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ARTICLE

Predicting academic performance in mathematics with NASA-TLX: A brief study with 15-year-old students in Spain

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Abstract: Performance in mathematics is highly linked to the capacity for abstraction and the cognitive demands of the different exercises and problems, which is a fact to take into account when planning academic activities. The present study involving 160 15-year-old students shows that mathematics study and grades are highly correlated with mental workload. Mental workload was calculated by means of the NASA-TLX test at the beginning of the school year, and was analyzed with the grades obtained at the end of the school year. The high correlation of the NASA-TLX test variables on mental workload, effort and performance (r = -.956***, -.944***, and -.933*** respectively) are an excellent predictor of future academic performance in mathematics grades.

Keywords: Nasa-TLX; mathematical performance; academic performance; cognitive load.

PREDICCIÓ DEL RENDIMENT ACADÈMIC A MATEMÀTIQUES AMB NASA-TLX: UN BREU ESTUDI AMB ESTUDIANTS DE 15 ANYS A ESPANYA

Resum: *El rendiment en matemàtiques està molt vinculat a la capacitat d'abstracció i a les exigències cognitives presents als exercicis i problemes, dada que cal considerar a l'hora de planificar les activitats acadèmiques. Aquest estudi, en el que hi van participar 160 estudiants de 15 anys, mostra que l'estudi i les qualificacions a matemàtiques estan altament correlacionades amb la càrrega cognitiva. La càrrega cognitiva es va mesurar amb el test NASA-TLX a l'inici del curs escolar, i es va analitzar amb les qualificacions obtingudes al final del curs escolar. L'alta correlació de les variables del test NASA-TLX sobre la càrrega mental, l'esforç i el rendiment (r = -.956***, -.944***, i -.933*** respectivament) són un excel·lent predictor del futur rendiment acadèmic en les notes de matemàtiques.*

Paraules clau*: Nasa-TLX; rendiment matemàtic; rendiment acadèmic; càrrega cognitiva.*

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PREDICCIÓN DEL RENDIMIENTO ACADÉMICO EN MATEMÁTICAS CON NASA-TLX: UN BREVE ESTUDIO CON ESTUDIANTES DE 15 AÑOS EN ESPAÑA

Resumen: *El rendimiento en matemáticas está muy vinculado a la capacidad de abstracción y a las exigencias cognitivas de los distintos ejercicios y problemas, lo cual es un dato a tener en cuenta a la hora de planificar las actividades académicas. El presente estudio, en el que participaron 160 estudiantes de 15 años, muestra que el estudio y las calificaciones en matemáticas están altamente correlacionados con la carga mental. La carga mental se midió mediante el test NASA-TLX al inicio del curso escolar, y se analizó con las calificaciones obtenidas al final del curso escolar. La alta correlación de las variables del test NASA-TLX sobre la carga mental, el esfuerzo y el rendimiento (r = -.956***, -.944***, y -.933*** respectivamente) son un excelente predictor del futuro rendimiento académico en las notas de matemáticas.*

Palabras clave: *Nasa-TLX; rendimiento matemático; rendimiento académico; carga cognitiva.*

Introduction

Mathematics is a fundamental subject that is necessary for success in many areas of life. However, for many students, mathematics can be a difficult and frustrating subject to learn. One possible reason for this difficulty is the high cognitive load associated with mathematical tasks. Cognitive load theory (CLT) posits that the human cognitive system has a limited capacity for processing information and that the difficulty of a task can be influenced by the amount of cognitive load it requires (Pass & Sweller, 2012).

In this study, we aim to explore the relationship between cognitive load and the difficulty of mathematical tasks, and how individual differences, such as prior knowledge and working memory capacity, can affect this relationship. We will also examine the role of cognitive variables, such as working memory, attention, and executive functions, in mathematical performance.

Mathematical difficulties refer to the difficulties that individuals experience in understanding and solving mathematical problems, which can have a negative impact on their academic and professional development (Gallistei & Gelman, 2005; Gilmore et al., 2018; Menon, 2016). Cognitive variables, such as working memory, attention, and executive functions, have been found to play a crucial role in mathematical performance (Bull & Scerif, 2001; Gallistei & Gelman, 2005; Gilmore et al., 2018; Menon, 2016).

The ease with which information can be processed in working memory is one of the main focuses of cognitive load theory (Van Merriënboer & Sweller, 2005). Working memory has a very limited duration and capacity to process new information, although different research has yielded different results. This may be attributed to the fact that the practical limits for working memory vary depending on the circumstances (Cowan, 2010). We can divide the cognitive load imposed on working memory into three categories according to its function (Paas & Sweller, 2012; Sweller et al., 1998; Van Merriënboer & Sweller, 2005).

Intrinsic cognitive load has its origin in the basic structure of the content that the learner must acquire. Therefore, it is unrelated to the procedures or didactic design used (Chen, Paas & Sweller, 2023; Renkl et al., 2009).

Extrinsic cognitive load is imposed on working memory by the way information or activities are presented to learners. Therefore, the design of the material may impose additional cognitive load that, in many cases, is unnecessary and extraneous to the learning objectives (Chen et al., 2023; Renkl et al., 2009).

Finally, the relevant cognitive load is the load related to processes that contribute to the construction and automatization of schemas (Paas & Sweller, 2012; Van Merriëmboer & Sweller, 2005).

Working memory, which refers to the cognitive system responsible for the temporary storage and manipulation of information, has been found to be a major determinant of mathematical performance (Gallistei & Gelman, 2005; Gilmore et al., 2018; Menon, 2016). Studies have shown that working memory capacity is positively related to mathematical performance and that individuals with lower working memory capacity are more likely to experience difficulties in mathematics (Bull & Scerif, 2001; Ganor-Stern, 2016; Lee & Bull, 2016; Swanson, 2004).

Attention, which refers to the cognitive process responsible for selectively focusing on certain stimuli, has also been found to play a crucial role in mathematical performance (Ganor-Stern, 2016; Lee & Bull, 2016; Swanson, 2004). Working memory, attention, and executive functions have been found to play a crucial role in mathematical performance. Individuals with lower working memory capacity are more likely to experience difficulties in mathematics and it can be influenced by physical activity (Mateu et al., 2022; Nicolau et al., 2022; Pizà-Mir et al., 2022). Attention deficit hyperactivity disorder (ADHD) can also affect mathematical performance, possibly due to difficulties in selectively focusing on mathematical problems. Poor executive functions can also lead to difficulties in mathematics (Barkley, 1997, Pizà-Mir & Suñe-Vela, 2022).

Executive functions, which refer to a set of cognitive processes responsible for planning, organizing, and monitoring behavior, have also been found to be related to mathematical performance and difficulties in mathematics (Bull & Scerif, 20011).

The cognitive load of a task can be measured using subjective measures such as the NASA-TLX (NASA Task Load Index) scale (Hart & Staveland, 1988). The NASA-TLX is a widely used, subjective measure of cognitive load that assesses the workload experienced by an individual during a specific task. The scale consists of six items: mental demand, physical demand, temporal demand, performance, effort, and frustration. These items are scored on a scale of 0-100, with higher scores indicating greater cognitive load.

Prior knowledge has been found to play an important role in reducing cognitive load and enhancing learning in mathematical tasks (Hollender et al., 2010; Morrison & Anglin, 2005). Working memory capacity, on the other hand, has been found to be a major determinant of cognitive load and performance in mathematical tasks (Kirschner et al., 2006).

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The results of this study will have important implications for the design and implementation of mathematical instruction. By understanding the relationship between cognitive load, difficulty, and individual differences, educators can design instruction that reduces cognitive load and enhances learning.

1. Methodology

1.1 Participants

The present study was conducted to investigate the relationship between cognitive load and academic performance in mathematics among a sample of high school students. A total of 160 participants about 15 years old were recruited from 14 different schools. Participants were selected through random sampling from a larger pool of eligible students. The study was conducted at the beginning of the school year and all data collection and analysis was completed by the end of the school year. 52,7% of the sample was male.

1.2 Measures

The primary measure used in this study was the NASA-TLX (Task Load Index), which was adapted to a 5-point scale to assess participants' subjective feelings towards mathematics. The NASA-TLX is a widely used, subjective measure of cognitive load that assesses the workload experienced by an individual during a specific task (Hart & Staveland, 1988). The original NASA-TLX scale consists of six items: mental demand, physical demand, temporal demand, performance, effort, and frustration, but in our study we measured all items except physical demand. These items were scored on a 5-point scale, with higher scores indicating greater load.

In addition to the NASA-TLX, participants' academic performance in mathematics was also collected at the end of the school year. This was done in order to examine any potential correlation between scores on the NASA-TLX and academic performance in mathematics. Academic performance was measured using standardized mathematics achievement tests and recorded as a percentage score.

1.3 Data collection and analysis

All data collection and analysis adhered to the relevant ethical guidelines and standards. Prior to the study, informed consent was obtained from the parents or legal guardians of all participants, as well as from the participants themselves. In addition, approval for the study was obtained from the school administration.

Data analysis was conducted using correlation and principal component analysis (PCA) to evaluate the degree of correlation between the different variables. Correlation analysis was used to determine the strength and direction of the relationship between scores on the NASA-TLX and academic performance in mathematics. PCA was used to identify any underlying patterns or structures in the data.

Before conducting the PCA, the data was evaluated for the assumptions of factorability using the Barlett's test of Sphericity (Tobias & Carlson, 1969) and the KMO measure of sampling

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adequacy (Dziuban & Shirkey, 1974). The Bartlett's Test of Sphericity and the Kaiser-Meyer-Olkin (KMO) measure serve as important statistical tools in educational research. The Bartlett's Test of Sphericity is used to assess the appropriateness of applying factor analysis to a set of variables by examining whether the correlation matrix is significantly different from an identity matrix. This test helps researchers determine if there is sufficient intercorrelation among variables to proceed with factor analysis, a technique commonly used in educational studies to identify underlying constructs or dimensions.

On the other hand, the KMO measure is employed to evaluate the sampling adequacy for factor analysis. It quantifies the proportion of variance in the variables that can be attributed to common factors. In educational research, the KMO measure aids in determining the suitability of the data for factor analysis, providing insights into whether the variables are sufficiently interrelated to extract meaningful factors. A higher KMO value suggests a stronger correlation among variables, indicating the potential for factor analysis to reveal underlying relationships in the data.

2. Results

The results of this study indicate a strong correlation between cognitive load, as measured by the NASA-TLX, and academic performance in mathematics. Table 1 shows the descriptive statistics (mean, median, mode, sum, standard deviation, minimum and maximum), as well as the W Saphiro-Wilk statistic for the different variables of the NASA-TLX and the score obtained in the mathematics subject.

	Score	Mental	Temporal	Effort	Frustration	Performance
Mean	5.44	2.81	3.92	2.60	2.58	2.26
Median	5.00	3.00	4.00	3.00	3.00	2.00
Mode	5.00	3.00	4.00	3.00	3.00	2.00
Sum	871	449	627	416	413	361
Standard deviation	2.62	1.25	582	1.16	507	1.11
Minimum	1.00	1.00	3.00	1.00	2.00	1.00
Maximum	10.0	5.00	5.00	5.00	4.00	5.00
Shapiro-Wilk W	949	908	751	898	656	864
Shapiro-Wilk p	< .001	< .001	< .001	< .001	< .001	< .001

Table 1. Descriptive statistics.

Figure 1 shows the descriptive statistics in the form of a boxplot of the different categories analyzed in the previous table. As can be seen, all variables except frustration have a high variability, in the case of frustration it is between 2 and 4 points. At the same time, it is observed

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that the category on time load has a more centralized tendency, which shows that the students do not consider that the mathematics exercises have a very long or short duration.

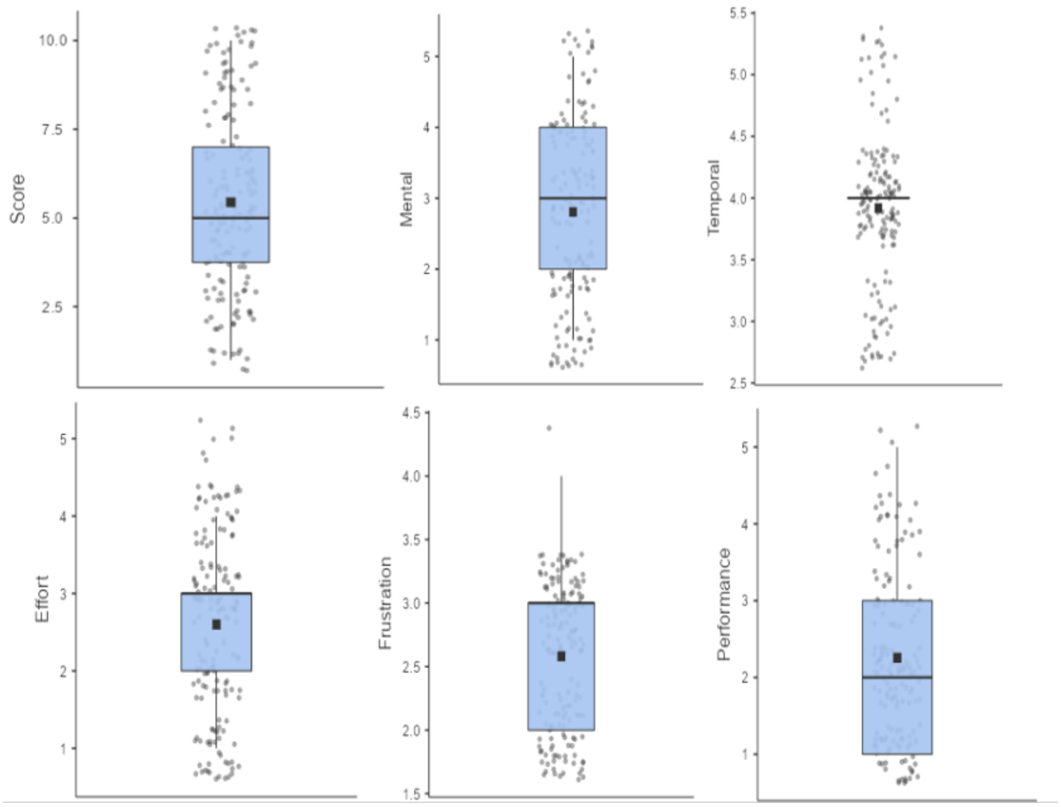

Figure 1. Boxplot of Maths' score and NASA-TLX variables.

Table 2 and Table 3 present Barlett's test of sphericity, as well as the KMO (Kaiser, Meyer and Olkin) Measure of Sampling Adequacy. The values of both tests indicate that the data allow a factor analysis.

χ^2	df	p
1290	15	< .001

Table 2. Bartlett's test of sphericity

	MSA
Overall	.891
Score	.837
Mental	.893
Temporal	.930
Effort	.897
Frustration	.966
Performance	.891

Table 3. KMO measure of sampling adequacy.

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Correlation analyses revealed a high correlation between mental demand, effort, and performance (r = -.956***, -.944***, and -.933*** respectively) and a moderate correlation between temporal demand and performance (r = .677***) as can be seen in Figure 2. Frustration showed a moderated correlation with performance, effort and mental demand (r = -.525***, .528*** and -.537*** respectively).

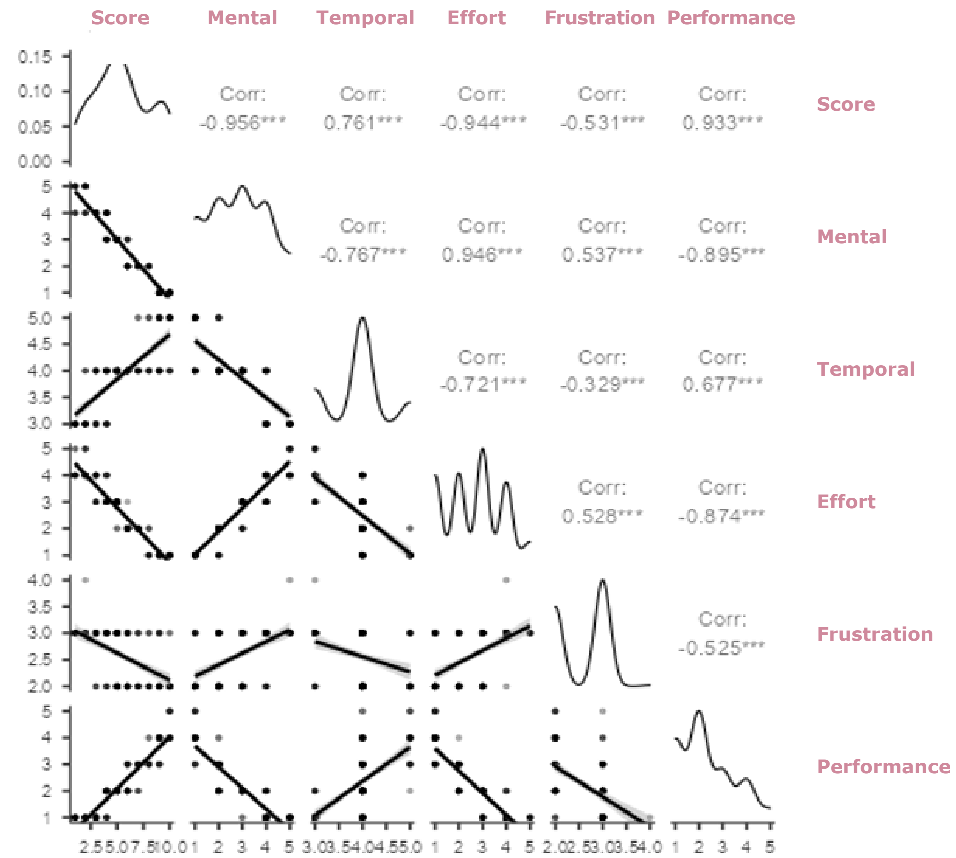

Figure 2. Correlation between variables.

Principal component analysis (PCA) was also conducted on the data, which revealed that performance was the most strongly correlated variable with academic performance in mathematics (r = .933***) as can be seen in Figure 3. This suggests that scores on the NASA-TLX, specifically in the performance dimension, can be used as a reliable predictor of future academic performance in mathematics.

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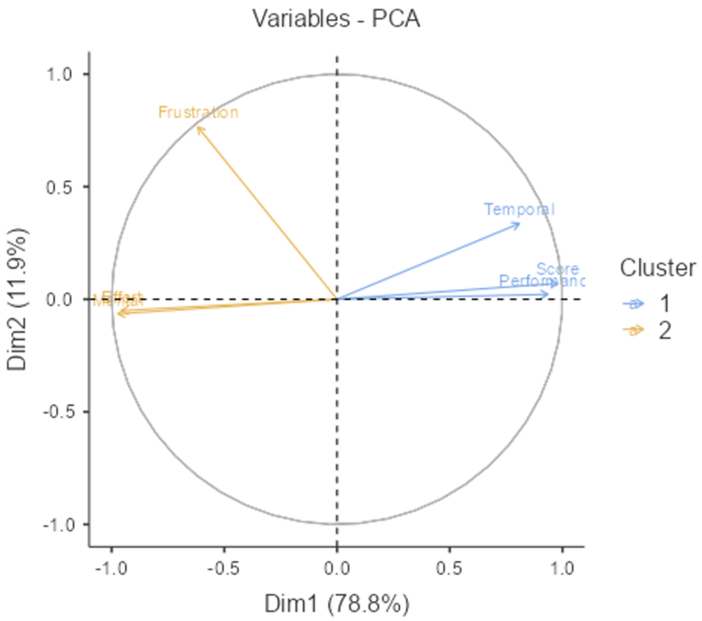

Figure 3. Principal component analysis.

It is important to note that the negative correlation between frustration, effort and mental demand with performance is due to the fact that these indicators are inversely proportional; a high value in frustration, effort or mental demand is negative, while a high value in performance or grade is positive.

3. Discussion

The present study aimed to investigate the relationship between cognitive load and academic performance in mathematics among high school students. Results indicated a strong correlation between cognitive load, as measured by the NASA-TLX, and academic performance in mathematics. Correlation analyses revealed a high correlation between mental demand, effort, and performance and a moderate correlation between temporal demand and performance. Furthermore, principal component analysis (PCA) revealed that the performance dimension of the NASA-TLX was the most strongly correlated variable with academic performance in mathematics. These results suggest that scores on the NASA-TLX, specifically in the performance dimension, can be used as a reliable predictor of future academic performance in mathematics. It is therefore important that the actions taken in the classroom are based on scientific evidence and that there is an interest on the part of the teaching staff to ensure that they are effective (Pizà-Mir et al., 2023).

These findings are consistent with previous research indicating a relationship between cognitive load and academic performance in mathematics (Menon, 2016; Ganor-Stern, 2016; Lee & Bull, 2016; Pizà-Mir et al., 2022; Swanson, 2004). For example, Gallistei & Gelman (2005) or recently Gilmore- et al. (2018) suggest that cognitive load plays a critical role in the

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acquisition of mathematical knowledge and that interventions aimed at reducing cognitive load can improve mathematical performance. Similarly, Swanson (2004), Ganor-Stern (2016), Lee & Bull (2016) found that working memory, a component of cognitive load, plays a critical role in mathematical problem-solving and that interventions aimed at improving working memory can lead to improved mathematical performance.

The results of this study have important implications for the field of mathematics education. The ability to predict academic performance in mathematics using a measure of cognitive load could have significant implications for the early identification of students at risk of poor performance in mathematics. This information could be used to provide targeted interventions to the curricula (Pizà-Mir, 2022a; Pizà-Mir 2022b) to improve mathematical performance and reduce the achievement gap in mathematics (Calhoon & Fuchs, 2003; Mull & Stilington, 2003; Wehmeyer et al., 2004).

In addition, understanding the relationship between cognitive load and academic performance in mathematics can inform the design and implementation of instructional strategies that aim to reduce cognitive load and improve mathematical performance (Sweller & Van Morriënboer, 1998; Van Morrënboer & Sweller, 2005).

4. Conclusions, measures, and prospective future research

The present study provides evidence for the relationship between cognitive load and academic performance in mathematics among high school students. The results of this study suggest that scores on the NASA-TLX, specifically in the performance dimension, can be used as a reliable predictor of future academic performance in mathematics. This information can be used to provide targeted interventions to improve mathematical performance and reduce the achievement gap in mathematics. Future research should focus on the development and implementation of interventions aimed at reducing cognitive load and improving mathematical performance.

The next paragraphs offer a series of possible measures and lines of future initiatives.

4.1 Measures

1. Longitudinal Study: Conducting a longitudinal study that follows high school students over an extended period would be beneficial. This would involve assessing cognitive load using the NASA-TLX and academic performance in mathematics at multiple time points to examine the predictive power of cognitive load on future performance. By tracking students' progress over time, researchers can gain a deeper understanding of how changes in cognitive load influence academic outcomes.

2. Intervention Studies: Designing and implementing interventions aimed at reducing cognitive load in mathematics education would be a promising area for future research. By employing instructional strategies that alleviate cognitive load, such as chunking information, providing scaffolding, or incorporating multimedia, researchers can investigate whether reducing cognitive load leads to improvements in mathematical performance. Comparing the effectiveness of different intervention approaches could provide valuable insights into optimizing instructional practices.

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4.2 Prospective Future Research

1. Individual differences: Exploring the role of individual differences in the relationship between cognitive load and academic performance would be valuable. Investigating factors such as working memory capacity, prior mathematical knowledge, and motivation could help identify specific student characteristics that moderate the impact of cognitive load on perform-ance. Understanding how these individual differences interact with cognitive load can guide the development of personalized interventions tailored to students' specific needs.

2. Metacognitive strategies: Investigating the use of metacognitive strategies in managing cognitive load during mathematics learning is another avenue for future research. Examining how students regulate their cognitive resources, such as through self-monitoring, self-reflection, and self-regulation techniques, could provide insights into effective strategies for reducing cognitive load. This line of inquiry could inform the development of interventions that promote metacognitive awareness and help students optimize their cognitive resources in mathematical problem-solving.

Overall, further research in these directions can contribute to a deeper understanding of the relationship between cognitive load and academic performance in mathematics. By exploring longitudinal patterns, implementing targeted interventions, considering individual differences, and examining metacognitive strategies, educators and researchers can work towards enhancing mathematics educatison by reducing cognitive load and improving students' mathematical performance.

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