Mathematical Resilience and Academic Science Emotion in Students: New Insights from Canonical Correlation Analysis

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Abstract: This research aims to explore the correlation between mathematical resilience and academic science emotion and provides new insights into this association through the application of canonical correlation analysis. The study involved a sample of 191 students from a state university in Central Java, Indonesia. Participants completed self-report measures to assess their levels of mathematical resilience and academic science emotion. Data was collected by randomly distributing questionnaires to students, evaluating five indicators of academic resilience (self-efficacy, planning, control, low anxiety, persistence) and three indicators of science emotions (class-related emotions, learning-related emotions, test emotions). Canonical correlation analysis was conducted to examine the multidimensional relationship between these variables and identify underlying patterns and associations. The analysis, conducted using R programming, yielded canonical correlation coefficients of 0.785, 0.396, and 0.119, indicating a significant positive linear relationship between the analyzed variables. These findings provide insight for educators and policymakers to design interventions that enhance both mathematical resilience and emotional well-being in science education.

Keywords: Academic; Canonical correlation; Mathematical resilience; Science emotion

Introduction

There is an urgent need to understand how mathematical resilience and academic emotion in science are interconnected. Both constructs play a vital role in students' success in mathematics and science education, yet research combining the two remains limited. Success in these subjects depends not only on conceptual understanding, but also on students' ability to manage challenges and regulate their emotions throughout the learning process. Unfortunately, many studies have found that students tend to show low interest in mathematics and science (Fong et al., 2021; Levy et al., 2021; Starr & Simpkins, 2021; Thompson, 2021). Furthermore, many studies have reported that Indonesian students have difficulties with the understanding of mathematics and science concepts (Mahmudah et al., 2022; Mulbar & Bahri, 2021; Nisrina

et al., 2021). These challenges have been exacerbated by the prolonged COVID-19 pandemic, which has further weakened students' academic resilience and emotional well-being. Although mathematical resilience refers to students' ability to overcome challenges in math, and academic emotions encompass their feelings during science learning (Knopik & Oszwa, 2021). Their interplay is still poorly understood, highlighting the need for research that explores their relationship in an integrated manner.

Previous research has indicated that student' emotions, such as anxiety, fear, or excitement, can significantly impact their ability to learn and retain information (Gómez-Rios et al., 2023). Anxiety, for instance, is one of the emotions commonly associated with learning. Students experiencing anxiety tend to have unpleasant feelings, such as restlessness, fear, or worry, which can disrupt their concentration and focus

during learning (Arribathi et al., 2021; Chamdani et al., 2021). Excessive anxiety can hinder students' cognitive processes, such as information processing, problem-solving, and memory recall of the learned content. By attending to and managing students' emotions, educators can create a positive and supportive learning environment, which, in turn, can enhance students' ability to learn, comprehend, and retain information taught within the contexts of mathematics and science.

Students' resilience in mathematics and science is vital for maintaining motivation and perseverance when faced with learning challenges. Mathematical resilience refers to their ability to overcome obstacles, including comprehending complex concepts, solving intricate problems, and grasping new mathematical tools. It involves confronting barriers, staying determined, and maintaining enthusiasm despite difficulties. Similarly, academic resilience in science is equally important as students encounter complex experiments, intricate theories, and challenging concepts. Resilient students are better equipped to persist, seek effective problem-solving strategies, overcome failures, and remain committed to deepening their understanding of the subject matter (Mahmudah et al., 2022).

However, the specific relationship between mathematical resilience and academic emotions in the context of mathematics and science education is still not well understood. This research aims to provide new and in-depth insights into the relationship between mathematical resilience and academic emotions through the use of canonical correlation analysis. This analysis will allow for the identification of potential relationships and patterns of association between variables in both constructs. It is expected that by employing this approach, this article can uncover a fresh understanding of how mathematical resilience and academic emotions mutually influence each other, as well as the potential factors that may play a role in this interaction.

By bringing together two important constructs that have been studied independently, this article addresses the need for research that links mathematical resilience and academic emotions. Using canonical correlation analysis, the article aims to uncover the underlying relationship between these variables and provide a comprehensive understanding of their interplay. Understanding the relationship between mathematical resilience and academic science emotions can have practical implications for educators, policy makers and practitioners. The findings of this research can be used to inform the development of interventions and strategies aimed at fostering mathematical resilience and the promotion of positive academic science emotions in students. These findings can guide the development of science learning strategies that are emotionally responsive and foster academic resilience, ultimately supporting more effective and inclusive STEM education.

Canonical correlation is used to measure the relationship between two multidimensional variables, treating one variable as dependent and the other as independent (Rohayana & Mahmudah, 2018). Canonical correlation analysis enables researchers to explore the multidimensional nature of mathematical resilience and academic science emotion simultaneously (Miao et al., 2021). By using this statistical technique, researchers can uncover the underlying patterns and connections between these constructs that may not be apparent through traditional correlation analyses (Wang et al., 2020). It offers a valuable analytical tool to investigate the complex interplay between mathematical resilience and academic science emotion. Instead of treating them as separate entities, this analysis allows for an examination of how the variables within each construct relate to one another and how they relate across constructs. This comprehensive perspective helps in identifying complex relationships and providing a more complete picture of the factors influencing academic outcomes.

Method

Data and Variables

This study was carried out in a university in Central Java. The sample data was obtained through the distribution of questionnaires to 191 samples that have been graduates of the mathematics and science courses or are currently in the process of graduation.

The validity and reliability tests found that the data could be analyzed further. Using the product moment correlation technique, it was found that all statement items were valid at the 0.05 significance level. Meanwhile, the Cronbach's alpha value produced a number of 0.60, which led to the fulfillment of the reliability test. Five academic resilience indicators: self-efficacy, planning, control, low anxiety, persistence (Martin & Marsh, 2006). The science emotions scale was based on the Achievement Emotions Questionnaire (AEQ) scale which included three indicators, namely class-related emotions, learning-related emotions, and test emotions (Pekrun et al., 2011). The questionnaire was designed using a Likert scale with four alternative responses: strongly agree, agree, disagree and strongly disagree. The 26-item and 24-item questions were used to measure the academic resilience in mathematics and science emotions variables, respectively.

An overview of the data in this study is as follows. The average age of respondents was 22 years old. The youngest respondent was 19 years old and the oldest was 24 years old. The majority of them were in their third year of study at university. More than half were

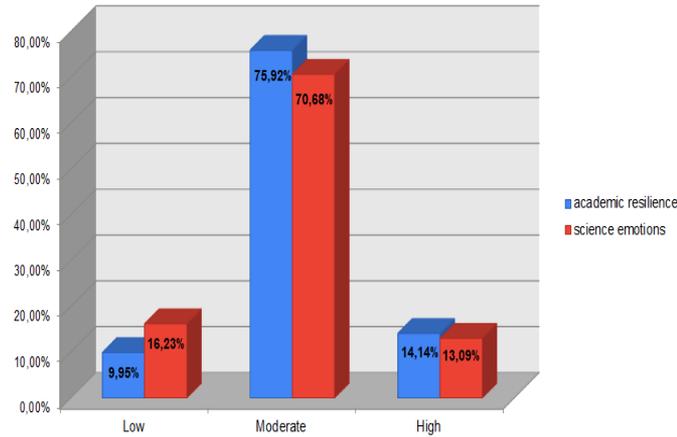female (56%). Meanwhile, 44% of respondents were male.

Figure 1. Levels of Student Academic Resilience and Science Emotions

In general, students' academic resilience in mathematics was in the moderate category, in which an indication that students had the ability to overcome obstacles, but were not completely free from difficulties. The majority of respondents had moderate academic emotions, in which more than 70% were in this category. Students who had low and high academic emotions were 16.23% and 13.09% respectively. These results indicated that the respondents' academic emotions were projected to be in the moderate category even though they were not supported by good conditions.

Canonical correlation analysis

Canonical Correlation Analysis (CCA) is a standard multivariate statistical analysis tool used to discover and quantify associations between two sets of variables (Rohayana & Mahmudah, 2018). CCA is aimed at maximizing the association between the low-dimensional projections of the two datasets. The CCA formulation can be explained as follows (Härdle & Simar, 2015). Suppose there are two random variables, namely $X\epsilon\mathbb{R}^q$ and $Y\epsilon\mathbb{R}^p$. The idea is to find an index that describes a relationship between X and Y. CCA is based on linear indices, that is, linear combinations of random variables $a^T X$ and $b^T Y$. The equation (1) is used to find the projections of a and b in maximizing correlation between the two indices (Härdle & Simar, 2015).

$$\rho(a,b) = \rho_a^T X_b^T Y \tag{1}$$

Suppose that

$$\begin{pmatrix} X \\ Y \end{pmatrix} = \left(\begin{pmatrix} \mu \\ v \end{pmatrix}, \begin{pmatrix} \Sigma_{XX} & \Sigma_{XY} \\ \Sigma_{YX} & \Sigma_{YY} \end{pmatrix} \right) \tag{2}$$

where the sub-matrices of this covariance structure are given by the following expressions.
$$Var(X) = \Sigma_{XX}(qXq)$$
$$Var(Y) = \Sigma_{YY}(pXp)$$
$$Cov(X,Y) = E(X-\mu)(Y-v)^T = \Sigma_{XY} = \Sigma_{YX}^T(qXp)$$

Then, the equation (3) can be written as follows

$$\rho(a,b) = \frac{a^T\Sigma_{XY}b}{(a^T\Sigma_{XX}a)^{\frac{1}{2}}(b^T\Sigma_{YY}b)^{\frac{1}{2}}} \tag{3}$$

Rescale projections a and b and thus we can solve the following problem

$$\max_{a,b} a^T\Sigma_{XY}b \tag{4}$$

With the constraints
$$a^T\Sigma_{XX}a = 1$$
$$b^T\Sigma_{YY}b = 1$$
Then,

$$\mathcal{K} = \Sigma_{XX}^{-\frac{1}{2}} \Sigma_{XY} \Sigma_{YY}^{-\frac{1}{2}} \tag{5}$$

Where $k = rank(\mathcal{K}) = rank(\Sigma_{XY}) = rank(\Sigma_{YX})$ and $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_k$ are the nonzero eigenvalues. Suppose $i = 1,2,\dots,k$ then the canonical correlation vectors are given by

$$a_i = \Sigma_{XX}^{-\frac{1}{2}} \gamma_i$$
$$b_i = \Sigma_{YY}^{-\frac{1}{2}} \delta_i \tag{6}$$

From the equation (6) can be derived the canonical correlation variables as follows.

$$\eta_i = a_i^T X$$
$$\varphi_i = b_i^T Y \tag{7}$$

Where the quantities $\rho_i = \lambda_i^{\frac{1}{2}}$ for $i = 1,2,\dots,k$ are called the canonical correlation coefficients (Härdle & Simar, 2015).

Result and Discussion

This research analyzed canonical correlations for the datasets X and Y, which were numerical resilience and academic science emotions. The canonical correlation analysis aimed to identify linear combinations of the X variables that had the highest correlation with linear combinations of the Y variables. The analysis produced three distinct dimensions, enabling a comprehensive examination of the significant relationships between the sets of variables. These

dimensions offer valuable insights into the underlying correlation patterns and structures that exist between numeracy resilience and academic science emotions. Leveraging the capabilities of R programming, the analysis revealed canonical correlation coefficients of 0.785, 0.396, and 0.119 for the first, second, and third dimensions, respectively. These coefficients represent the strength of the linear relationship between the variables. Specifically, they reflect the extent to which numeracy resilience and academic science emotions co-vary within each dimension.

The obtained coefficients hold substantial implications for understanding the interplay between numeracy resilience and academic science emotions. A coefficient of 0.785 in the first dimension indicates a strong positive linear relationship between the variables, highlighting a significant association between numeracy resilience and academic science emotions. Similarly, the coefficient of 0.396 in the second dimension signifies a moderate positive relationship, further demonstrating the interconnectedness between the two constructs. Although less pronounced, the coefficient of 0.119 in the third dimension still signifies a positive linear relationship between numeracy resilience and academic science emotions, albeit to a lesser degree.

These findings suggest that higher levels of numeracy resilience are likely to be accompanied by more positive academic science emotions. The significant positive relationships unveiled through the canonical correlation analysis provide empirical evidence supporting the notion that numeracy resilience and academic science emotions are interrelated constructs. Consequently, it can be inferred that enhancing numeracy resilience has the potential to positively impact students' emotional experiences in academic science settings.

Overall, this analysis sheds new light on the intricate connections between numeracy resilience and academic science emotions, advancing our understanding of the factors influencing students' learning experiences in mathematics and science education. By revealing the specific dimensions of their interrelationship and the magnitude of their association, this study contributes valuable insights for educators and researchers in devising effective strategies to foster both numeracy resilience and positive academic science emotions among students.

Table 1 presents the estimated coefficients of canonical correlation that elucidate the relationship between the variables of numerical resilience (X) and academic science emotions (Y). These coefficients serve as essential indicators, quantifying the linear combinations of variables involved in the canonical correlation analysis. By analyzing these coefficients, we can gain valuable insights into the strength and nature of the association between numerical resilience and academic science emotions, unveiling the underlying patterns and structures that characterize their interplay.

Table 1. The estimated coefficients of canonical correlation

Estimated coefficients		Dimension 1	Dimension 2	Dimension 3
Numerical resilience (X)	self-efficacy (X1)	0.073	-0.50	0.220
	planning (X2)	-0.159	0.337	0.539
	control (X3)	-0.025	0.235	-0.401
	low anxiety (X4)	-0.332	-0.322	-0.451
	persistence (X5)	-0.298	0.293	-0.013
Academic science emotions (Y)	class-related emotions (Y1)	-0.122	-0.467	0.336
	learning-related emotions (Y2)	-0.061	0.317	0.360
	test emotions (Y3)	-0.218	0.149	-0.472

The coefficients presented in Table 1 offer valuable insights into the strength and direction of the relationship between the variables within the numerical resilience and academic science emotions sets. These coefficients shed light on the significance and contribution of each variable to the corresponding canonical variate in X and Y. It is crucial to highlight that these coefficients are determined through the maximization of correlation between the canonical variates. The process involves solving an eigenvalue problem, where the eigenvalues provide information about the variance explained by each pair of canonical variates. The estimated coefficients are carefully selected to optimize the correlation between the canonical variates, ensuring a robust representation of the relationship between numerical resilience and academic science emotions.

Furthermore, in order to visualize the canonical correlation results from the linear combination of variables of numerical resilience and academic science emotions, they are given in Figure 1.

In Figure 1, the plot on the right provides an overview of the individuals included in the analysis, representing a randomly selected sample. However, it is the plot on the left that holds greater significance and relevance. The graph on the left provides the precise information sought through the analysis, effectively illustrating the directions of the original variables

represented by the two dimensions on the axes. By examining the proximity of the variables on the graph, we can gain insights into the relationships between the variables within the numerical resilience and academic science emotions data sets. This proximity reflects the degree of association or similarity between the variables, enabling us to discern patterns and interconnections that exist among them. In essence, the graph serves as a visual tool that enhances our understanding of the complex relationships and dependencies between the variables, thereby contributing to a more comprehensive interpretation of the numerical resilience and academic science emotions data.

Figure 1. Graphical outputs for canonical correlation analysis

In other words, The plot in Figure 1 is particularly meaningful, as it visualizes the relationships between variables across the two constructs—mathematical resilience and academic science emotions—by mapping them onto two key dimensions. The proximity of variables in this plot reflects the strength of their interconnection, allowing us to identify clusters of variables that share similar behavioral patterns. This visual representation enhances our understanding of the complex, multidimensional relationships that exist between emotional and resilience-related factors in science learning.

In contrast, Figure 2 presents the correlation pattern between the variables, commonly referred to as the correlation matrix. This matrix provides a comprehensive overview of the pairwise correlations among the variables within the numerical resilience and academic science emotions data sets. Figure 2 presents a comprehensive correlation matrix that quantifies the pairwise relationships among all variables in the two constructs. The matrix reveals the strength and direction (positive or negative) of each correlation, providing deeper insight into how specific variables within mathematical resilience align or diverge from emotional variables in the science learning context. Together, these outputs offer a detailed and nuanced view of how cognitive and emotional attributes interact in the academic environment, particularly in mathematics and science education.

Figure 2. correlation matrices

By examining the values within the correlation matrix, we can discern the strength and direction of the relationships between each pair of variables. The correlation matrix serves as a valuable tool for identifying variables that exhibit high positive or negative correlations, offering insights into the interdependencies and associations between the variables. It enables researchers and analysts to identify potential relationships and dependencies that may exist, further enhancing our understanding of the complex dynamics within the numerical resilience and academic science emotions domains.

The correlation matrix utilized in canonical correlation analysis is a comprehensive table that provides insights into the extent of correlation between each pair of variables within the numerical resilience and academic science emotions data sets. This matrix serves as a valuable tool in elucidating correlation relationships among all variables encompassed by both data sets. By examining the values within the correlation matrix, we can determine the strength and direction of the correlations between each variable pair, thereby identifying which variables exhibit a strong correlation and which variables do not. Furthermore, the correlation matrix enables us to discern the intricate patterns and structures that define the correlation relationships between the two sets of variables. This information plays a crucial role in understanding the interdependencies, associations, and potential influences that exist between the numerical resilience and academic science emotions domains, ultimately contributing to a more comprehensive analysis and interpretation of the data. Furthermore, the results of the tests of canonical dimensions are presented in the subsequent table, providing crucial information regarding the statistical significance of the obtained results. The significance test involves the utilization of three essential statistical tests.

Table 2. Canonical Dimensions Tests

Tstat	Dimension	Stat	Approx.	df1	df2	p-value
Wilks/ Lambda	1 to 3	0.319	17.253	15	506	0.000
	2 to 3	0.831	4.468	8	368	0.000
	3 to 3	0.986	0.891	3	185	0.447
Hotelling-Lawley	1 to 3	1.801	21.818	15	545	0.000
Trace	2 to 3	0.201	4.614	8	551	0.000
	3 to 3	0.014	0.895	3	557	0.444
Pillai-Bartlett Trace	1 to 3	0.787	13.156	15	555	0.000
	2 to 3	0.171	4.251	8	561	0.000
	3 to 3	0.014	0.902	3	567	0.440

These statistical tests play a fundamental role in assessing the validity and reliability of the obtained results, allowing researchers to make informed decisions regarding the significance and interpretation of the canonical dimensions. By employing these statistical tests, researchers can gauge the extent to which the observed associations and patterns between the numerical resilience and academic science emotions variables are statistically significant, thereby enhancing the credibility and robustness of the findings.

Table 2 displayed above presents the comprehensive analysis conducted to determine the significance of each dimension in the study. The significance of the dimensions is assessed through rigorous statistical testing, which provides valuable insights into the relationships and patterns observed. The results obtained from the statistical tests reveal important information regarding the significance of each dimension and their combined effects.

Firstly, the analysis examines the combined significance of dimensions 1 and 3. The statistical tests performed indicate a significant relationship between these dimensions (F=417.253, p-value=0.000), demonstrating a strong association between the variables represented by these dimensions. This finding suggests that the variables encompassed within dimensions 1 and 3 collectively contribute to the overall understanding of the research phenomenon. Subsequently, the analysis extends to assess the significance of combining dimensions 2 and 3. The obtained results reveal a statistically significant relationship between these dimensions (F=4.468, p-value=0.000), indicating a meaningful association between the variables represented by these dimensions. This finding implies that the variables within dimensions 2 and 3 jointly contribute to the understanding of the research domain, highlighting their interdependence and shared influence on the study's outcomes. Lastly, a specific examination is conducted to evaluate the significance of dimension 3 individually. The statistical tests indicate that dimension 3 does not exhibit statistical significance (F=0.891, p-value=0.447), implying that the variables within this dimension do not play a substantial role in explaining the research phenomenon. This finding suggests that dimension 3 may not contribute significantly to the overall understanding of the relationships under investigation.

The first dimension primarily represents the intersection between mathematical resilience **and** positive academic emotions, such as interest, confidence, and enjoyment in science learning. Students scoring highly on this dimension tend to demonstrate strong perseverance in the face of mathematical challenges and maintain a constructive emotional orientation toward science subjects.

For students in this category, science instruction should incorporate challenge-based and inquiry-driven

approaches, such as problem-based learning, open-ended experiments, and exploratory projects. These learners thrive in environments that emphasize autonomy, curiosity, and active engagement. Leveraging their intrinsic motivation and emotional readiness, teachers can design tasks that push cognitive boundaries while maintaining emotional support. The second dimension, by contrast, reflects the association between negative academic emotions (e.g., anxiety, frustration) and low levels of mathematical resilience, characterized by self-doubt, avoidance of complex problems, and limited persistence. Students in this group are more emotionally vulnerable and may disengage when faced with challenging science content.

To support these students, science instruction should emphasize emotional scaffolding and structured guidance. Strategies may include step-by-step instructions, regular positive feedback, emotionally safe classroom environments, and interventions aimed at reducing anxiety—such as mindfulness practices or growth mindset training. Pair or group work and mentoring systems can also be used to gradually build students' confidence and resilience.

In summary, based on the results of the statistical tests, it can be concluded that dimensions 1 and 2 are both statistically significant, indicating their importance in explaining the research phenomenon. On the other hand, dimension 3 is found to be statistically insignificant, suggesting that the variables within this dimension have limited impact on the research outcomes. These findings provide valuable insights into the relative significance and contributions of each dimension, offering researchers a deeper understanding of the complex relationships and patterns within the study domain.

The significance of the dimensions refers to their contribution in explaining the observed variations in the data. When both dimension 1 and dimension 2 are considered significant, it indicates that these dimensions have a meaningful impact on the differences observed in the data. The test results reveal a strong relationship between dimension 1 and dimension 2 with the variables or phenomena under investigation, suggesting that these dimensions capture important patterns or characteristics. However, when dimension 3 is deemed non-significant, it implies that dimension 3 does not play a significant role in explaining the variations in the data. It could suggest that dimension 3 lacks a strong influence on the variables or phenomena under study, or there may be other dominant factors at play. In summary, these findings highlight the importance of dimension 1 and dimension 2 in influencing the data, while emphasizing that dimension 3 does not contribute significantly to the observed differences.

Conclusion

This research analyzed the correlation between academic resilience in mathematics and science emotions of undergraduate students by using canonical correlation analysis. The findings demonstrated a large and relevant relationship between academic resilience in mathematics and academic scientific emotions. Higher levels of mathematical resilience were connected with more pleasant and adaptive science emotions, whereas lower levels of mathematical resilience were associated with negative and maladaptive academic scientific emotional experiences. Furthermore, the analysis highlighted specific dimensions within mathematical resilience and academic science emotion that had the strongest associations. These findings provide valuable insights into the factors contributing to students' academic success, emotional well-being, and engagement in mathematics and science education. Specifically, higher levels of mathematical resilience were associated with more positive and adaptive academic science emotions, while lower levels of mathematical resilience were related to negative and maladaptive emotional experiences in the academic science domain. The implications of this research suggested the importance of fostering mathematical resilience and promoting positive academic science emotions among students. Educators, policymakers, and practitioners could utilize these insights to develop interventions and strategies aimed at enhancing students' resilience, emotional well-being, and overall academic performance in the fields of mathematics and science.

Conflicts of Interest
The author declares that there are no conflicts of interest in this research.

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