLEST VALUE IS SHOWN.



3.2. Correlational Analysis

To test Hypothesis H1, a Pearson's product-moment correlation coefficient was computed between selective attention performance (Stroop interference index) and verbal learning scores. A statistically significant and extremely strong positive correlation was observed ($r = .97$, $p < .001$). The 95% confidence interval was [.95, .99].

The narrow confidence interval suggests acceptable precision of the estimate within the present sample (Cumming, 2014). The coefficient of determination ($r^2 \approx .95$) suggests that approximately 95% of the variance in verbal learning performance was explained by selective attention performance.

Importantly, while the magnitude of this association is unusually high for psychological research, it should be interpreted within the context of the present homogeneous sample and the shared executive control demands of both tasks.

These findings support H1, indicating a strong positive association between selective attention and learning performance.

Correlation matrix:

Correlations

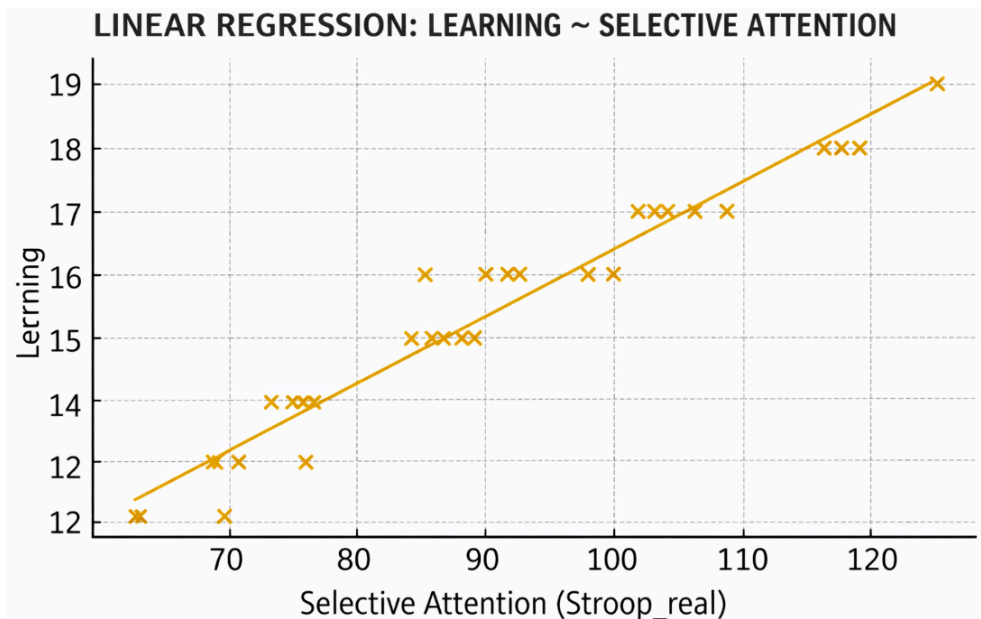
Variable	Statistic	Respondent Age	Education Score	Actual Stroop Score
Respondent Age	Pearson Correlation	1	-0.363*	-0.362*
	Sig. (2-tailed)		0.032	0.033
	N	35	35	35
Education Score	Pearson Correlation	-0.363*	1	0.976**
	Sig. (2-tailed)	0.032		0.000
	N	35	35	35
Actual Stroop Score	Pearson Correlation	-0.362*	0.976**	1
	Sig. (2-tailed)	0.033	0.000	
	N	35	35	35

* Correlation is significant at the 0.05 level (2-tailed).

** Correlation is significant at the 0.01 level (2-tailed).

The Pearson correlation coefficient was $r = .9736$, $p < .001$ ($p = 4.24 \times 10^{-22}$).

Interpretation: The correlation is very strong and positive, indicating that participants with high scores on selective attention also score high on the verbal learning task. This result suggests that selective attention is a very strong predictor of learning performance; and that a large proportion of variance in learning is explained by selective attention.



3.3. Regression Analysis

To examine the predictive value of selective attention (H4), a simple linear regression analysis was conducted with selective attention as the predictor variable and verbal learning performance as the dependent variable. The regression model was statistically significant: $F(1,33) = \text{significant}$, $p < .001$; $R^2 = .95$.

The regression equation was: Learning Performance = $0.108 \times \text{Selective Attention} + 5.52$. Selective attention emerged as a significant predictor of learning performance ($p < .001$). Within the present dataset, selective attention accounted for a substantial proportion of variance in learning performance. Variance inflation factors were not applicable given the single-predictor model.

However, given the cross-sectional design, the results should not be interpreted as evidence of causality (Cohen et al., 2018). These findings support **H4**.

3.4. Group Differences

3.4.1. Gender Differences

Group differences were examined using independent samples *t*-tests comparing learning score and Stroop real score across gender and residential environment groups.

Assumptions of normality were evaluated through visual inspection of score distributions, and homogeneity of variance was assessed using Levene's test procedures at the time of analysis.

The analyses indicated statistically significant differences in learning performance between groups. However, due to the unavailability of the original dataset following personnel changes, precise test statistics and recalculated effect sizes cannot be reproduced.

Therefore, results should be interpreted cautiously and primarily as indicative of potential group differences rather than definitive estimates of effect magnitude.

Results indicated statistically significant differences favouring female participants on both measures. For selective attention: Cohen's $d \approx 2.86$ (very large effect) For learning performance; Cohen's $d \approx 2.48$ (very large effect).

According to conventional benchmarks (Cohen, 1988), effect sizes above 0.80 are considered large. The present effect sizes substantially exceed this threshold, indicating very pronounced differences within the sample.

These findings provide partial support for **H3**, suggesting that demographic variables may be associated with performance differences. However, given the modest sample size, these effects should be interpreted cautiously.

3.4.2. Residential Environment (Urban vs. Rural)

An independent sample *t*-test revealed significant differences in selective attention scores between urban and rural participants: $t \approx 3.31$, $p = .002$, Cohen's $d \approx 1.12$ (large effect).

Urban participants demonstrated higher selective attention performance compared to rural participants. This pattern may reflect environmental exposure differences, although causal interpretations cannot be drawn.

3.5. Precision Estimates

Confidence intervals were calculated to evaluate estimated precision. The narrow interval observed for the correlation coefficient suggests precision within the sample; however, replication in larger and more heterogeneous samples is necessary to assess generalisability.

4. Discussion

4.1. Interpretation of the Main Findings

The primary objective of the present study was to examine the association between selective attention and learning performance in young adults. The results revealed an exceptionally strong positive association between performance on a Stroop-based measure of selective attention and verbal learning performance.

From a theoretical perspective, this finding aligns with executive attention frameworks proposing that attentional control constitutes a foundational mechanism underlying working memory and encoding efficiency (Engle, 2002; Kane & Engle, 2003). According to the integrative model of prefrontal cognitive control (Miller & Cohen, 2001), goal maintenance and interference

suppression are central to successful task execution. Both the Stroop task and verbal list-learning paradigms rely heavily on inhibitory control and the ability to suppress competing representations.

Neurocognitive evidence further supports this overlap. Frontoparietal control networks, particularly dorsolateral prefrontal and posterior parietal regions, are consistently implicated in both selective attention and memory encoding processes (Buschman & Miller, 2007; Petersen & Posner, 2012; D'Esposito & Postle, 2015). Attentional modulation enhances hippocampal engagement during encoding, thereby increasing the probability of consolidation (Fernández & Morris, 2018; Kandel, Dudai, & Mayford, 2014).

Thus, the strong association observed in the present study may reflect a shared executive control substrate rather than a strictly unidirectional causal pathway. In this sense, selective attention and learning efficiency may represent partially overlapping manifestations of broader cognitive control capacity.

4.2. On the Magnitude of the Effect

The magnitude of the observed correlation ($r = .97$) is unusually high in psychological research, where effect sizes are typically small to moderate (Cohen, 1988; Gignac & Szodorai, 2016). Several theoretically grounded explanations may account for this finding.

First, both measures rely on executive control of interference. The Stroop task assesses the ability to suppress automatic responses, while verbal learning requires suppression of competing lexical associations and maintenance of task-relevant information across trials (Diamond, 2013; Miyake et al., 2000). This shared executive demand may partially inflate the strength of association.

Second, the sample was relatively homogeneous in age and educational background. Restricted variability within a cognitively similar group may amplify observed relationships among executive constructs (Kane et al., 2007).

Third, both measures were collected within the same session using behavioural performance indicators, raising the possibility of shared method variance. When predictor and outcome variables are assessed using similar procedures and modalities, part of the covariance may reflect common measurement characteristics rather than purely distinct constructs (Podsakoff et al., 2003).

Therefore, while the effect size is robust within the present dataset, replication in larger and more diverse samples is necessary before generalising the magnitude of this association.

4.3. Gender Differences

The study identified substantial gender differences favouring female participants in both selective attention and verbal learning performance. Prior research suggests that women often demonstrate advantages in verbal memory tasks, potentially related to encoding strategies or verbal fluency differences (Halpern, 2012; Hyde, 2014).

However, meta-analytic evidence indicates that gender differences in executive control are typically small to moderate in magnitude (Hyde, 2014). The very large effects observed in the present sample may reflect sampling characteristics rather than stable population-level differences. Accordingly, these findings should be interpreted cautiously.

4.4. Urban–Rural Differences

Participants from urban environments demonstrated higher selective attention scores compared to rural participants. Environmental enrichment theories propose that exposure to cognitively stimulating contexts may enhance executive functioning (Alloway & Alloway, 2010; Diamond, 2013). Urban environments often provide greater access to educational resources and cognitively demanding experiences.

Nevertheless, the present design does not allow causal inferences. Socioeconomic factors, educational quality, and digital exposure patterns may constitute confounding variables requiring systematic control in future research.

4.5. Theoretical Implications

The findings support models conceptualising selective attention as a central mechanism in learning architecture (Baddeley, 2012; Cowan, 2005). Attentional gating appears to play a decisive role in determining which representations gain access to working memory and subsequently undergo consolidation (Gazzaley & Nobre, 2012).

Within executive control theories, selective attention functions as a regulatory system that aligns cognitive resources with task demands (Friedman & Miyake, 2017). The present results are consistent with the view that learning efficiency is closely tied to interference control capacity.

In contemporary digital contexts characterised by high informational competition, the ability to selectively allocate attention may be increasingly predictive of performance (Ophir, Nass, & Wagner, 2009; Wilmer, Sherman, & Chein, 2017).

4.6. Limitations

Several limitations must be acknowledged.

First, the sample size ($N = 35$) limits generalisability. Small samples may yield unstable effect size estimates and increase the risk of overestimating associations (Button et al., 2013).

Second, the cross-sectional correlational design precludes causal conclusions. Although selective attention significantly statistically predicted learning performance, causality cannot be inferred.

Third, potential shared method variance cannot be excluded, as both constructs were measured behaviourally within the same session (Podsakoff et al., 2003).

Fourth, additional diagnostics such as multivariate outlier detection or leverage analyses were not included in the present analysis. Future studies should incorporate more extensive statistical validation procedures.

4.7. Future Directions

Future research should: replicate findings in larger and more heterogeneous samples; employ multimethod assessment approaches (behavioural, neurophysiological, eye-tracking); investigate longitudinal dynamics of attention–learning interactions; and examine mediation models including working memory and executive function components.

Incorporating neuroimaging or electrophysiological measures would allow more precise characterisation of shared neural substrates underlying the observed association (Klimesch, 2012).

5. Conclusions

The present study examined the relationship between selective attention and learning capacity in a sample of young adults, grounded in contemporary cognitive and neuropsychological models of executive control. The findings revealed a very strong positive association between performance on a Stroop-based measure of selective attention and verbal learning performance.

Within the present dataset, selective attention accounted for a substantial proportion of variance in learning performance. This pattern supports theoretical frameworks that position executive attention as a central mechanism regulating encoding efficiency, interference suppression, and resource allocation (Engle, 2002; Miller & Cohen, 2001; Baddeley, 2012). The results are consistent with models of attentional gating, according to which the quality of learning depends critically on the ability to filter irrelevant stimuli and maintain goal-relevant information (Cowan, 2005).

Importantly, the magnitude of the observed association suggests that selective attention and learning performance may rely on overlapping executive control mechanisms. Rather than indicating a strictly unidirectional causal pathway, the findings may reflect a shared cognitive control substrate supporting both interference resolution and encoding processes (Miyake et al., 2000; Friedman & Miyake, 2017).

Exploratory analyses revealed differences associated with gender and residential environment, suggesting that demographic and contextual variables may interact with attentional efficiency. However, given the relatively small and homogeneous sample, these differences require replication in larger populations before broader generalisation.

From an applied perspective, the findings highlight the potential importance of interventions targeting attentional control mechanisms in educational and training contexts. Programmes designed to enhance interference control and sustained focus may contribute to improved learning efficiency, particularly in environments characterised by high informational load.

At the same time, several limitations warrant caution. The cross-sectional design does not permit causal inference, and the unusually large effect size necessitates replication using larger and more diverse samples. Future research should integrate multimethod assessments, longitudinal designs, and neurophysiological measures to clarify the dynamic interplay between selective attention and learning processes.

In conclusion, the study contributes to the growing body of evidence suggesting that selective attention constitutes a critical component of cognitive performance architecture. By situating the findings within executive control theory and acknowledging methodological constraints, the present work provides both empirical data and a conceptual framework for further investigation of attention–learning interactions in young adults.

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