Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 7, 518-528
2025
Publisher: Learning Gate
DOI: 10.55214/25768484.v9i7.8646

The influence of students' working memory capacity on solving calculus problems

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Abstract: This study aims to investigate the influence of students' working memory capacity (WMC) on their ability to solve calculus problems, particularly within the topic of integral calculus. A total of 98 undergraduate mathematics education students from a state Islamic college in Makassar, Indonesia, participated in this quantitative study. Data were collected using two validated instruments: a modified complex span task (CST) to assess WMC, and a calculus problem test (CPT) to evaluate calculus problem-solving performance. Statistical analyses, including t-tests, F-tests, regression modeling, and the coefficient of determination, revealed a significant positive relationship between WMC and calculus problem-solving ability, with WMC accounting for 74.5% of the variance in students' performance. The results show that students with higher WMC outperformed those with lower WMC on complex calculus tasks, indicating that WMC plays a critical role in mathematical cognition. These findings underscore the need for educators to consider cognitive load and individual memory capacity when designing instructional strategies. Practical implications suggest incorporating cognitive training and tailored scaffolding into the curriculum to support students with lower WMC. The study contributes new insights by focusing specifically on integral calculus—a domain rarely examined in WMC research—highlighting the importance of cognitive resources in advanced mathematics learning.

Keywords: *Cognitive skills, Integral calculus, Mathematics education, Problem solving, Working memory capacity.*

1. Introduction

The continuous advancement of educational practices has brought increased attention to individual cognitive differences as key determinants of learning outcomes. Among these, working memory capacity (WMC) has been recognized as a vital cognitive resource, particularly in mathematics, where tasks require students to engage in abstract reasoning, sequential problem-solving, and the retention of intermediary steps. WMC refers to the cognitive system responsible for temporarily storing and manipulating information essential for complex cognitive tasks like learning, reasoning, and problem-solving [1-4]. Furthermore, it plays a crucial role in various activities, from a simple task like remembering phone numbers to more complex ones, like mental arithmetic and chess [5]. WMC varies among undergraduate students, and is generally associated with better performance on complex cognitive and academic inquiries [5]. However, higher WMC can sometimes lead to the use of overly complex strategies that may not be optimal for certain tasks [5, 6].

The concept of working memory has gained widespread use over the past three decades, extending beyond cognitive psychology to various areas of cognitive science and neuroscience, with applications in fields such as education, psychiatry, and cognitive training [2, 7]. This fact is

History: Received: 21 April 2025; Revised: 9 June 2025; Accepted: 12 June 2025; Published: 7 July 2025
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especially true with mathematics. Calculus, a cornerstone of higher mathematics, challenges students with its reliance on abstract principles and symbolic reasoning. These characteristics impose high cognitive demands, making success in this domain dependent on an individual's ability to simultaneously store and manipulate information. Such tasks engage multiple components of working memory as described by the Baddeley's model, which comprises the central executive (responsible for attention and coordination), the phonological loop (processing verbal information), and the visuospatial sketchpad (handling spatial and visual data) [8, 9]. In the context of calculus, students frequently rely on the central executive to manage the simultaneous demands of symbolic manipulation and stepwise reasoning, while the visuospatial sketchpad supports the visualization of mathematical concepts and relationships [10, 11]. In addition, the phonological loop aids in retaining numerical or verbal problem descriptions during problem-solving processes [21].

Students with lower WMC are often at a disadvantage when tackling tasks with high cognitive demands. Research has consistently shown that WMC limitations can lead to cognitive overload, especially in complex problem-solving situations [12-14]. Cognitive load theory posits that tasks exceeding an individual's WMC capacity impair learning efficiency, resulting in errors, incomplete solutions, and slower problem-solving performance [12, 15]. In mathematics education, this dynamic is particularly highlighted, as WMC is strongly correlated with problem-solving success [3, 16]. For example, Peng, et al. [5] that WMC is a robust predictor of academic performance in mathematics and related disciplines [5]. Similarly, Titz and Karbach conducted a meta-analysis showing that WMC contributes significantly to mathematical performance across various age groups and educational levels [17].

Several studies have also highlighted the broader educational implications of WMC. Jaeggi, et al. [18] found that students with higher WMC consistently perform better in tasks requiring sustained attention and cognitive flexibility, while those with lower WMC struggle with multitasking and memory retention [18, 19]. These findings underscore the critical role of WMC in mathematics, where success often depends on managing multi-step processes and maintaining focus under high cognitive loads. Adding to the discussion, Wiley and Jarosz elaborated that WMC influences the efficiency of mental operations, such as the ability to retrieve relevant information and integrate it with new data during problem-solving [6, 20].

Despite the growing body of research on WMC and its relationship with academic performance, specific investigations into its role in advanced mathematical domains, such as integral calculus, remain limited. Calculus is a fundamental topic in higher mathematics with wide-ranging applications across various fields. It plays a crucial role in physics, engineering, economics, and computer science [7, 11, 21]. These subjects encompass methods for computing areas, volumes, and other quantities using mathematical models [7]. While calculus can be challenging to learn, mastering common techniques such as substitution, partial fractions, and integration by parts is essential for solving complex problems [11]. The concept of definite integrals can be generalized to curvilinear, surface, and multiple integrals, each with specific physical and mechanical interpretations [21]. Despite its importance, students often face difficulties when calculating integrals. To address this, educators should focus on preventing common errors and emphasize the connections between different types of integrals and their practical applications [7, 21]. The inherently abstract and sequential nature of calculus tasks makes them ideal for exploring how cognitive resources like WMC influence learning and performance. Understanding these relationships is expected to provide insights into tailoring instructional strategies that accommodate individual cognitive differences, ultimately enhancing educational outcomes.

Moreover, the educational implications of these findings are significant. Students with limited WMC often require structured interventions to alleviate cognitive overload during learning. Instructional strategies such as scaffolding, worked examples, and problem decomposition have been shown to improve learning efficiency by reducing extraneous cognitive load [12, 13]. Additionally, research indicates that WMC is a malleable trait that can be enhanced through targeted training programs, including memory span exercises and dual-task paradigms [18, 22]. These interventions could potentially equip students with the cognitive tools necessary to manage the complexities of calculus and other high-demand tasks.

This study aims to examine the influence of WMC on students' ability to solve calculus problems, focusing on the differences in performance between students with high and low WMC. By employing validated instruments to measure WMC and problem-solving proficiency, this study sought to bridge the gap between cognitive psychology and mathematics education. The findings are expected to inform evidence-based instructional strategies, offering practical solutions to support students in overcoming cognitive challenges in advanced mathematics.

The novelty of this study lies in its focus on integral calculus—an advanced and cognitively demanding topic rarely examined in WMC research. By isolating this area, the study provides new insights into how cognitive capacity affects higher-level mathematics and offers practical implications for targeted instruction and cognitive training interventions in mathematics education.

2. Research Method

This research adopted a quantitative approach. It engaged 98 undergraduate students (27 male and 71 female) majoring in Mathematics Education at a State Islamic College located in Makassar, Indonesia. Two assessment tools were utilized: the Complex Span Task (CST) for measuring students' working memory capacity (WMC), and the Calculus Problem Test (CPT) for assessing their skills in solving calculus problems [23]. The CST instrument was adapted from the original version, and permission for use was granted by the creator. Both instruments underwent content and feasibility validation by three associate professors in mathematics education, achieving scores of 3.85 and 3.90 out of a possible 4.00. A pilot test was conducted with ten Mathematics Education undergraduates from a private university in Enrekang Regency, Indonesia. From the CST, two students showed high WMC (final score ≥ 110 out of 157), while eight had low WMC (score < 110). For the CPT, two students scored high (≥ 80), five scored low (≤ 59), and the remainder fell in the medium range. Both tools had moderate difficulty indices (0.784 and 0.733) and discrimination values (0.677 and 0.751). In follow-up empirical tests, difficulty indices were 0.751 and 0.85, with discrimination coefficients of 0.672 and 0.79, respectively. Validity coefficients were 0.854 and 0.891. Using a Cronbach's Alpha at a 5% significance level, reliability values were found to be 0.811 and 0.794.

The study followed a detailed timeline. Initially, all 98 participants completed the CST to identify their WMC levels, after which they were categorized into high or low WMC groups based on established research standards. Two days later, participants sat for the CPT in a controlled, supervised session lasting 120 minutes. During the session, students independently solved calculus problems. Supervision was provided by the lead researcher and a faculty member familiar with the participants to ensure a standardized environment.

This methodology, incorporating validated tools and clear procedures, was designed to ensure the research's accuracy and reproducibility. It effectively captured the participants' cognitive and mathematical capabilities, providing a strong foundation to assess the relationship between WMC and performance in calculus. Students were categorized into high, medium, and low groups based on CPT scores.

Data analysis began with a normality test using the Chi-Square formula: $x^2 = \sum \frac{(O_i - E_i)}{E_i}$, where O = observed value and E = expected value. Expected frequencies were derived by multiplying the normal distribution table values by the total number of cases (N). The analysis was performed in SPSS Version 26. If the significance level exceeded 0.05, the CST and CPT data were considered normally distributed.

According to Nuryadi [24] the homogeneity test determines whether different sample groups have equal variances [24]. The test decisions were based on two criteria: if the significance value <

0.05, data variances are not homogeneous; if > 0.05, they are. Following Sugiyono [25] if the data is normally distributed, variance homogeneity is tested using the F test: F = largest variance / smallest variance. SPSS Version 26 was used to conduct the test. If the CST and CPT significance levels were > 0.05, the samples were considered to come from populations with homogeneous variances.

A multiple linear regression analysis was conducted to evaluate the impact of WMC on calculus problem-solving [25]. The hypothesis testing equation used was $Y = a + b_1X_1 + b_2X_2$. Coefficients were calculated using the formulas: $b_1 = \frac{(\sum X_2^2)(\sum X_1Y)-(\sum X_1X_2)(\sum X_2Y)}{(\sum X_1^2)(\sum X_2^2)-(\sum X_1X_2)^2}$ and $b_2 = \frac{(\sum X_1^2)(\sum X_2Y)-(\sum X_1X_2)(\sum X_1Y)}{(\sum X_1^2)(\sum X_2^2)-(\sum X_1X_2)^2}$ and $= \frac{\sum Y - b_1\sum X_1 - b_2\sum X_2}{n}$, where Y=Dependent Variable, a=Constant, b_1,b_2=Regression Coefficient and X_1,X_2=Independent variables. The hypothesis used is as follows:

H_0: There is no significant influence of students' working memory capacity in solving calculus problems.

H_1: There is a significant influence of students' working memory capacity in solving calculus problems.

To test the above hypothesis, the t-test and F-test using SPSS Version 26 were done, where the rules are as follows:

For the t-test and F-test, if significance (sig.) <0.05 then H_0 is rejected, H_1 is accepted. In this study, SPSS Version 26 was used to conducted the hypothesis test**.**

3. Results

3.1. Descriptive Statistical Analysis

This research, conducted within the Undergraduate Mathematics Education Program at a State Islamic University in Makassar, Indonesia, yielded the following findings:

For the Complex Span Task (CST), students achieved a minimum score of 42 and a maximum of 136 out of a possible 157 points. The mean score was 100.5 with a standard deviation of 16.36. Based on CST results, 28 students were identified as having high working memory capacity (final score ≥ 110 of 157), while 70 students fell into the low working memory category (final score < 110). In terms of the Calculus Problem Test (CPT), those with high working memory capacity demonstrated the ability to solve calculus problems at 89.35% of the maximum achievable score. In contrast, students with low working memory capacity achieved 55.26% of the maximum score. The CPT scores ranged from a low of 42 to a high of 91, with a mean of 67.93 and a standard deviation of 9.47. The CPT results showed that 10 students earned high scores (≥ 80), 71 students were in the medium score range (60 to 79), and 17 students were classified as low scorers (≤ 59).

3.2. Data Analysis Requirements Test

3.2.1. Normality Test

The normality assessment for this research was carried out using SPSS Version 26, with the results as follows:

Table 1.
Working Memory Capacity (CST) Data Normality Test.

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	**df**	**Sig.**	**Statistic**	**df**	**Sig.**
Working Memory Capacity	0.057	98	.200*	0.984	98	0.267

Note: *. This is a lower bound of the true significance.
a. Lilliefors Significance Correction.

Based on SPSS analysis, the significance value obtained was 0.200. Since this value exceeds 0.05 (sig. > 0.05), it indicates that the Working Memory Capacity (WMC) data follows a normal distribution, thus validating the use of parametric statistical methods for data analysis.

Table 2.
Calculus Problem Test (CPT) Data Normality Test.

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	**df**	**Sig.**	**Statistic**	**df**	**Sig.**
Calculus Problem Test	0.057	98	0.200*	0.995	98	0.973

Note: *. This is a lower bound of the true significance.
a. Lilliefors Significance Correction.

Again, the SPSS results indicated a significance value of 0.200. As this is greater than 0.05 (sig. > 0.05), it confirms that the CPT data is also normally distributed.

3.2.2. Homogeneity Test

The SPSS Version 26 was also used for homogeneity testing. The following results were obtained:

Table 3.
Working Memory Capacity (CST) Data Homogeneity Test.

		Levane Statistic	df1	df2	Sig.
Working Memory Capacity	Based on Mean	0.176	1	96	0.676
	Based on Median	0.099	1	96	0.754
	Based on Median and with adjusted df	0.099	1	93.157	0.754
	Based on trimmed mean	0.183	1	96	0.670

From this data, the CST significance level is 0.676, which is greater than 0.05 (sig. > 0.05), indicating that the sample originates from a population with homogeneous variance.

Table 4.
Calculus Problem Test (CPT) Data Homogeneity Test.

		Levane Statistic	df1	df2	Sig.
Calculus Problem Solving	Based on Mean	5.461	1	96	0.223
	Based on Median	5.268	1	96	0.245
	Based on Median and with adjusted df	5.268	1	94.901	0.244
	Based on trimmed mean	5.416	1	96	0.027

The calculated significance for the CPT is 0.223, which also exceeds 0.05 (sig. > 0.05), confirming that this data set comes from a population with equal variance.

3.2.3. Hypothesis Test

3.2.3.1. Regression Test

There were two regression tests used in this study, namely the t-test and the F-test. The t-test was used to determine how much influence the Working Memory Capacity (WMC) of students had in Calculus Problem Test (CPT) partially, while the F-test was used to determine how much influence the Working Memory Capacity (WMC) of students had in Calculus Problem Test (CPT) simultaneously. To find out the t-test, see Table 5 below.

Table 5.
t-Test.

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	**Std. Error**	**Beta**		
1	(Constant)	60.932	5.971		10.204	0.000
	CST	0.070	0.059	0.120	2.187	0.000

Note: a. Dependent Variable: CPT.

Based on Table 3, the constant coefficient value was 60,932, and the CST coefficient value was 0,070, so that a regression equation can be made as follows:

$$Y = 60{,}932 + 0{,}07X$$

X is WMC, and Y is Solving Calculus Problems. Based on Table 3, for CST, the t count was 2.187 > 1.986, and the significance value (sig.) was 0.000 < 0.05, so there was not enough evidence to accept H_0. It means that H_1 was accepted, and that there was an influence of students' working memory capacity on students' ability to solve calculus problems.

Furthermore, the simultaneous F test was used to determine how much influence the working memory capacity (WMC) had on students' ability to solve calculus problems simultaneously. The results of the F test can be seen in Table 6 below.

Table 6.
F-Test

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	125.909	1	125.909	3.409	0.000[b]
	Residual	8578.591	96	89.360		
	Total	8704.500	97			

Note: a. Dependent Variable: CPT.
b. Predictors: (Constant), CST.

Based on Table 4, the calculated F was 3.409 > F table of 2.70, and the significance value (sig.) was 0.000 < 0.05, so there was not enough evidence to accept H_0. Therefore, H_1 was accepted, and students' working memory capacity simultaneously had a significant influence on students' ability to solve calculus problems.

To find out how much influence was given by the working memory capacity of students on their ability to solve calculus problems, it can be seen from the determination coefficient value, which can be read in the R Square value. The results of the determination coefficient are presented in Table 7 below.

Table 7.
Determination Coefficient Results.

Model Summary				
Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**
1	0.767[a]	0.745	0.748	1.453

Note: a. Predictors: (Constant), Working Memory Capacity.

Based on Table 7, it shows that the R Square value was 0.745 = 74.5%. In other words, the working memory capacity of students affected the ability of students to solve calculus problems by 74,5%, and there were only 25,5% of other variables that were not studied in influencing the ability of students to solve calculus problems. The following is the regression graph.

ISSN: 2576-8484
Vol. 9, No. 7: 518-528, 2025
DOI: 10.55214/25768484.v9i7.8646

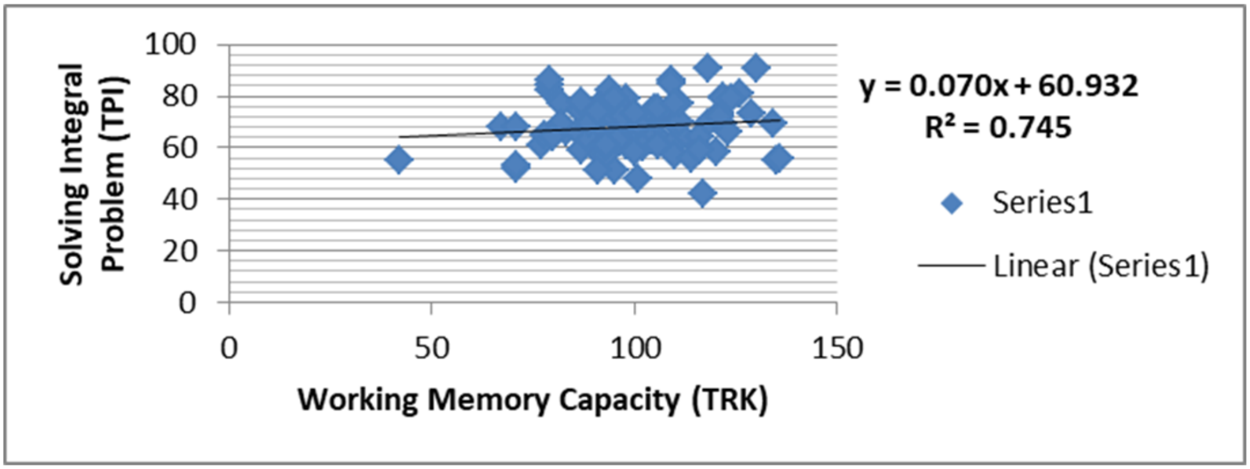

Figure 1.
Regression Graph.

The following is a graph of working memory capacity and students' ability to solving calculus problems.

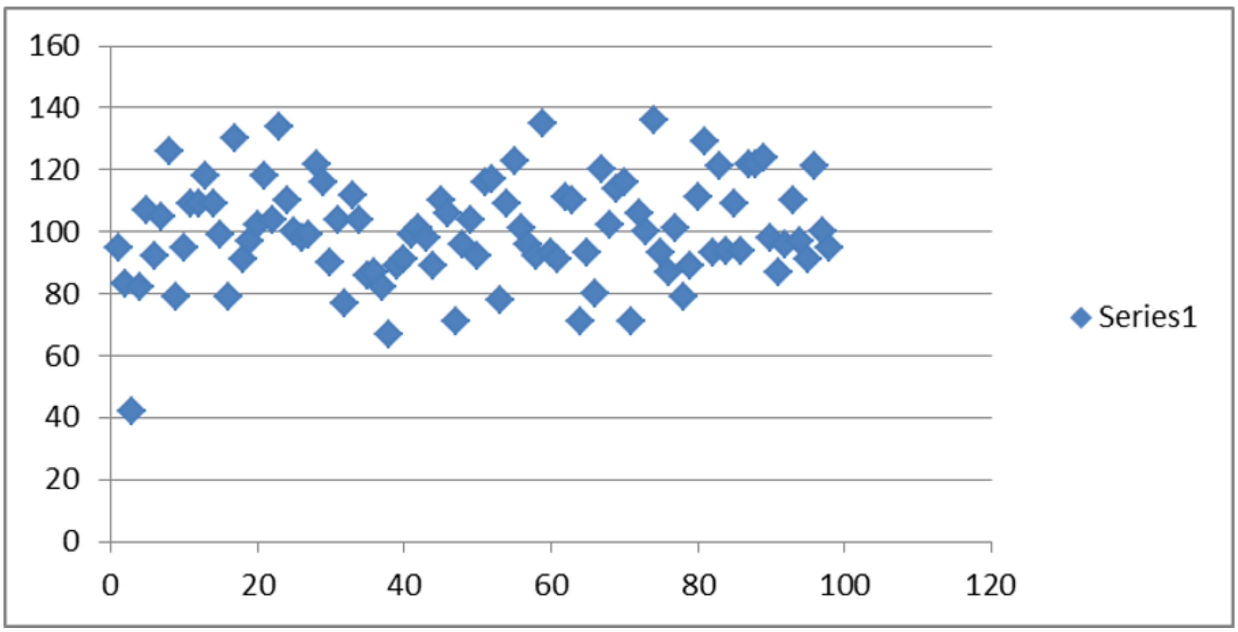

Figure 2.
Working Memory Capacity (CST) Graph.

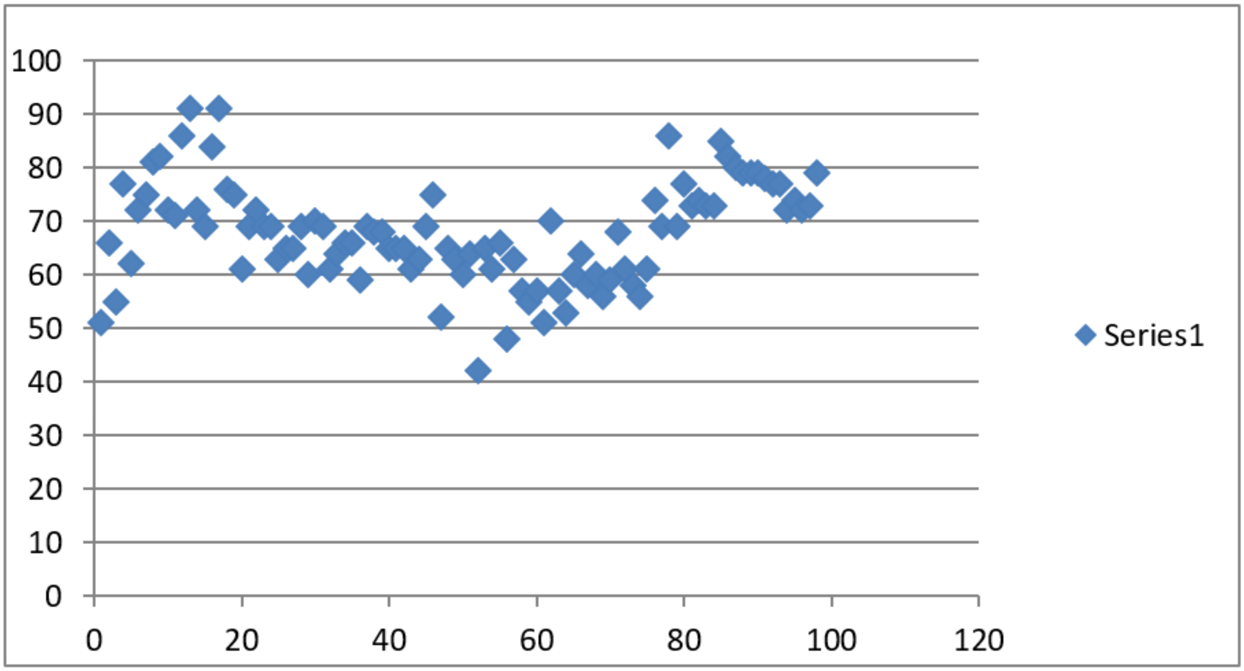

Figure 3.
Solving Calculus Problems (CPT) Graph.

4. Discussion

This study reveals a statistically significant impact of students' working memory capacity (WMC) on their ability to solve calculus problems, indicating that WMC plays a critical role in mathematical cognition. These findings align with recent research demonstrating that WMC contributes to problem-solving abilities in various cognitive domains, including mathematics, as it supports attention control, information retention, and manipulation [1, 8, 18]. Specifically, students with higher WMC demonstrated superior performance in solving calculus problems, suggesting that their enhanced cognitive resources allow them to process complex mathematical tasks more effectively. This result is supported by a study conducted by Peng, et al. [5] who emphasized the role of WMC in tasks that require high cognitive load and strategic manipulation of information [5].

To further clarify the relationship between WMC and problem-solving ability in calculus, this study has provided a detailed breakdown of the indicators used to measure both variables. WMC was measured using the Digit Span Task (forward and backward), a validated assessment tool in cognitive psychology [11]. The specific indicators included the Digit Forward Score, which measures the capacity to temporarily store and recall numerical sequences in the order presented, reflecting the phonological loop's efficiency in working memory [8]. The Digit Backward Score evaluates the ability to store and manipulate numerical information by recalling sequences in reverse order, assessing both the phonological loop and the central executive [26]. The Total Working Memory Score, which combines the forward and backward digit span scores, provides a comprehensive measure of the student's overall working memory capacity [18, 20].

Additionally, the problem-solving ability of students in calculus, especially integral material, was assessed using the Calculus Problem Test (CPT). Key indicators included Accuracy of Solutions, which evaluates the correctness of integral problem solutions, reflecting computational and procedural fluency [10]. The problem-solving steps completion indicator measures whether students correctly executed the necessary steps in solving calculus problems, indicating procedural knowledge and strategy application [5]. The use of appropriate integration techniques assesses the selection of

ISSN: 2576-8484
Vol. 9, No. 7: 518-528, 2025
DOI: 10.55214/25768484.v9i7.8646

suitable methods, such as substitution, integration by parts, and partial fraction decomposition [7, 11]. Other than that, error analysis identifies the types and frequencies of errors made in the problem-solving process, revealing cognitive constraints in information retention and manipulation [12, 13]. Additionally, the time taken to solve problems measures efficiency in problem-solving, which is linked to cognitive load and working memory constraints [3, 16].

The findings suggest that students with lower WMC experience difficulties with mathematical tasks that involve multi-step calculations and integration principles. This is consistent with the theory stating that individuals with limited WMC may struggle with simultaneous storage and processing requirements, as supported by previously conducted research on cognitive load theory [12, 13]. Students with lower WMC often experience cognitive overload during complex problem-solving, resulting in reduced accuracy and incomplete solutions. Moreover, WMC has been shown to be an important predictor of academic success in mathematics [17] reinforcing the argument that WMC directly correlates with proficiency in high-demand cognitive tasks, such as calculus problem-solving.

Furthermore, this study highlights potential educational interventions. For instance, WMC can be developed and enhanced through targeted cognitive training exercises, potentially improving students' abilities in areas that require sustained attention and information manipulation [18]. Such training could be especially beneficial for students in mathematics, where WMC is essential for managing complex tasks [22]. Educators might consider incorporating WMC assessments and exercises into the curriculum to identify students at risk of cognitive overload in advanced mathematics and provide them with tailored support to enhance learning outcomes.

By specifying the indicators of WMC and integral problem-solving ability, this study offers a clearer framework for understanding the cognitive processes involved in mathematics education. Finally, future studies should explore how individual differences in WMC interact with instructional methods and curricular designs to optimize learning experiences. Given that WMC is a trainable skill [22] integrating cognitive training into mathematics education may yield substantial benefits, particularly in fields that demand high levels of cognitive processing.

5. Conclusion

This study concludes that working memory capacity (WMC) significantly influences students' ability to solve calculus problems, with students exhibiting high WMC showing stronger problem-solving performance compared to those with low WMC. This highlights WMC as an essential cognitive asset in managing the complex, multi-step nature of calculus tasks, which require simultaneous information storage and processing.

5.1. Suggestions

Based on these findings, educators are encouraged to consider students' cognitive capacities as a factor in instructional design for mathematics courses. Implementing cognitive support strategies, such as structured problem-solving frameworks and periodic mental breaks, may alleviate cognitive load for students with lower WMC. Additionally, incorporating activities that strengthen working memory, such as memory span exercises, may provide students with the cognitive flexibility needed to tackle complex mathematical problems more effectively.

5.2. Recommendations for Future Research

Future research should explore the long-term impact of enhancing WMC through cognitive training on mathematics performance and whether these interventions can narrow the achievement gap between students with varying WMC levels. Additionally, studies investigating how different instructional methods may interact with WMC to optimize learning outcomes in mathematics would offer valuable insights. Such research could contribute to developing evidence-based educational practices tailored to cognitive differences among students, ultimately enhancing academic success across diverse learning contexts.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

Acknowledgements:

The authors gratefully acknowledge the support provided by the Lembaga Pengelola Dana Pendidikan (LPDP) under the Ministry of Finance of the Republic of Indonesia, as well as the Center for Higher Education Funding and Assessment (PPAPT) under the Ministry of Higher Education, Science, and Technology (KEMDIKTISAINTEK), through the Indonesian Education Scholarship (BPI) and the sponsorship of the author's doctoral studies. The opinions expressed in this paper are those of the authors and do not necessarily represent the views or policies of the supporting institutions.

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