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Exploring The Interconnected Factors Of Students' Problem-Solving Ability: A Structural Equation Modeling Approach

[1]Bea Heart P. Javier, [2]Kayla M. Estimoso, [3]Venus S. Cendaña, [4]Skezeer John B. Paz
[1]Research Scholar, [2]Pre-service Teacher, [3]Pre-Service Teacher, [4]College Professor
[123]College of Education, Notre Dame of Marbel University
[4]College of Arts and Sciences, Notre Dame of Marbel University
[1]Notre Dame of Marbel University, Koronadal City, South Cotabato, Philippines

Abstract: This study explores the underlying constructs on students' problem-solving ability. In particular, a path analyses on the interrelated connections between students' algorithmic knowledge, mathematical vocabulary and comprehension, and the mediation of conceptualization were thoroughly performed. Participants were college students taking Mathematics in the Modern World subject enrolled at Notre Dame of Marbel University. An assessment testing students' calculation ability, vocabulary and comprehension, conceptual understanding and problem-solving skills was administered during the classes' regular schedules. Structural equation modeling was used for the data analysis, and utilized smartPLS 4 software for the statistical computations. Jamovi software was also used for the model test and fit indices. First, a validity and reliability test were administered to the measurement model. Then, a structural equation model was developed. Results revealed that students' algorithmic knowledge and conceptualization directly and positively impact problem-solving ability while vocabulary and comprehension partially affect problem-solving ability. It was also found out that conceptualization has a complete mediation between vocabulary and comprehension to students' problem-solving ability. Results recommended that educators should ensure that students have a firm understanding of mathematical concepts, with expanded knowledge on mathematical language as essential tools in comprehending these mathematical word problems. They can also design multiple strategies that utilize a combination of English language and conceptual modeling.

Index Terms – Structural Equation Modeling (SEM), Latent Constructs, Algorithmic Knowledge, Vocabulary and Comprehension, Conceptualization, Problem-Solving.

INTRODUCTION

Solving mathematical problems has historically been regarded as an essential component of mathematics, mathematics instruction, and mathematics learning (Liljedahl et al., 2016). According to Ahmad et al. (2010), in order to arrive at a logical solution, mathematics problem-solving takes a careful selection of methods and the implementation of logical reasoning. The process of solving word problems is also an essential component of mathematical problem solving since it involves the integration of real-life situations and practical applications. However, numerous studies have shown that pupils have significant challenges when it comes to solving word problems or comprehending narrative-based mathematical tasks (Tambychik, 2010; Phonapichat, 2014; Yayuk, 2020).

The result of students' performance in Mathematics in the Program for International Student Assessment (PISA) shows that the Philippines' mean score ranked 73 out of 75 countries and is one of the lowest among PISA-participating countries and economies in 2018 (Organization for Economic Cooperation and Development [OECD], 2019). Moreover, the Southeast Asia Primary Learning Metric (SEA- PLM) Assessment Framework (2017) reported that around 41% of the Filipino Grade 5 students failed to reach the ideal level of proficiency in Mathematics by the end of the lower elementary level. The Philippines had been consistently performing poorly in Mathematics in the global assessments. It had not been able to improve from the bottom 5 ranks since it joined Trends in Mathematics and Science Study (TIMSS) in 1999 (Mullis et al., 2004).

On the other hand, previous studies identified problem-solving as one of the students' difficulties in Mathematics. It was concluded that difficulties were experienced due to lack of language skills, mastery of numbers' facts, information skills, and cognitive abilities (Tambychik & Meerah, 2010). In addition, according to Xin et al. (2023), inability to solve mathematical word problems results in poor mathematical performance and may fail to meet the normal achievement level. Many studies have identified factors that affect students' problem-solving ability. Emanuel et al. (2021) found out that laziness in reading long questions, lack of interest in math, memorizing materials that hinder conceptual understanding, lack of understanding in arithmetic operations, few practices, low motivation, and ineffective teaching strategy cause problem-solving difficulties in students.

Above these factors, there is the range of cognitive factors which this study mainly focused on that affect students' achievement in mathematical problem-solving. Supported in the study of Bahar and Maker (2015), these cognitive factors are algorithmic knowledge,
vocabulary and comprehension and conceptualization. Proficiency in vocabulary and comprehension significantly impacts students' competence and achievement in mathematics. These abilities are essential for understanding and resolving mathematical word problems in terms of their text format instead of straightforward numbers and symbols, which form the core of mathematical application in the classroom settings. While algorithmic knowledge which is the students' knowledge and ability to use this knowledge to perform numerical calculation using legal mathematics procedure and translation of words in symbols and equations is an essential asset in Math, problem-solving application for these enables students to accurately compute the necessary calculations to resolve the problem, which is the fundamental essence of mathematics. Furthermore, the conceptualization process of students is often overlooked and neglected in mathematics classes due to its abstract nature, which cannot be directly observed during instructional and assessment activities.

Conceptualization enables students to integrate accumulated knowledge acquired via experience, observations, and the information provided in the set of mathematical application problems in order to answer the issue. This latent variable is an essential component in processing the necessary information for accurate logical reasoning and determining the correct approach to solve issues.

Some studies also focused on teaching approaches and strategies to enhance students' problem-solving ability. Sari et al. (2019) found that problem-solving abilities can be enhanced through a variety of ways in presenting teaching materials. The study of Mulyono and Hadiyanti (2018) arrived with result of a teaching approach that revolves on problem-based learning that will mainly be focused on problem-solving activity in learning Mathematics.

Research was done to address students' difficulties in problem-solving. A lot of factors were identified and investigated that have an effect on a student's problem-solving skills. However, the Filipino performance in Mathematics in the 2018 results on PISA and 2019 SEAPLM were still at the top 5 lowest rank. Upon review, no research that investigates how algorithmic ability, vocabulary and comprehension, and conceptualization affects each other and its impact on students' problem-solving skills using a Structural Equation Modeling (SEM) approach has been found.

This present study investigated how these abstract variables work and construct a structural equation model that will present their corresponding effect on each other and have a comprehensive explanation that can be grasped through a visual framework. This research is significant for it (a) provides a rationale in mathematical problem-solving ability of students, (b) offers significant research reviews that support the importance of Mathematics vocabulary and algorithmic knowledge in enhancing student's problem-solving ability, and (c) shows relationship between the underlying constructs, specifically, Mathematics, vocabulary and comprehension, and algorithmic knowledge mediated by conceptualizing ability of the students through SEM.

THEORETICAL FRAMEWORK

This study was anchored on the APOS theory of Ed Dubinsky (2001) an acronym of Actions, Process, Objects, Schemas. This constructivist theory discussed ways of concepts in mathematics taking place. According to Dubinsky (2001), mathematical knowledge of a person enabled them to analyze situational problems in Mathematics and draw their possible solutions through reflections on the problems and connecting it in a social context. Based on the study of Arnon et al. (2014), as cited in Borji et al. (2018), application of APOS theory in learning mathematics showed that cognitive structures which every individual already has, should be utilized to construct additional new and powerful structures for dealing with more complex mathematics. These structures include APOS. Action is the formation of external mathematical concepts. These external concepts are obtained from previous learning in an external observation, not imagined and transformed explicitly into other conceptions. Upon repetition and reflection on this action, an interiorized mental process occurred. Process is similar to action, but process operates in mind. Processes perform operations in mind without external execution and with this mental transformation, a cognitive object is formed as the product of these processes. Coherent organization of these actions, processes, and objects into a framework is the schema. This schema helps the person on what and how these cognitive constructions would be used in solving mathematical situational problems. The researchers of this present study based their assumptions in this theory that states that there exist cognitive constructions that influence students' mathematical problem-solving ability. Researchers of this study specified that these cognitive constructs behind students' problem-solving ability are the algorithmic knowledge, vocabulary and comprehension, and conceptualization ability, and their relationship to each other was assumed to affect a students' problem-solving ability.

Action is a student's algorithmic knowledge and vocabulary learned from observation, practices, and experiences from previous levels of their education (e.g. from what they had read, solving numbers using PEMDAS rule, substitution and transposition in algebra). Process is the students' conceptualizing ability that takes place inside the student's mind. Process is the construction or assembly of identified concepts from actions and reconstructing or combining it to form a more powerful and complex knowledge, which is the new object. An organization for utilization of these knowledge (vocabulary and algorithmic), for retrieval of concepts, and construction of concepts is the schema of the students in order to find a solution to a mathematical Problem situation.

STATEMENT OF THE PROBLEM

This study determined the relationships of the underlying constructs of students' problem-solving ability, which are the students' algorithmic knowledge, vocabulary and comprehension, and conceptualization. It also created a model using Structural Equation Modeling (SEM). Specifically, it sought to answer the following questions:

1. What are the test scores of the students in the following constructs:
1.1 algorithmic knowledge
1.2 vocabulary and comprehension
1.3 conceptualization, and
1.4 problem-solving ability
2. How does vocabulary and comprehension correlate to algorithmic knowledge?
3. How do vocabulary and comprehension and algorithmic knowledge correlate to students' problem-solving ability?
4. How does conceptualization mediate the relationship between vocabulary and comprehension and problem-solving ability; and algorithmic knowledge and problem-solving ability?
5. How do all variables correlate to students' problem-solving ability?
6. What structural equation model can be created based on the results?

HYPOTHESIS

Null Hypotheses (H_0)

1. Vocabulary and comprehension have no significant correlation to algorithmic knowledge.
2. Vocabulary and comprehension, and algorithmic knowledge have no significant correlation on students' problem-solving ability.
3. Conceptualization has no significant mediation on the relationship between vocabulary and comprehension and problem-solving ability; and algorithmic knowledge and problem-solving ability.
4. All variables have no significant correlation on students' problem-solving ability.
5. The structural equation model created does not significantly fit based on results.

Alternative Hypotheses (H_1)

1. Vocabulary and comprehension significantly correlate to algorithmic knowledge.
2. Vocabulary and comprehension, and algorithmic knowledge have a significant correlation on students' problem-solving ability.
3. Conceptualization completely mediates on the relationship between vocabulary and comprehension, and problem-solving ability; and algorithmic knowledge and problem-solving ability?
4. All variables have a significant correlation to students' problem-solving ability.
5. The structural equation model created does significantly fit based on results.

METHODOLOGY

The study used a quantitative correlational research approach by utilizing the SEM to investigate the relationship between students' algorithmic knowledge, vocabulary and comprehension, and conceptualization, and their relation to students' problem-solving ability. The respondents were college students enrolled in Notre Dame of Marbel University (NDMU). The sample for the study consisted of 261 students enrolled at MST 111 (Mathematics in the Modern World). The research instrument that was utilized in the study was a test questionnaire constructed by the researchers, which consisted of four different parts: test on algorithmic knowledge, test on vocabulary and comprehension, test on conceptualization, and problem-solving test. The instrument was checked by an expert, and scores were gathered from students enrolled in MST 111 classes during the 2023-2024 school year, Second Semester. The scores were analyzed based on the given rubrics for the different parts. After the data were gathered, the researchers used Microsoft Excel for data distribution, organization, and the computation of the mean score and standard deviation. Then the researchers imported the Excel file to the smartPLS software for the assessment of construct validity, reliability and the relationships through modeling. There were two different phases of modeling, first is the measurement modeling, and second is the structure modeling. In the first phase of modeling, measurement modeling, Cronbach's Alpha and Composite Reliability were used in checking the reliability of each construct. According to Collins (2007), Cronbach's Alpha is a statistical measure used to evaluate the reliability of a measurement instrument. On the other hand, in an information taken from Lai (2021), Composite Reliability provides an excessively positive measure of reliability coefficient, for it ignores one major source of error, which is the sampling error associated with cluster means. For assessing the validity of the constructs, Discriminant Validity and Convergent Validity test was conducted to check the overall validity of the observed constructs. AVE (Average Variance Extracted) was also used in assessing the Discriminant Validity. Fornell-Larcker Criterion (Square Root of AVE must be higher than the correlation of other constructs), Cross Loadings (value must be higher than 0.70) and HTMT (Heterotrait-Monotrait Ratio of Correlation), that should have a value less than 0.85, was used to measure Discriminant Validity. Additionally, the researcher used t-statistics to determine the significance of the mediation. For the Model Fit Indices, Jamovi software were used with the following statistical measures: Chi-Squared ($\chi 2$), Standardized Root Mean Square Residual (SRMR), Root Mean Square Error of Approximation (RMSEA), Comparative Fit Index (CFI), Tucker Lewis Index Bentler-Bonet Non-Normed Fit Index (NNFI), Relative Non-Centrality Index (RNI), Bollen's Incremental Fit Index (IFI), and Parsimony Normed Fit Index (PNFI).

RESULTS AND DISCUSSION

Table 1: Construct Validity and Reliability

	Cronbach's alpha	Composite reliability (ρ_a)	Composite reliability (ρ_c)	Average variance extracted (AVE)
Algorithmic Knowledge	0.623	0.755	0.761	0.420
Conceptualization	0.813	0.820	0.869	0.571
Problem Solving Ability	0.707	0.741	0.803	0.455
Vocabulary and Comprehension	0.635	0.726	0.759	0.397

The findings show that Algorithmic Knowledge had $\alpha = 0.623$ (AVE = 0.420), Conceptualization had $\alpha = 0.813$ (AVE = 0.571), Problem Solving had $\alpha = 0.707$ (AVE = 0.455), followed by Vocabulary and Comprehension with $\alpha = 0.635$ (AVE = 0.397). According to Hamid (2017), Cronbach's Alpha and Composite Reliability should have an acceptance value in the range of 0.6-0.7. This means that the four constructs are considered reliable. In addition, AVE measures the convergent validity of the constructs, this defines how well the items in each test represent the constructs. Moreover, according to Hamid (2017) and Latif (2020), the AVE should have a value > 0.5 to have an acceptable validity. Results showed that only Conceptualization has AVE > 0.5, meaning, some items in the Algorithmic Knowledge, Problem Solving, and Vocabulary and

Comprehension tests failed to measure what they intended to measure; they are reliable, but some are convergently invalid. This calls for a thorough finding to identify which specific item is invalid, as shown in the outer loadings matrix in Table 2.

Table 2: Outer Loadings Matrix

	Algorithmic Knowledge	Conceptualization	Problem Solving Ability	Vocabulary and Comprehension
AK1	0.16			
AK2	0.64			
AK3	0.76			
AK4	0.60			
AK5	0.85			
C1		0.71		
C2		0.74		
C3		0.69		
C4		0.81		
C5		0.81		
PS1			0.76	
PS2			0.79	
PS3			0.62	
PS4			0.67	
PS5			0.49	
VC1				0.61
VC2				0.62
VC3				0.42
VC4				0.67
VC5				0.77

Table 2 shows the outer loadings matrix which is a statistical tool used in factor analysis. Also, this identifies which items failed to represent their corresponding constructs. Indicators with values less than 0.50 means they do not represent their construct well, and the greater the value, the greater its power to represent its construct. Table 2 shows that in the algorithmic test, item 1 failed to represent AK, thus, it was removed. While in the conceptualization test, all indicators represented the C very well. This is followed by the problem-solving test where item 5 failed to represent PS; thus, it was removed. Lastly, in the vocabulary and comprehension tests, item 1 has a weak representation and item 4 failed to represent VC; thus, the two items were removed. Items not representing its construct well were removed to qualify all the constructs for the structural equation analysis.

Table 3: Validity and Reliability of Modified Constructs

	Cronbach's alpha	Composite reliability (ρ_a)	Composite reliability (ρ_c)	Average variance extracted (AVE)
Algorithmic Knowledge	0.703	0.756	0.811	0.522
Conceptualization	0.813	0.820	0.869	0.571
Problem Solving Ability	0.697	0.735	0.809	0.520
Vocabulary and Comprehension	0.575	0.679	0.768	0.533

Table 3 shows the overview of the validity and reliability of modified constructs. It includes information on Cronbach's Alpha, Composite Reliability ρa, Composite Reliability ρc, and Average Variance Extracted (AVE) as discussed in Table 2. Table 3 shows the results of reliability and validity of the constructs after some modification. All items included in each variable are reliable and convergently valid, thus, qualified for structural analysis.

Table 4: Discriminant Validity: Fornell-Larcker Criterion

	Algorithmic Knowledge	Conceptualization	Problem Solving Ability	Vocabulary and Comprehension
AK	0.722			
C	0.367	0.756		
PS	0.467	0.491	0.721	
VC	0.276	0.434	0.278	0.730

In Table 4, Fornell-Larcker Criterion was used to check the discriminant validity of measurement models. With this, the square root of the AVE of a construct must be greater than the correlation between the construct and any other construct. Results show that AK has a root AVE = 0.722 (>0.367, > 0.467 and > 0.276); this means that the root of AVE is greater than the root AVE of other correlating constructs and, thus, there is no anomaly in the discriminant validity of AK. On the other hand, C had a root AVE = 0.756 (>0.367, > 0.491 and > 0.434). This means that there is no anomaly in the discriminant validity of C. This was followed by PS that had a root AVE = 0.721 (>0.467, > 0.491 and > 0.278). Last is VC that has a root AVE = 0.730 (>0.276, > 0.434 and > 0.278). Overall, Table 4 shows that all constructs have a good discriminant validity.

Table 5: Discriminant Validity: Cross Loadings

	Algorithmic Knowledge	Conceptualization	Problem Solving Ability	Vocabulary and Comprehension
AK2	0.645	0.152	0.249	0.132
AK3	0.744	0.340	0.329	0.279
AK4	0.626	0.219	0.207	0.103
AK5	0.851	0.307	0.484	0.234
C1	0.196	0.716	0.228	0.327
C2	0.189	0.749	0.236	0.383
C3	0.412	0.685	0.435	0.261
C4	0.253	0.813	0.442	0.353
C5	0.288	0.808	0.439	0.333
PS1	0.447	0.408	0.792	0.167
PS2	0.352	0.439	0.825	0.320
PS3	0.198	0.273	0.586	0.147
PS4	0.307	0.255	0.653	0.136
VC2	0.195	0.213	0.092	0.559
VC4	0.183	0.279	0.156	0.725
VC5	0.233	0.415	0.299	0.872

Table 5 shows Cross Loadings in Structural Equation Modeling (SEM) indicate how much indicators (items) of a latent variable load onto latent variables other than their intended one. It is crucial to manage cross loadings carefully to maintain the clarity and validity of SEM models, ensuring accurate interpretation of the relationships between latent variables and their indicators. According to Latif (2020), indicators should have greater loadings under their corresponding constructs to be considered valid. In Table 5, it is highlighted that each indicator loaded significantly higher under their supposed constructs compared to their loadings in the other constructs, thus, the indicators are strongly valid.

Table 6: Discriminant Validity: Heterotrait-Monotrait Ratio of Correlation (HTMT)

	Algorithmic Knowledge	Conceptualizatio	Problem Solving Ability	Vocabulary and Comprehension
AK				
C	0.452			
PS	0.595	0.603		
VC	0.405	0.607	0.381	

Table 6 presents a discriminant validity test using the Heterotrait-Monotrait Ratio of Correlation (HTMT). This measure compares the correlation between a pair of variables from different constructs (heterotrait) to the correlation between a pair of variables from the same construct (monotrait). With this, it can be determined whether the observed relationships between variables from different constructs are stronger than the relationships between variables from the same construct. According to Latif (2020), in order to say that constructs are discriminating using HTMT, the intersecting values must be less than 0.85. Result shows in the matrix that the pair of C and AK is 0.452, the pair of PS and AK is 0.595, and the pair of PS and C is 0.603 which is less than 0.85. Furthermore, the pair of VC and AK is 0.405, while the pair of VC and C is 0.607, and lastly the pair of VC and PS is 0.381. All pairs present have a value less than 0.85, this means that no existing issue was found in the discriminant validity of each construct using HTMT. Thus, all constructs are discriminating.

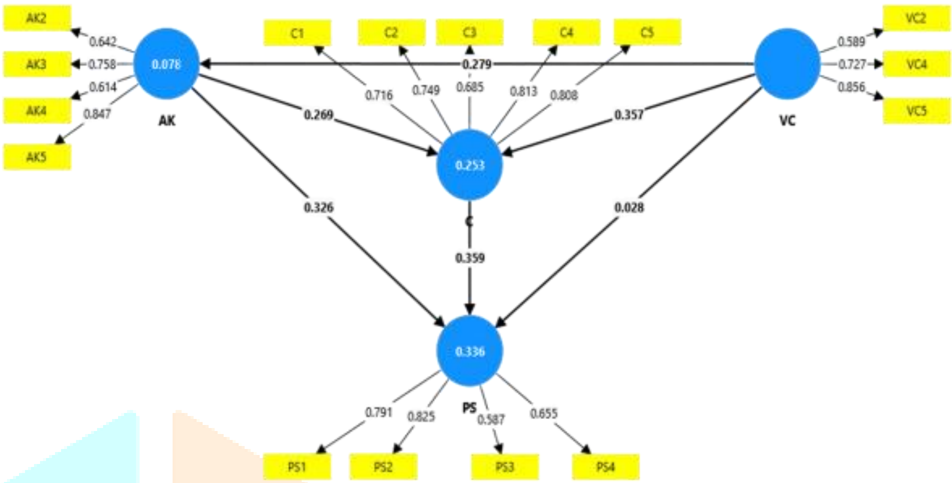

Figure 1: Graphical Measurement Model

Figure 1 illustrates the general framework of the Measurement Model, and it is shown that all items and constructs have no issue on their validity and reliability and have met the quality criteria, thus, they are qualified to be subject for structural modeling.

Table 7: Path (Direct Effect)

Coefficients	Standard Path Coefficient	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AK -> C	0.269	0.274	0.063	4.286	0.000
AK -> PS	0.329	0.334	0.065	5.034	0.000
AK -> VC	0.279	0.289	0.066	4.226	0.000
VC -> AK	0.279	0.289	0.066	4.226	0.000
C -> PS	0.360	0.361	0.065	5.558	0.000
VC -> C	0.356	0.359	0.061	5.885	0.000
VC -> PS	0.024	0.022	0.064	0.371	0.711

Table 7 shows the beta coefficient or the path coefficients (β), the t value of each path, and the effect size (f-square). According to Latif (2020), there is a significant impact on the paths if the $\beta>0.20$ and $T>1.960$. The path from VC to AK has $\beta=0.279$ with $t=4.226$ ($f^2 = 0.085$). Therefore, VC has a significant impact on AK with a small effect size ($f^2 < 0.14$). The path from AK to PS has $\beta=0.329$ with $t=5.034$ ($f^2 = 0.138$). Therefore, AK has a significant impact on PS with a small effect size. The path from VC to PS has $\beta=0.024$ with $t=0.371$ ($f^2 = 0.001$). Therefore, the VC does not have a direct significant impact on PS. It is also shown that AK and VC have a significant impact on C, and VC has a good enough effect size to C ($f^2 > 0.15$). In addition, C has a direct significant impact to PS with a good enough effect size.

Table 8: Indirect Effect

	Standard Path Coefficient	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AK -> PS	0.097	0.098	0.028	3.455	0.001
VC -> C	0.075	0.079	0.025	3.012	0.003
VC -> PS	0.247	0.255	0.044	5.618	0.000

Table 9: Specific Indirect Effect

	Standard Path Coefficient (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AK -> C -> PS	0.097	0.098	0.028	3.455	0.001
VC -> C -> PS	0.128	0.129	0.031	4.125	0.000
AK -> VC -> C -> PS	0.036	0.037	0.013	2.818	0.005
VC -> AK -> C -> PS	0.027	0.028	0.010	2.727	0.006
AK -> VC -> C	0.099	0.104	0.031	3.183	0.001
VC -> AK -> C	0.075	0.079	0.025	3.012	0.003
AK -> VC -> PS	0.007	0.007	0.019	0.347	0.729
VC -> AK -> PS	0.092	0.097	0.032	2.878	0.004

Table 10: Total Effect

	Standard Path Coefficient	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AK -> C	0.269	0.274	0.063	4.286	0.000
AK -> PS	0.426	0.433	0.063	6.718	0.000
C -> PS	0.360	0.361	0.065	5.558	0.000
VC -> AK	0.279	0.289	0.066	4.226	0.000
VC -> C	0.431	0.437	0.057	7.620	0.000
VC -> PS	0.271	0.277	0.071	3.837	0.000

Table 8-10 shows the indirect effect, specific indirect effect and total effect that were used for the analysis of mediation. Partial mediation, as described by Latif (2020), occurs when a mediator variable explains part, but not all of the relationship between an independent variable and a dependent variable. In this case, both the direct effect (the influence of the independent variable on the dependent variable without considering the mediator) and the indirect effect (the influence of the independent variable on the dependent variable through the mediator) are statistically significant. This suggests that while the mediator plays a meaningful role in linking the two variables, the independent variable also exerts a direct influence on the dependent variable beyond the mediator's contribution. In contrast, complete mediation occurs when the direct effect is insignificant, while the indirect effect remains significant, demonstrating that the mediator fully explains the connection.

Table 11: Model Fit Indices of SEM

Fit Indices	Criterion	Result
Chi-Squared ($\chi 2$)	Non-significant	332 ($p<0.001$)
Standardized Root Mean Square Residual (SRMR)	S-RMR<0.05	0.083
Root Mean Square Error of Approximation (RMSEA)	0.05<RMSEA<0.10 (Moderate Fit) RMSEA<0.05 (Good Fit)	0.106
Comparative Fit Index (CFI)	CFI>0.95	0.961
Tucker Lewis Index	TLI>0.90	0.952
Bentler-Bonet Non-Normed Fit Index (NNFI)	NNFI ≥ 0.95	0.952
Relative Non-Centrality Index (RNI)	RNI ≥ 0.95	0.961
Bollen's Incremental Fit Index (IFI)	IFI > 0.90	0.961
Parsimony Normed Fit Index (PNFI)	PNFI > 0.50	0.769

Table 11 summarizes the model test and fit indices of the structural equation model. Table 11 presents a Chi-square value of x^2= 332, with degrees of freedom, df = 98 (see Appendix C), and p-value of $p<0.001$. According to Kyriazos (2018), the Chi-square test with a large sample size affects the precision and replicability of results in structural equation modeling which affects the goodness of fit indices and it gives a significant result even in slight differences. Thus, the results presented above typically support a significant probability, for the population size in the study exceeded above 200. As mentioned in the study of Fadlelmula (2011), Chi-square over degrees of freedom ratio (x^2 /df) can be used for large sample sizes. Ratio less than 5 indicates a good fit between observed and reproduced correlation matrices. This study has a model where x^2 /df = 332/98 3.39, indicating a good fit. Table 11 also presents the SRMR which has a value of 0.083 and means an acceptable fit. According to Hair et al. (2021) as cited in Jatmika and Abdurrahman (2023), SRMR has a good fit with a value less than 0.08, and in Karin et al. 2003 as cited in Jatmika and Abdurrahman (2023), 0.08 - 0.10 also indicates acceptable fit model. RMSEA also showed a moderate fit. In addition, model test using CFI, TLI, NNFI, RNI, IFI, and PNFI have had a result indicating a very good fit and thus conclude that the model well represents the results of the study and the relationships of all underlying constructs.

Table 12: Test Scores of the Students in each Constructs

Latent Variable	Mean	SD	Total Score
Algorithmic Knowledge	8.74	4.47	20.00
Vocabulary and Comprehension	8.36	4.70	20.00
Conceptualization	10.12	6.31	20.00
Problem Solving Ability	3.93	3.61	20.00

Table 12 shows the test scores of the students. Average scores of students on AK is 8.74 (SD = 4.47) out of 20-point tests. Followed by the average score of students on VC is 8.36 (SD = 4.70), C is 10.12 (SD = 6.31). Lastly, PS has the lowest average of 3.94 (SD = 3.61). Every test in each construct showed that the students' scores are significantly different or lower from the supposed average score of each test. These results are aligned with the findings of Tambychik (2010), Phonapichat et al. (2014), and Yayuk and Husama (2020) saying that students experience significant challenges in dealing with word problems and mathematical comprehension. The results also show that most of the students found it difficult to apply mathematical ideas successfully, specifically in arithmetic calculations, conceptual understanding, and its application and word problems. These deficiencies highlight an urgent need for educators to focus on students' algorithmic knowledge, vocabulary and comprehension, and conceptualization skills to uplift students' problem solving ability.

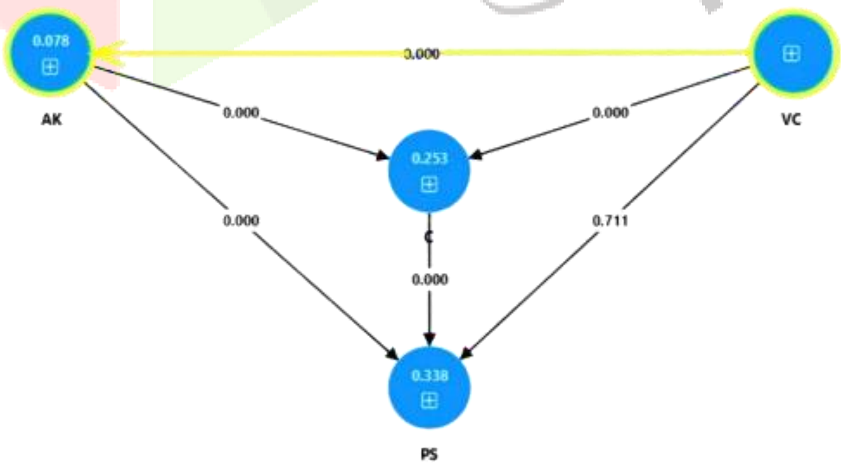

Figure 2: Correlation of Vocabulary and Comprehension to Algorithmic Knowledge

Figure 2 shows the Structural Equation Model (SEM), with emphasis on the path of vocabulary and comprehension to algorithmic knowledge. The latent constructs are students' vocabulary and comprehension represented by three indicators VC2, VC4, and VC 5, and the students' algorithmic knowledge is represented by AK2, AK3, AK4, and AK5. These indicators are the types of questions given to the students which were validated in the measurement analysis.

The researchers initially hypothesized that vocabulary and comprehension of the students have a significant relationship and direct effect on their algorithmic knowledge. The structural model revealed that vocabulary and comprehension of the students significantly affect the algorithmic knowledge of the students with a t-value of 4.226 and R^2 of 0.279. This means that students' vocabulary knowledge explains about 27.9% of the variance in students' algorithm in solving math. This suggests that in the teaching of mathematics, keeping in mind the relationship between algorithmic knowledge, and vocabulary and comprehension is important, for these constructs should work hand-in-hand for students to be able to translate words into mathematical expressions that demonstrate their algorithmic knowledge. In this situation, teachers should put emphasis in helping pupils learn vocabulary and comprehension, particularly with certain words and terminologies that have various mathematical meanings. Students will be able to accurately convert words into equations or mathematical expressions through this. Comprehension is closely linked to algorithmic knowledge and the ability to apply procedures and strategies in problem-solving. As highlighted by Chen et al. (2024), understanding student epistemology is crucial for effective pedagogy. By integrating algorithmic knowledge into pedagogical content knowledge frameworks, educators can better support students' learning processes.

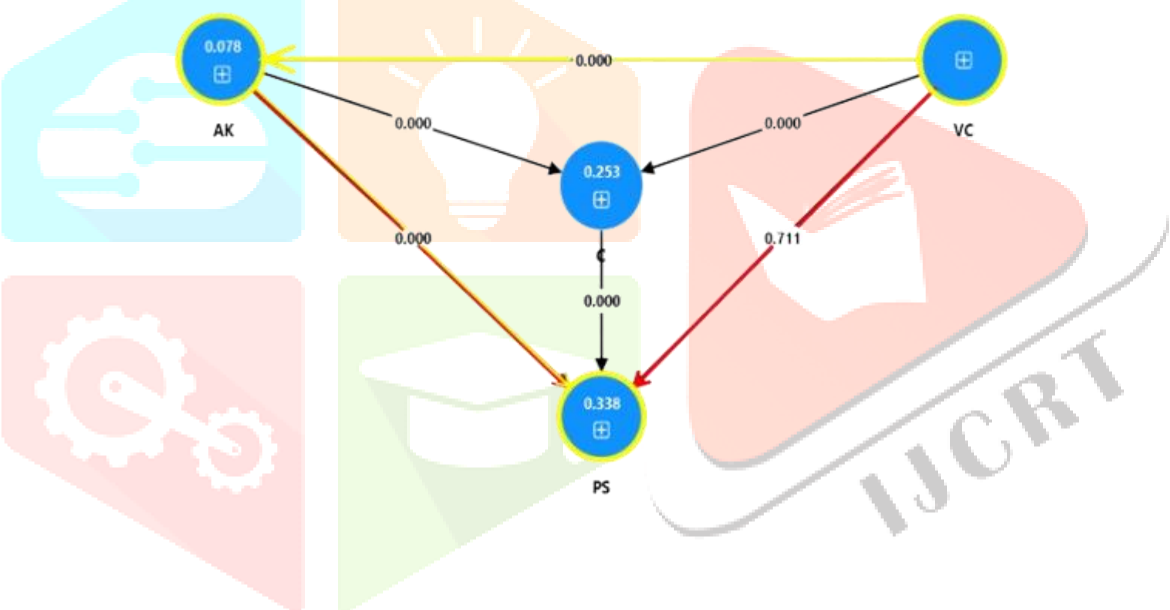

Figure 3: Correlation of Vocabulary and Comprehension and Algorithmic Knowledge to Students' Problem Solving Ability

Figure 3 shows the Structural Equation Model, with emphasis on the path of vocabulary and comprehension to algorithmic knowledge to students' problem-solving ability. In this path, problem-solving ability is the additional construct represented by four indicators, PS1, PS2, PS3, and PS4. The researchers initially hypothesized that the relationship of vocabulary and comprehension, and students' algorithmic knowledge has a significant relationship and direct effect on students' problem-solving ability. Results show that AK affects PS significantly in an independent manner while VC has an insignificant effect on PS, (see appendix C Table C7) with an R^2 of 0.329 and 0.024 respectively. Also, AK being affected by VC also has a significant impact on PS with an R^2 of 0.092. This means that the relationship of students' vocabulary and comprehension, and algorithmic knowledge has a significant relationship and direct effect on student's ability in solving mathematical word problems, and about 9.2% of the variance in students' problem-solving ability is explained by the relationship of VC and AK while about 32.9% and 2.4% of the variance in PS is explained by AK and VC, respectively. This indicates that with AK, students' capability of solving mathematical problems is increased. When presented with numerical equations, they have a higher chance of solving them. However, VC has an insignificant effect on PS, which indicates that students have little chance of solving arithmetic problems by simply comprehending the supplied word problem. Moreover, since VC correlates to AK, this will have a more positive impact on students' problem-solving ability. For example, when students are given a word problem and if they have vocabulary and comprehension skills, they will be able to express the words into numerical form. When students possess algorithmic knowledge, they will be able to solve the numerical expressions with solutions provided. Considering these findings, which show that VC by itself has no significant effect on PS, teachers ought to place greater attention on helping students develop their vocabulary and comprehension in order to help them gain the appropriate algorithmic knowledge that will enhance their problem-solving abilities, supplying them with adequate materials and instructional techniques so they can learn these abilities.

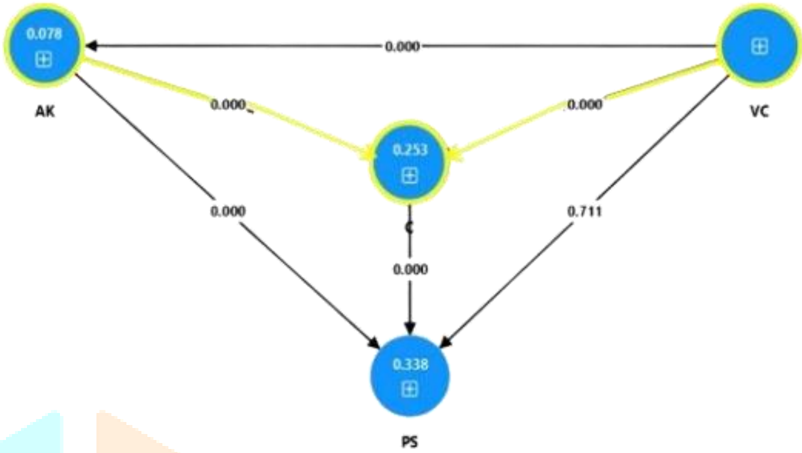

Figure 4: Mediation of Conceptualization on the Relationship between Vocabulary and Comprehension and Problem Solving-Ability; and Algorithmic Knowledge and Problem-Solving Ability

Figure 4 shows the Structural Equation Model (SEM), with emphasis on the mediation of conceptualization as the relationship of VC to AK affects PS. Conceptualization is represented by indicators C1, C2, C3, C4, and C5. The researchers initially hypothesized that there is a complete mediation of conceptualization in the relationship of VC to AK to PS. Results show that conceptualization completely mediates between VC to PS since the direct effect from VC to PS is insignificant, and the specific indirect effect is significant. This means that students with vocabulary and comprehension skills should also acquire conceptualization in order to have a positive impact on their problem-solving ability. With a strong foundation on VC, students will be able to recognize important details to solve problems. Understanding mathematical texts and problems helps students develop stronger mental models of mathematical ideas. This is how VC improves conceptualization, which will help them solve mathematical problems successfully.

However, the result also reveals that conceptualization only has a partial mediation between AK and PS. Even though AK already has a significant impact on PS alone, the relationship of algorithmic knowledge and conceptualization is an effective motivating factor that enhances problem-solving ability. Students who have a strong conceptual basis are more likely to think critically and try out various ways to problem-solving. Also, algorithmic knowledge provides students with a structured approach to solving problems, helping them break down complex problems into simpler steps. Moreover, about 12.8% change in PS is attributed to the mediation of C in VC to PS, 9.7% change in PS is from the mediation of C in AK to PS. The mediation of C in the relationship of VC and AK as it affects PS is also significant with 2.7% changes in PS being attributed to the relationship of the three constructs.

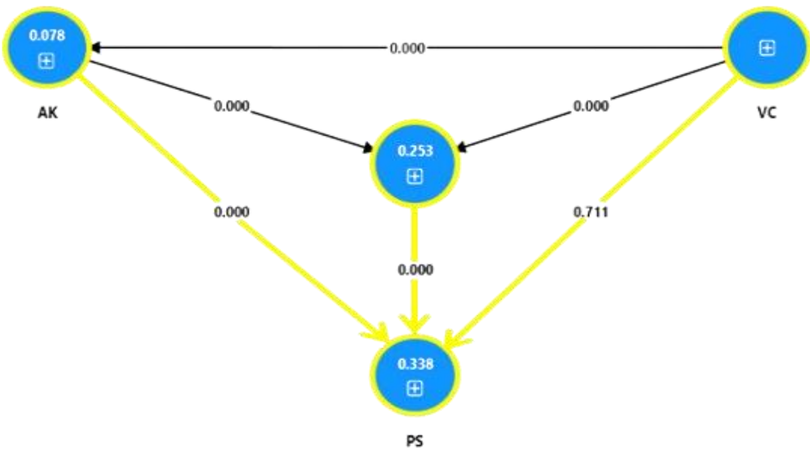

Figure 5: Correlation of all Constructs to Students' Problem-Solving Ability

For Statement of Problem 5, the findings reveal that most variables exert a significant direct impact on problem-solving (PS), with the notable exceptions of vocabulary (VC) and comprehension (C). This indicates that while many factors contribute directly to PS, vocabulary and comprehension do not show a statistically significant direct influence to PS. There is also a partial mediation in all correlating variables except in the correlation of VC to C to PS. Also, the relationship between vocabulary and comprehension (VC) and algorithmic knowledge (AK), as mediated by comprehension (C) and its subsequent influence on problem-solving (PS), is significant. This finding highlights the intricate dynamics among these variables, underscoring the importance of comprehension as a bridge linking vocabulary to algorithmic knowledge and to problem-solving skills.

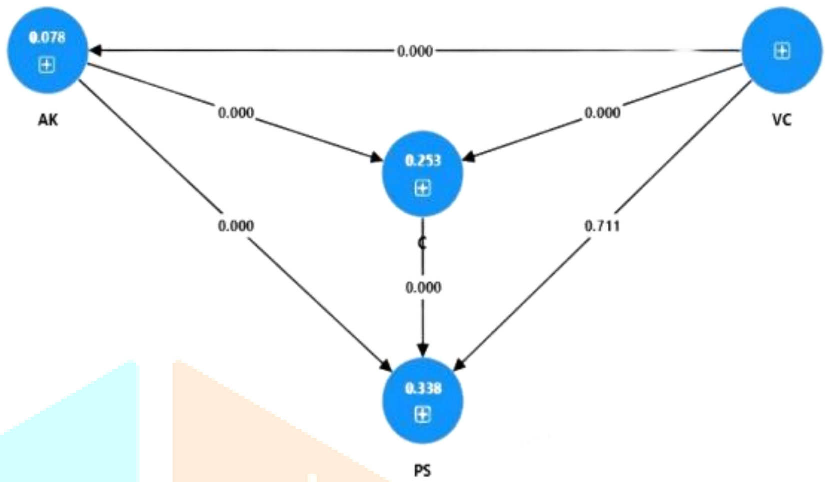

Figure 6: The Created Structural Equation Model

The Structural Equation Model based on the data acquired from the scores of NDMU students is a good fit structural equation model, showing the pathways of the relationships of all the constructs.

CONCLUSION

In this study, the interrelationships among the identified underlying constructs of students' problem-solving ability, particularly the algorithmic knowledge, vocabulary and comprehension, and conceptualization as mediating variables were examined. A hypothesized model was initially constructed to represent the possible relationships among the constructs. Though some of the relationships have been tested in some studies, this research extended the literature by providing a model that included the interplay of conceptualization in the relationships of vocabulary and comprehension, and algorithmics affecting students' mathematical application ability. Overall, the findings supported a lot of hypothesized relationships, and found additional knowledge on students' cognitive processes.

Briefly, there were two main constructs that had a significant positive impact on students' problem-solving ability; these are students' algorithmic knowledge and conceptualization. On the other hand, vocabulary and comprehension only had a partial positive impact on students' problem-solving ability. Vocabulary and comprehension also had a positive significant impact on students' algorithmic knowledge, as supported in many literatures which found out that mathematical vocabulary predicted changes in calculation and applied problem-solving skills over time. This suggests a potential avenue to target an intervention between vocabulary and arithmetic fluency to increase positive results on students' mathematical application. In addition, conceptualization also had a significant positive impact on students' problem-solving ability. This suggests that mathematical instructions should employ creative modeling activities that will help enhance conceptual understanding, in order to improve students' ability to apply their mathematical knowledge effectively and promote better problem-solving skills.

Another major finding in this study is the mediating relationships: only between vocabulary and comprehension, and problem-solving ability does conceptualization completely. This means that in order to utilize vocabulary and comprehension well in the mathematical application, the ability of the students' enhanced conceptual understanding should also be well established to the students. This suggests that educators should incorporate and give emphasis in conceptual understanding while enhancing students' comprehension in mathematical applications. Lastly, the overall complex interrelatedness of the underlying constructs suggested that there should be an equal weight of treatment in these variables which an educator should enhance, for the students to effectively apply their mathematical knowledge in real life. Imbalance on the level of ability can significantly impact students' mathematical performance and can further affect their view in the realm of numbers.

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