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Principal Component Analysis of Cognitive Executive Function: A Predictive Model of Academic Performance of Students in Mathematics in Secondary Schools

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

There is a growing interest from instructional scientists in using parameters of brain executive functions to unfold cognitive disorders, Mathematical Learning Difficulties (MLD), and assessment of learners' academic performance. Thus, it is imperative to investigates, extracts and classify the major principal components of learners' cognitive executive functions that predict academic performance of students in Mathematics and science related courses in secondary schools. An ex post facto quasi-experimental design was adopted for the study. Students' cognitive profile was measured using a validated and reliable cognitive assessment Battery (CAB) and its regressional

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effect on students' predicts students' academic performance in the subject matter. There were significant positive correlations between cognitive executive functions and academic performance of students in Mathematics. The major components of the executive functions that accounted for substantial effects on academic performance of students in Mathematics include working memory, conceptual memory, short-term memory, inhibition, updating, focus attention, divided attention, auditory perception, and visual perception. Also, processing speed, shifting, planning, hand-eye coordination and response time accounted for moderate effects on academic performance of students in Mathematics. Consequently, instructors should reinforce learners' cognitive processes using cognitive retraining programmes, personalized learning, differentiated instructional strategies for exceptional students, and offer therapeutic interventions on the identified cognitive parameters that could reduce extraneous cognitive loads. These could facilitate mental internalization of external perception during instructional delivery and learning.

Keywords: Academic performance; executive functions; mathematics; principal component analysis.

1. INTRODUCTION

1.1 Background of the Study

The design and utilization of adaptive learning environments are functions of instructors' awareness of learners' cognitive executive functions. Understanding and interpreting cognitive executive functions and its roles in academic performance of learners would foster the creation of robust intelligent tutoring systems for personalized learning experiences. Executive functions are higher-order neurocognitive processes that allow learners to regulate their thoughts, and behaviours aimed at achieving defined goals and objectives (Zelazo and Carlson, 2012). Its constitutes a cognitive architecture that allow learners to respond flexibly to the learning environment and engage in deliberate, goal-directed thoughts and actions [1]. There are numerous structural classifications of cognitive executive functions which includes, working memory, inhibitory control, planning and cognitive flexibility. Working memory retains information in a short-term, manipulates and transforms data to plan and guide behaviours in major cognitive activities such as mathematical calculations [2]. Inhibitory control helps to suppress impulsive dominant of irrelevant behaviours, noise, while stimulating appropriate thoughtful processes and decision-making during instructional delivery and learning [3]. Cognitive flexibility connotes the ability to switch and generates different solutions to both routine and non-routine problems, while planning envisages the foresight to execute a task correctly and apply appropriate strategy [4].

1.2 Statement of the Problem

Some meta-analyses and correlational studies have shown the contributions of cognitive executive functions on academic performance of learners in Mathematics [5,1]. Apparently, there is lack of classification of the major components or parameters of executive functions in order to identify the weights of their contributions towards mathematical learning abilities and academic performance of students in Mathematics. Inferably, a robust classification and identification of cognitive executive functions would be necessary to guide instructors on creating intervention strategies. This could be achieved using a general and scientifically validated cognitive assessment battery (CAB); a web-based based platform via www.cognifit.com. It's a neuropsychological testing kits that measures at least twenty three (23) domains of cognitive executive functions. Thus, the present study will determine the correlational effects of cognitive executive functions on academic performance of students in Mathematics. Additionally, the study will classify the major principal components of cognitive executive functions and it regressional effects, towards predicting to a large extent the variances they accounted for in academic performance of students in Mathematics.

1.3 Theoretical Framework

Neo-Piagetian and Vygostkian constructs in Cognitive Theory underpins this study. Cognitive Learning Theory focuses on in-depth understanding and interpretation of internal information processing system constituted by brain functional networks; organization, storage, retrieval and its influence on behavioural changes or acquisition of knowledge (Sawyer, 2006; Prichard, 2009). Routine and non-routine processing of information and learning tasks in the brain at neuronal level requires creating of cognitive schemes; assimilation, accommodation, and adaptations in cognitive architecture (Young, 2011). Evidently, complexities of cognitive memory model is far from sensory, short and long term-memory classifications [6]. Its connotes many superordinate adaptive processes of the cognitive executive function; attention, perceptions, memories, processing speed, cognitive flexibility, and coordination [7].

Imperatively, learners' need to plan ahead, focus attention, update the working memory, remember past experience and previous knowledge in all subjects, but these abilities are particularly important in Mathematics [8]. Attention initiates learning, and maintaining attention is necessary when learners are exposed to new materials (Valenzeno, Alibali, & Klatzy, 2003). Learners pay attention when actively involved in the learning experience while ignoring/inhibiting irrelevant stimuli [9]. The ability to inhibits learning tasks voluntarily involves restraining initial response to the task and rethinking better strategies or ideas [10]. Inhibitory control depends on Stop-Signal Delays (SSD); processing speed or the amount of time available to detect the stop signal and countermand the "go" response, before a "go" response is executed [11]. In the same vein, perceptions as a way of interpreting objects and learning scenarios are cognitive processes. Accurate perceptions are essential to learning, because learners' perceptions of what they see, hear, touch, and taste are encoded into the working memory, and longterm memory [12]. Inappropriate perception leads to inappropriate decoding of information from the long term memory. Inferably, inability to retrieve (phonological) information from the long-term memory degenerates to major Mathematical Learning Difficulties; dyscalculia, dyslexia, and so on [13]. This contributes to difficulties with monitoring of different problem solving steps or with keeping track of intermediate results while calculating the answers of maths tasks [14]. Interference suppression (impairment) of visuo-spatial working memory, or visuo-spatial short memory has been categories as dominant features of developmental dyscalculia in children (Szucs, Devine, Soltesz, Nobes, Gabriel, 2013). Classroom instructions would be effective and efficient, if instructors could reduce the extraneous cognitive loads in some parameters of the cognitive executive functions (Watson, Gable, Morin, 2016).

1.4 Empirical Review

Recently, there is a growing interest by instructional scientist on the use of neuroscientific techniques such as electroencephalograph(EEG) biosensor signals to detects learners' cognitive profiles (e.g focused attention, and working memory) as correlates of academic performance [15]. In Sezer, Inel, Seckin, & Ulucinar (2016), EEG-biosensor devices were used to predict learners' attention levels in relation to classroom participation. It was shown that there exists a moderate positive relationship between learners' attention levels and classroom participation. This could be attributed to the activation of theta brainwave domain in the EEG frequency spectrum. Inhibitory control and attention-shifting processes were related to measures of mathematics and literacy skills [16] Learners with higher inhibitory control, and attention achieved at higher levels in Mathematics [17]. Learners with low working memory capacity encounter cognitive deficit in mathematical abilities and difficulties in shifting and evaluating new strategies while dealing with mathematics tasks [18,19]. Studies found out that verbal working memory is related to mathematical skills (Monette, et al, 2011), and predicts future mathematics performance [20]. The relationship between verbal working memory and mathematical skills could be reduced age-wise [21].

This link has been interpreted as being due to the need to use verbal codes for counting or retaining interim solutions. Holmes and Adams [22] opted that visual spatial working memory predicted all aspects of learners' mathematics achievement while controlling variances associated with phonological memory, and measures of executive functions.

2. METHODOLOGY

2.1 Research Design

The study adopts Ex Post Facto research design. A quasi-experimental design which examines contributions of Executive Functions in predicting and accounting for variances on the Mathematics performance of students. The independent variables are cognitive executive functions; Processing Speed (PRS), Shifting (SHG), Planning (PLG), Naming (NAG), Contextual Memory (CTM), Auditory Memory (AUM), Short-Term Memory (STM), Working Memory (WKM), Non-Verbal Memory (NVM),Visual-Short Term Memory (VSTM), Updating (UPG), Inhibition (INH), Focus Attention (FAN), Divided Attention (DAN), Response Time (RST), Hand-to-Eye

Table 1. Reliability coefficient of general cognitive assessment battery (CAB)

Cognitive Domain	Internal consistency	Test-Retest Reliability
Shifting	0.726	0.842
Width Field of View	0.806	0.998
Hand-Eye Coordination	0.779	0.876
Naming	0.687	0.782
Focus	1.000	0.782
Visual Scanning	0.862	0.922
Estimation	0.761	0.986
Inhibition	0.661	0.697
Auditory Short-Term Memory	0.915	0.698
Contextual Memory	0.884	0.775
Visual Short-Term Memory	0.866	0.743
Short Term Memory	0.853	0.721
Working Memory	0.85	0.696
Non-Verbal Memory	0.783	0.73
Spatial Perception	0.611	0.907
Visual Perception	0.751	0.886
Auditory Perception	0.652	0.904
Planning	0.765	0.826
Reaction to Change	0.571	0.88
Recognition	0.864	0.771
Response Time	0.873	0.821
Processing speed	0.888	0.764
Divided Attention	0.866	0.850

Coordination (HEC),Estimation (EST), Visual Perception (VIP), Spatial Perception (SPP), Auditory Perception (AUP), Recognition (RCN), Visual Scanning (VIS), and Width Field of View (WFF). On the other hand, the dependent variable is students' academic performance.

2.2 Sampling Procedure

The population of the study consisted of Upper Basic Science and Technology Education students (JSS1-3) across secondary schools in Akwa Ibom State. This study adopted a multi-stage clustered sampling technique. During the stage-wise processes, a multistage sampling technique were used to select three hundred (300) students from ten (10) arms of Junior Secondary two students of 2020/2021 academic session in Uyo Metropolis, Akwa Ibom State. Additionally, these schools met the criteria of selection; because they have competence mathematics teacher and effective computer-aided instruction (CAI) laboratory**.**

2.3 Research Instruments

The instrument used for data collection was an online cognitive survey test provided by Cogni Fit; General Cognitive Assessment Battery (CAB) accessible via www.cognifit.com. It's a neuropsychological testing tool that measures five (5) major cognitive parameters; reasoning, memory, attention, coordination, and perception. Furthermore, it is divided into twenty-three (23) sub-cognitive do- mains, which help to identify the strength, weaknesses and difficulties related to brain functions. The numeric scores of the cognitive executive functions vary from 0-800, with a categorization of the profile as low (scores less than 200) moderate (scores between 200 and 400), and high (scores greater than 400). The reliabilities of CAB are measured using Cronbach's alpha (internal consistency between domains), and test-retest approach (stability of each domain over time) (Cognitive Assessment Battery [CAB], 2016).

In Table 1, the statistic was calculated using the data gathered from 500 sample users of CogniFit web-based app for the respective reliabilities. Observe that, the reliability coefficient is .8 in more than 50 percent of the cases, and

the rest are between 0.6 and 0.7. Using George and Mallery (2003) classification, this result shows that the CogniFit web-based app for assessing cognitive executive functions is accurate and reliable without discrepancies among the datasets.

2.4 Research Procedure

The General Cognitive Assessment Battery (CAB) was administered to each participant due for completion within 30-40mins via www.cognifit.com. The results generated were forwarded automatically to the instructors. A machine learning technique; principal component analysis was used to extract and classify the major principal component of the cognitive executive functions. A further analysis was carried out using Multiple Regression analysis were used to model and fit-in the classified component of cognitive executive functions with academic performances of the study participants

3. RESULTS AND DISCUSSION

3.1 Correlation Analysis

Datasets generated from the General Cognitive Assessment Battery (CAB) were pre-processed using correlation matrix to ascertain the correlation coefficients between the executive functions.

The correlation matrix in Table 2 is a positive definite matrix with positive determinant value. Hence, there exist positive relationships amongst the cognitive variables. One independent variable; Width Field of View (WFF) was removed being an outlier to avoid redundancy during data analysis.

The datasets were subjected to KMO and Bartlet's test of sphericity to ensure the adequacy of the sampling processes prior to the use of principal component analysis. Table 3 showed a KMO value of 0.707 and significant at p-value ($p < .05$). Hence, there exist a statistically significant relationship between cognitive executive functions shown in the correlation matrix.

3.2 Principal Component Analysis and Extraction of Executive Functions

Fig. 1 is a profile of Kaiser's eigenvalues against the principal component of the variables under investigation. It shown that a set of six (6) major principal components of the executive functions have eigenvalues greater than one (1) and could be retained for further analysis. Evidently, extracted component would account for major variances amongst the independent variables (cognitive executive functions) in the study.

Table 2. Correlation matrix of cognitive executive function

Correlation Matrix

	PRS	NVM	VIS	NAG	SHG	AUM	STM	RST	EST	HEC	UPG	CTM	FAN	DAN	INH	APN	WKM	VIP	SPN	RCN	VSTM	PLG
PRS																						
NVM	0.175																					
VIS	-0.107	-0.364																				
NAG	0.112	0.06	-0.037																			
SHG	-0.214	0.025	0.037	-0.123																		
AUM	0.301	0.639	-0.458	-0.008	-0.103																	
STM	0.026	-0.66	0.38	-0.034	-0.169	-0.592																
RST	0.168	0.342	0.13	0.112	-0.041	0.041	0.135															
EST	0.274	0.066	0.282	-0.041	-0.011	0.035	0.012	0.324														
HEC	-0.028	0.151	-0.025	-0.037	0.087	0.047	-0.145	0.299	0.133													
UPG	0.056	0.047	-0.128	0.219	-0.216	0.297	-0.136	-0.011	0.123	0.019												
CTM	-0.024	-0.753	0.325	-0.002	-0.181	-0.706	0.757	0.042	0.075	-0.084	0.024											
FAN	-0.204	-0.459	0.41	0.178	0.242	-0.551	0.399	-0.068	-0.083	-0.14	0.043	0.466										
DAN	-0.214	-0.584	0.446	0.026	0.249	-0.579	0.604	-0.002	0.113	-0.035	-0.032	0.584	0.728									
INH	-0.296	-0.684	0.422	0.291	-0.045	-0.682	0.663	0.042	-0.03	-0.144	0.081	0.763	0.674	0.692								
APN	-0.414	-0.687	0.461	-0.039	0.362	-0.671	0.571	-0.096	0.015	-0.163	-0.076	0.587	0.726	0.811	0.751							
WKM	-0.066	-0.662	0.316	-0.081	-0.079	-0.651	0.932	0.115	-0.084	0.059	-0.232	0.746	0.376	0.581	0.637	0.544						
VIP	-0.066	-0.521	0.424	-0.019	-0.043	-0.482	0.458	-0.072	0.208	-0.208	-0.091	0.557	0.384	0.502	0.491	0.495	0.445					
SPN	0.166	-0.078	-0.105	-0.151	-0.216	-0.024	-0.013	-0.15	-0.038	-0.033	-0.088	0.122	-0.173	-0.19	-0.067	-0.155	0.034	0.079				
RCN	-0.025	-0.288	0.214	-0.019	0.118	-0.284	0.393	0.047	-0.034	-0.037	-0.477	0.306	0.105	0.228	0.179	0.271	0.387	0.301	0.162			
VSTM	0.403	0.532	-0.31	0.134	-0.165	0.395	-0.481	-0.072	0.183	-0.059	-0.095	-0.467	-0.364	-0.538	-0.541	-0.593	-0.511	-0.181	-0.012	-0.168		
PLG	0.524	0.456	0.23	0.133	-0.305	0.224	0.121	0.541	0.309	0.047	-0.046	-0.169	-0.317	-0.264	-0.205	-0.429	0.001	-0.173	-0.052	-0.018	0.305	

Table 3. KMO and Bartlett's Test

Kaiser-Meyer Olkin of Measure of Sampling Adequacy		**0.707**
Bartett's Test of Measure of Sphericity	Approx. Chi- Square	966.17
	DF	231
	Sig.	000

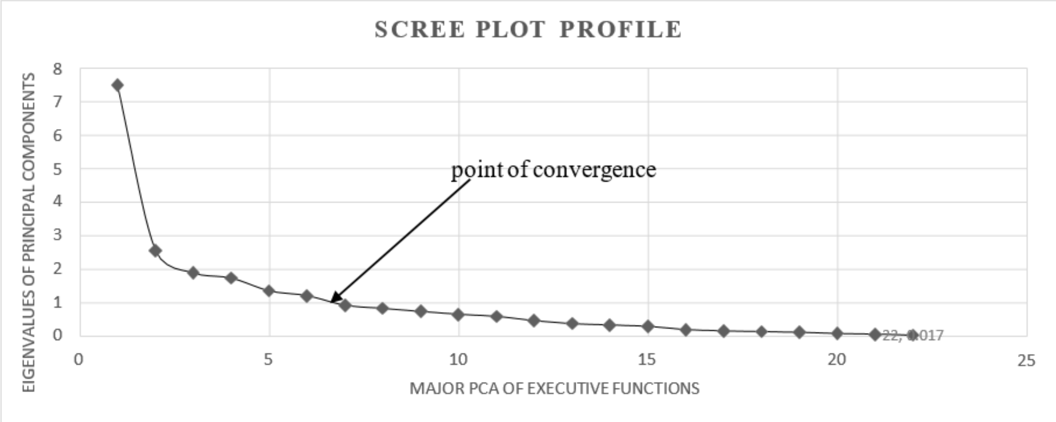

Fig. 1. Graph of eigenvalues versus components of cognitive executive functions

Table 4. Eigenvalue analysis of the correlation matrix of cognitive executive functions

	Eigenvalues			**Extracted S Squares**		
Component	**Total**	**Variance**	**Cumulative**	**Total**	**Variance**	**Cumulative**
1	7.497	34.079	34.079	7.497	34.079	34.079
2	2.560	11.635	45.714	2.560	11.635	45.714
3	1.884	8.565	54.279	1.884	8.565	54.279
4	1.728	7.857	62.136	1.728	7.857	62.136
5	1.345	6.112	68.248	1.345	6.112	68.248
6	1.200	5.457	73.704	1.200	5.457	73.704
7	.914	4.154	77.858			
8	.820	3.725	81.583			
9	.727	3.302	84.886			
10	.644	2.927	87.813			
11	.578	2.628	90.441			
12	.453	2.057	92.498			
13	.363	1.652	94.149			
14	.322	1.462	95.612			
15	.278	1.264	96.876			
16	.186	.848	97.723			
17	.145	.659	98.382			
18	.123	.559	98.941			
19	.101	.460	99.402			
20	.067	.306	99.708			
21	.047	.213	99.921			
22	.017	.079	100.000			

Using principal component analysis (PCA), the cognitive variables were clustered by dimensionality reduction. Table 4 indicates the extracted total eigenvalues of the major principal components which accounts for a total variance of 73.70% amongst the cognitive variables. The first major principal component with eigenvalue 7.497 explains 34.08% of the total variance. The second major principal component with eigenvalue 2.560 explains 11.635% of the total variance in the model. The eigenvalues decreases, while the percentages of variances accounted for by each component increases cumulatively

Table 5 yields the rotated factor loadings of the principal components. Its illustrates the classification of cognitive variables and major principal components with factor loadings. The first major principal component (*PCA*1) measures memories; contextual memory (CTM), short-term memory (STM), working memory (WKM), updating (UPG), Auditory Memory (AUM), and visual short term memory (VSTM). Also, its measures attention; inhibition (INH), focused attention (FAN), and divided attention (DAN). Perceptions; visual perception (VIP), and auditory perception (APN) were classified in the first component. The secondmajor principal component (*PCA*2) measures reasoning; shifting (SHG), processing speed (PRS), and planning (PLG).

Furthermore, an observation in Table 5 shows that coordination; hand-to-eye coordination (HEC), and response time (RST) were loaded in fourth principal component (*PCA*4). In the same vein, other cognitive variables were distributed across the remaining principal components. The factor loadings of cognitive variables on the major principal components were higher than absolute value of 0.5. These cluster loadings on the respective major principal component could be attributed to the measuring of similar constructs of the cognitive variables. Thus, the factor loading scores are suitable for further regression analysis to predict students' academic achievement in Mathematics.

3.3 Regression Model

The analysis of variance (ANOVA) in Table 6 were used to test a statistically significant and multiple correlational effects of cognitive executive functions on students' academic performance in mathematics [R = .72, R^2 = .52, F (6, 53) = 9.66, p < .05)]. The remaining percentage would be attributed to the effects of extraneous or non-cognitive variables on dependent variable. Hence, the components scores predict students' academic performance in Mathematics. Similarly, the principal components that accounted for the significant

Table 5. Rotated factor loading of principal component of cognitive executive functions

Cognitive Variables	PCA1	PCA2	PCA3	PCA4	PCA6	PCA6
Contextual Memory (CTM)	898					
Inhibition (INH)	879					
Short-Term Memory (STM)	867					
Working Memory (WKM)	857					
Updating (UPG)	825					
Auditory Memory (AUM)	757					
Auditory Perception (APN)	753					
Divided Attention (DAN)	745					
Visual Short-Term Memory (VSTM)	658					
Focused Attention (FAN)	609					
Visual Perception (VIP)	579					
Shifting (SHG)		748				
Processing Speed (PRS)		676				
Planning (PLG)		668				
Non-Verbal Memory (NVM)			896			
Recognition (RCN)			715			
Response time (RST)				728		
Hand to Eye Coordination (HEC)				721		
Estimation (EST)					850	
Visual Scanning (VIS)					556	
Naming (NAG)						753
Spatial Perception (SPN)						602

Table 6. ANOVA of predictor variable and mathematics achievement score

Model	Sum of Squares	df	Mean Sum of Squares	Sig.	F-ratio
Regression	6266.878	6	1044.48	9.66	.000∗
Residue	5732.772	53	108.17		
Total	11999.650	59			

R = .723,[a] R^2 = .522, p < .05

(a) Predictor Variables (Loadings of cognitive variables on major PCAs): PCA1, PCA2, PCA3, PCA4, PCA5, PCA6

(b) Dependent Variable: Students Academic Performance in Mathematics ∗ significant at p < .05

Table 7. Beta coefficients of major principal component using a regression model

Model	Unstandardized coefficient		Standardized coefficients		
	Beta	Std Error	Beta	t-value	Sig.
Constant	69.150	1.343		51.502	.000
*PCA*1	2.903	1.354	.204	2.144	.037∗
*PCA*2	7.832	1.354	.549	5.784	.000∗
*PCA*3	.965	1.354	.068	.713	.479
*PCA*4	5.399	1.354	.379	3.988	.000∗
*PCA*5	1.913	1.354	.134	1.413	.164
*PCA*6	1.646	1.354	.115	1.215	.230

Dependent variable: Mathematics Achievement Test (MAT) ∗ sig at p < .05

relationship were identified using beta coefficient of the component scores in Table 7. The standardized beta coefficients showed the components that yields statistically significant relationships between the cognitive variables and students' academic performance in mathematics. The first, second and fourth components (*PCA*1, *PCA*2, *PCA*4) have statistically significant relationships on academic performance of students in mathematics [b = .204, $t(5)$ = 2.14, p = .037; b = .55, $t(5)$ = 2.14, $p < .05$; b = .38, $t(5)$ = 3.99, $p < .05$], respectively. The beta coefficient shows that academic achievement increases by 0.204 unit for every unit increase of cognitive executive functions clustered in the first component (*PCA*1); contextual memory, inhibition, short term memory, working memory, updating memory, auditory memory, auditory perception, divided attention, visuo-spatial short term memory, focused attention, and visual perception. . In the second major principal component (*PCA*2), academic achievement increases by 0.55 unit for every unit increase of reasoning (processing speed, shifting, and planning). The fourth component (*PCA*4) increases students' academic achievements in Mathematics by 0.379 unit which measures coordination (response time, and hand-to-eye coordination). In the same vein, other components had no significant contributions to the relationships between cognitive executive functions and students' academic achievement. This could be attributed to some legitimate outliers retained during data analysis.

3.4 Discussion of Results

The present study shows that major components of meta-cognitive executive functions (memory, attention, and perceptions) have statistically significant and correlational effects on academic performance of students in Mathematics. In perspective, metacognitive memory; working memory, short-term memory, contextual memory, visual and non-verbal memory explained significant and positive correlations on academic performance of students in Mathematics. Analogously, Visu-Petra, Cheie, Benga, and Miclea (2011) reported that visual-spatial short-term memory (STM), verbal working memory (VWM), and inhibition contributed to average performance of students in Mathematics. Working memory had highest predictive weights for mathematical performance (Pacual, Munoz, Robres, 2019). In this study, attention of students towards learning reinforced their academic achievements in Mathematics. Explicitly, focused attention, divided attention and ability to inhibit responses are variables that yields significant effect on students' performance scores in Mathematics. This could be attributed to stochastic-free and flexibility of the learning environment. Conversely, Gray, Rogers, Martinussen, and Tannock [23] opted that in-attention influences learners' ability to correctly capture external stimuli. Reasoning skills; planning, shifting, and processing speed contributed to substantial increase in achievement scores of students in Mathematics. Yeniad, et al (2012) in a meta-analysis concerning the relationship between shifting and Mathematics, shown that higher level of performance on shifting tasks were related to higher level of performance on Mathematics tasks. Coordination; hand-eye coordination and response time have moderate significant relationships on academic achievements of students in Mathematics. These results are in line with previous studies reporting substantial links between eye to hand coordination, interceptive timing, motor skills training and Mathematical skills abilities (Pitchford, Papini, Outhwailes, and Gulliford, 2016;) [24,25]. According to Piaget, learners with better sensory motor system often manipulate objects with their hands and develops higher order thinking in later cognitive developmental stages [26,27].

4. CONCLUSION

This paper applied principal component analysis and regression model on cognitive executive functions to predicts students' academic performance in Mathematics. In this study, a total of six (6) major principal component were extracted and classified, in relation to the dependent variable. The principal component analysis shows that the major cognitive variables such as memories, attention, coordination, and perception accounted for a total of 73.70% variances on academic performance of students in Mathematics. As a limitation of the study, some moderator variables such as age, gender, parental background, socio-economic factors were not considered in the study. In further study, a structural equation modelling would be explored to measure the contribution of all classified clusters of cognitive parameters inline with students' academic performance in the subject matter and related science courses.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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