

Perceived Teaching Behavior and Academic Resilience as Predictors of Learning Motivation in Science: A Forecasting Study

Jabes V. Pontongan

Holy Cross of Davao College

DOI: <https://doi.org/10.47772/IJRISS.2026.100400375>

Received: 18 April 2026; Accepted: 23 April 2026; Published: 11 May 2026

ABSTRACT

Low motivation of students in science remains. This study examined learning motivation in science as predicted by perceived teaching behavior and academic resilience. Predictive research design was used. 178 randomly selected data from STEM students were analyzed via multiple linear regression. It was found that learning motivation in science was significantly forecasted by the predictors, partly affirming self-determination theory. Future studies may include other variables, replication of the method in other settings to account for the remaining 76% variance in the strength of the model. Qualitative study may identify themes which may be considered as potential factors.

Keywords: Teaching behavior, academic resilience, predictors of learning motivation, science, forecasting study

INTRODUCTION

Low motivation of students in science remains a problem in education (Mullis et al., 2020). Evidence shows that the students' loss in motivation is widespread across various educational (Ekmekci & Serrano, 2022). Similarly, García-Pérez & Peñaloza (2025) affirmed that science motivation is particularly fragile in middle school and is prone to stagnate or even decline.

In Israel, studies have demonstrated that there has been a remarkable decline in students' motivation in learning science (Fortus & Tuitou, 2021). Comparative research has shown that students exhibit no interest and have little internal motivation for science in various grade settings (Teppo, 2021). Similarly, studies in Asian settings have shown changes and a decrease in motivation for science across different grade levels (Van Vo & Csapó, 2022).

In the Philippines, students have a problem with their motivation in learning various STEM-related subjects (Punzalan, 2022). Also, Veneracion (2023) noted that a large portion of high school students find it difficult to remain motivated to learn science. In addition, Cubero and Villocino (2024) conducted research on student motivation in Davao City and found that students lose their motivation for science as they progress from the earlier years of schooling.

The decline in students' motivation in science is a serious issue as international assessments and systematic reviews have shown that the motivation toward science still declines (Mullis et al., 2020; Potvin & Hasni, 2021). This issue demands action, as motivation is a feature most often referred to as a prerequisite for long-term involvement and continuous participation in science learning (Schunk et al., 2020). Addressing this issue is crucial as it significantly impacts the academic performance of students. This study seeks to investigate the influence of perceived teaching behavior and academic resilience on students' motivation in learning science. By clarifying how improvements in these instructional practices can strengthen motivation, the research adds to the existing literature and supports efforts to promote stronger scientific interest and engagement.

Significance of the Study

This study addresses the decline in students' motivation in science by examining the perceived teaching behavior and academic resilience. It supports Sustainable Development Goal 4 (Quality Education) by

promoting improved teaching practices that enhance student engagement and lifelong learning. For the Department of Education (DepEd), the findings provide evidence to strengthen learner-centered instruction and develop resilient, motivated learners. For Holy Cross of Davao College, the study aligns with its vision-mission of forming competent, values-driven, and socially responsible individuals by fostering motivation and academic perseverance. Moreover, the study benefits teachers in improving instructional strategies and helps students build resilience, ultimately contributing to better academic performance and sustained interest in science learning.

Statement of the Problem

This study determined the significance of perceived teaching behavior and academic resilience as predictors of learning motivation in science among senior high school students. The study specifically aims:

1. To determine the levels of perceived teaching behavior in terms of instructional behavior, negative teaching behavior, socio-emotional behavior, and organizational behavior; academic resilience in terms of perseverance, reflective and adaptive help seeking, and negative effect and emotional response; and learning motivation in science in terms of intrinsic motivation, career motivation, self-determination, self-efficacy, and grade motivation;
2. To determine the significance of the correlation between perceived teaching behavior, and academic resilience, and the learning motivation in science; and
3. To determine the significance of the strength of the model for learning motivation in science, using perceived teaching behavior and academic resilience as predictors.

Hypotheses

Ho1: Perceived teaching behavior and academic resilience do not significantly correlate learning motivation in science.

Ho2: The model to predict learning motivation in science using teaching behavior and academic resilience as predictors is not significant

Theoretical Framework

This study is grounded on Deci and Ryan's Self-Determination Theory (1985, 2000), which focuses on human personality and motivation concerned with how the individual interacts with and depends on the social environment (Legault, 2017). Motivation comes when the three psychological needs; autonomy, competence and relatedness will be met.

In this study, the perceived teaching behavior variable indicated by Pössel et al. (2013) reconnects with relatedness. Likewise, academic resilience variable indicated by Glynn et al, (2011) relates with competence. Finally, students' learning motivation in science indicated by Cassidy (2016) associates with the motivation when the psychological needs will be met. Hence, only the competence and relatedness were used in the theory. Autonomy was excluded.

METHODOLOGY

This chapter presents the methods and procedures that the researcher used in conducting the study. It includes research design, locale of the study, sample and sampling technique, research instrument, data gathering procedures, data analysis, and ethical considerations.

Research Design

This study utilized predictive research design. Predictive research design is a type of research that focuses on forecasting future outcomes based on existing data and identified relationships among variables. It goes beyond explaining past phenomena by developing models that can estimate or predict future events or

behaviors (Gonzalez-Nucamendi, 2023). The goal of this design is to forecast future trends or outcomes and help in anticipating future outcomes and trends (Brand et al., 2023).

Locale of the Study

The respondents of this study are Grade 11 and 12 senior high school students enrolled in the STEM strand. They will be from public high schools in the Division of Island Garden City of Samal. These schools are chosen because of their established STEM programs, which equip students with a solid background in science, technology, engineering, and mathematics. Being public institutions, they serve a wide range of learners, giving the study access to varied perspectives on STEM education. At the same time, these schools play a central role in the city's educational system, making them ideal for exploring how perceived teaching behavior and learning motivation in science influence students' academic resilience. Including them in the study ensures that the findings are grounded in real classroom contexts, producing insights that are both practical and relevant for improving science education.

Sample and Sampling Technique

In this study, STEM students from the Division of Island Garden City of Samal enrolled during the school year 2025–2026 were selected as respondents. These students were chosen due to their extensive exposure to and experience in science-related subjects compared to learners from other academic strands. The respondents consisted of both minor and adult learners. For school selection, total enumeration sampling was employed, ensuring that all schools offering the STEM strand were included in the study. In selecting individual participants, simple random sampling was utilized, allowing each member of the population an equal chance of being chosen, as described by Thapa (2020). This approach minimizes sampling bias and enhances the representativeness of the sample. Using the Raosoft sample size calculator, a total of 178 respondents was determined. Subsequently, the Microsoft Excel random number generator was used to finalize participant selection. This process ensured the inclusion of diverse perspectives, thereby strengthening the generalizability and reliability of the study's findings.

Data Gathering Technique

The survey technique was used in gathering data. Survey methodology involves gathering data from a sample population through structured questionnaires to outline the traits, views, or actions of a broader group. In research, it enables efficient evaluation, testing, or extrapolation of results to a specific population (Goodfellow, 2023). Key benefits include access to vast and varied groups, generation of measurable data for identifying trends, facilitation of generalizations, quicker data gathering, and enhanced reproducibility via uniform protocols (Zimba & Gasparian, 2023).

In this study, three adapted and modified survey questionnaires were used. The first instrument, the teaching behavior questionnaire (TBQ-S) was adapted from the study of Pössel et al. (2013). It consists of 37 items designed to assess students' perceptions of concrete and specific teaching behaviors. A four-point Likert scale was used to describe the degree to which respondents perceived teaching behavior. The adapted instruments were pilot tested for reliability, with a Cronbach's alpha of 0.786.

The second instrument measured academic resilience and was adapted from Cassidy (2016). It is composed of 30 items, developed to measure the multidimensional construct of academic resilience. This questionnaire also utilized a four-point Likert scale to determine the extent of academic resilience. Pilot testing revealed Cronbach's alpha of 0.834.

The third instrument, which assessed learning motivation in science, was adapted from the study of Glynn et al. (2011). It includes 25 items focusing on factors that may affect students' motivation to learn science. Similar to the previous tools, this instrument employed a four-point Likert scale to measure the level of students' motivation on learning science and a Cronbach's alpha of 0.918.

Data Analysis Technique

There are three data analysis techniques used in this research. They are descriptive analysis, correlation analysis and multiple linear regression analysis.

Descriptive data analysis, also known as descriptive statistics, is the process of organizing, summarizing, and presenting data to describe its main characteristic. Measures such as mean, and standard deviation is used as statistical treatment. It is primarily used to answer the question by identifying patterns, trends, and distributions within a dataset (Blbas, 2024; Dong, 2023). This type of analysis is typically applied at the initial stage of quantitative research to summarize large datasets and present the basic features of variables and respondents, serving as a foundation for further statistical analysis (Wolniak, 2023). Its advantages include simplifying complex data, enhancing interpretation, improving the clarity of data presentation, and supporting informed decision-making through objective and systematic reporting (Blbas, 2024; Wolniak, 2023).

Correlation analysis is a statistical method used to measure the strength and direction of the relationship between two quantitative variables, typically expressed through a coefficient ranging from -1 to $+1$ (Khatoon et al., 2024). It is applied when researchers aim to examine associations between variables in observational studies and is often used as a preliminary step before conducting more advanced analyses such as regression while it uses Pearson's r as its statistical treatment (Zhao & Jiang, 2023). Its advantages include simplicity, ability to identify relationships, usefulness in prediction, and its role as a foundation for further statistical analysis, although it does not establish causation (Sutradhar et al., 2023).

Regression analysis is a statistical method used to model and examine the relationship between a dependent variable and one or more independent variables, with the primary goal of predicting outcomes and determining how changes in predictor variables affect the response variable (Anandhi & Nathiya, 2023). It is applied when researchers aim to forecast trends, test hypotheses, and determine the effect or influence of one variable on another, particularly in quantitative and observational research (Khan, 2023). It used Beta coefficients as statistical treatment. Its advantages include its ability to predict future outcomes, identify significant variables, measure the strength of relationships, and support advanced statistical analysis, making it a powerful tool in research and data analysis (Zapf et al., 2024).

In describing the level of the variables, the following classification scheme was employed.

| Scale | Level | Perceived behavior | teaching | Academic Resilience | Learning motivation in Science |
|-------------|-----------|--------------------|----------|---------------------|--------------------------------|
| 1.00 - 1.74 | Very low | Very Poor | | Very Weak | Very Weak |
| 1.75 - 2.49 | Low | Poor | | Weak | Weak |
| 2.50 – 3.74 | High | Good | | Strong | Strong |
| 3.75 – 4.00 | Very High | Very Good | | Very Strong | Very Strong |

For the interpretation of the Standard Deviation, the following classification was applied:

| Range | Description | Interpretation |
|------------------|---------------------------------|--------------------------------|
| $SD \leq 0.50$ | Highly consistent Responses | Strong and uniform perception |
| $SD = 0.51-1.00$ | Moderately consistent responses | Acceptable consistency |
| $SD = 1.01-1.50$ | Low Consistency Responses | Differing views or experiences |

| | | |
|-----------|--------------------------------|--|
| SD > 1.50 | Very low Consistency Responses | High variability and lack of consensus |
|-----------|--------------------------------|--|

For the interpretation scale of r-value, the following scheme is used as proposed by Guilford (1956):

| Computed <i>r</i> | Descriptive Interpretation |
|-----------------------------|-----------------------------|
| +/- 1.00 | Very High Correlation |
| Between +/- 0.75 – +/- 0.99 | High Correlation |
| Between +/- 0.51 – +/- 0.74 | Moderately High Correlation |
| Between +/- 0.31 – +/- 0.50 | Moderately Low Correlation |
| Between +/- 0.01 – +/- 0.30 | Low Correlation |
| 0.00 | No Correlation |

The following is the standard measure in describing the strength of the influence a variable:

| β Value Range | Strength of Relationship |
|-----------------------|--------------------------|
| $\pm 0.00 - \pm 0.09$ | Very Weak |
| $\pm 0.10 - \pm 0.29$ | Weak |
| $\pm 0.30 - \pm 0.49$ | Moderate |
| $\pm 0.50 - \pm 0.69$ | Strong |
| ± 0.70 and above | Very Strong |

RESULTS

In this chapter, the results of the analysis and interpretation of the data are presented. Specifically, presented are descriptive analysis, correlation analysis, linear regression analysis, and the summary of findings.

Descriptive Results

Table 1 is the descriptive table. It contains the variables involved in the study, namely, perceived teaching behavior, academic resilience, and learning motivation in science. It also contains the number of samples, the mean, and their descriptive interpretations

Table 1: Descriptive Statistics (n = 178)

| Variables | Standard Deviation | Mean | Descriptive Level |
|------------------------------------|--------------------|-------------|-------------------|
| Perceived Teaching Behavior | 0.32 | 2.87 | High |
| <i>Instructional Behavior</i> | <i>0.40</i> | <i>3.30</i> | Very High |
| <i>Negative Teaching Behavior</i> | <i>0.63</i> | <i>2.02</i> | Low |
| <i>Socio-emotional Behavior</i> | <i>0.42</i> | <i>2.96</i> | High |

| | | | |
|---|-------------|-------------|-------------|
| <i>Organizational Behavior</i> | 0.42 | 3.20 | Very High |
| Academic Resilience | 0.30 | 2.94 | High |
| <i>Perseverance</i> | 0.29 | 3.04 | High |
| <i>Reflective and Adaptive Help-seeking</i> | 0.43 | 3.43 | Very High |
| <i>Negative Effect and Emotional Response</i> | 0.63 | 2.35 | Low |
| Learning Motivation in Science | 0.45 | 3.21 | High |
| <i>Intrinsic Motivation</i> | 0.49 | 3.38 | Very High |
| <i>Career Motivation</i> | 0.53 | 3.22 | High |
| <i>Self-determination</i> | 0.52 | 3.13 | High |
| <i>Self-efficacy</i> | 0.49 | 3.17 | High |
| <i>Grade Motivation</i> | 0.62 | 3.16 | High |

For the variable Perceived Teaching Behavior, the overall mean score is 2.87, described as high. It indicates that students perceive their teacher’s teaching behavior as good. One indicator, namely negative teaching behavior obtained a mean score described as low, another indicator, namely socio-emotional behavior has a mean score described as High, while two other indicators namely instructional behavior and organizational behavior got a mean described as very high. Moreover, the Academic Resilience variable obtained an overall mean score of 2.94, which is categorized as high. It indicates that students have strong academic resilience. The indicator negative effect and emotional response obtained a mean score described as low, another indicator named perseverance obtained a mean described as high and finally one indicator that is reflective and adaptive help-seeking obtained a mean described as very high. Finally, the statistical results reveal that the respondents Learning motivation in science obtained a mean of 3.21, described as high. It denotes that the respondents have strong learning motivation. Among its indicators, only intrinsic motivation obtained a mean described as very strong; the rest are described as high.

Students perceived teaching behavior, academic resilience, and learning motivation in science positively, indicating generally strong levels across all variables, although teaching behavior and academic resilience showed some weaker areas related to negative behaviors and emotional responses. In comparison, learning motivation appeared to be the strongest among the three variables, with intrinsic motivation standing out the most, while the other variables showed a mix of high and very high positive indicators.

Correlation Results

Table 2 is the correlation table. It contains the two predictive variables, namely, perceived teaching behavior and academic resilience, and the criterion variable, which is students’ learning motivation in science. The table presents data on their r-value, p-value, the decision on the hypotheses, and its interpretation.

Table 2: Correlation Table (n=178)

| Variables | Learning Motivation in Science | | | |
|-----------------------------|--------------------------------|---------|-------------------|------------------------------------|
| | r-value | p-value | Decision on H_0 | Interpretation |
| Perceived Teaching Behavior | 0.40 | 0.001 | Reject H_0 | Moderate Low Positive, Significant |
| Academic Resilience | 0.42 | 0.001 | Reject H_0 | Moderate Low Positive, Significant |

As shown, the correlation between Perceived Teaching Behavior and learning motivation in science obtained a p-value of 0.001 which is less than 0.05 level of significance. This indicates that the correlation is significant. The corresponding r-value of 0.40 indicates that the correlation is moderate. This implies that for every unit change in perceived teaching behavior, there is a corresponding unit change in learning motivation in science. In addition, the correlation between Academic Resilience and learning motivation in science exhibits a p-value of 0.001 which is also less than 0.05 level of significance. It signifies that the correlation is significant. The corresponding r-value of 0.42 denotes that the strength of the correlation is moderate. This implies that for every unit change in academic resilience, the learning motivation in science also changes.

Both perceived teaching behavior and academic resilience have significant relationships with learning motivation in science, and the strength of their relationships is similar, as both show a moderate level of correlation. However, academic resilience shows a slightly stronger relationship with learning motivation in science compared to perceived teaching behavior.

Regression Results

Table 3 is the regression table. It contains the predictors, namely, perceived teaching behavior and academic resilience, and the criterion variable, which is learning motivation in science. The table also includes several columns: Predictor, Estimate, Standard Estimate, SE (Standard Error), t (t-value), p (p-value), and Decision on null hypothesis.

Table 3: Regression Table (n=178)

| Learning Motivation in Science | | | | | | | |
|--------------------------------|------|-----------------------------|---------------------------|------|-------|----------------------------|--------------------------------|
| | | Unstandardized Coefficients | Standardized Coefficients | | | | |
| Variables | B | Std. Error | Beta | t | Sig. | Decision on H ₀ | Interpretation |
| (Constant) | 0.70 | 0.33 | – | 2.09 | 0.038 | – | – |
| Perceived Teaching Behavior | 0.39 | 0.10 | 0.28 | 3.96 | 0.000 | Reject H ₀ | Positive Significant Influence |
| Academic Resilience | 0.46 | 0.10 | 0.31 | 4.38 | 0.000 | Reject H ₀ | Positive Significant Influence |

$$R = 0.49 \quad | \quad R^2 = 0.24 \quad | \quad F = 28.1 \quad | \quad p = 0.001$$

The regression analysis showed that the predictive model $LMS=0.39PTB+0.46AR + 0.70$ was statistically significant in explaining learning motivation in science, as evidenced by $F=28.1$, $p=0.001$. The p-value obtained which is less than 0.05 level of significance leads to the rejection of the null hypothesis. This signifies that the model for learning motivation in science is significant. It further indicates that the model provides a good fit to the data and reliably predicts students learning motivation in science.

Furthermore, the R^2 obtained as shown in the regression table [$R^2=0.24$] is denoting that the model to predict the criterion is weak but significant.

Summary of Findings

Based on statistical results, it was specifically found that:

1. Perceived teaching behavior and academic resilience variables have positive significant correlation with learning motivation in science.
2. The model to predict learning motivation in science, using perceived teaching behavior and academic resilience as predictors, is significant.

DISCUSSIONS

This chapter discusses the results of the descriptive, correlational, and regression analyses from the study. These discussions emphasize how the findings align with and support prior research. It also presents conclusions and recommendations drawn from the results and discussions.

Teaching Behavior and Academic Resilience, and the Learning Motivation in Science Correlation

The finding of the study stating that the perceived teaching behavior and academic resilience variables are significantly correlated with learning motivation in science, supports the claim that teacher support and teaching practices significantly influence students' learning motivation, indicating that the way teachers deliver instruction, provide feedback, and support students emotionally plays a major role in shaping students' motivation to learn (Asadpour et al., 2025). In addition, the current finding affirms the study of Guo et al., (2025) explaining that academic resilience is positively associated with students' motivation and learning engagement, suggesting that students who are more resilient academically tend to show higher motivation and persistence in their learning tasks.

On the other hand, the current finding contradicts Berdida (2023) who claims that academic resilience does not always directly relate to students' learning motivation, as it may instead function as a mediating or indirect factor influenced by other variables such as academic stress and self-directed learning, rather than having a direct significant relationship with motivation. While the study of Berdida was focused only on the urban area, the current finding was based on the data coming from both rural and urban area.

Model that predicts learning motivation in science using teaching behavior and academic resilience.

The claim of the study that the model to predict learning motivation in science, using perceived teaching behavior and academic resilience as predictors is significant, aligns with the study of Guo et al. (2025) claiming that teacher-related factors significantly predict students' motivation and learning outcomes, demonstrating that instructional support and teacher behavior can serve as strong predictors in models explaining student motivation and engagement. Moreover, the current finding also affirms Jara Cerdan et al. (2025) who explains that academic resilience significantly predicts students' motivation and related learning behaviors, confirming that resilience functions as a key predictor variable in models explaining student engagement and motivation.

In contrary, the present finding negates the idea of Abdolrezapour et al. (2023), explaining that academic resilience and related learner characteristics do not always directly predict academic motivation, as other factors such as self-efficacy may serve as stronger or more significant predictors, indicating that resilience alone may have limited direct predictive power in explaining students' motivation. It is worth mentioning that the study of Abdolrezapour et al. relied on a sample of only 120 respondents, while the present finding was drawn from a larger dataset of 178 respondents.

CONCLUSION

Based on the findings, it is concluded that students learning motivation in science significantly predicted by perceived teaching behavior and academic resilience, although the strength of the model to predict criterion variable is only 24%. With this, self-determination theory was partly affirmed positing that learning motivation in science can be significantly predicted by students' teaching behavior and academic resilience.

RECOMMENDATIONS

Based on the conclusion, future studies may include other potential variables to strengthen the model and to account for the remaining variance (76%) to predict the learning motivation in science. Additionally, this study may be replicated to other locale and involving different respondents. Finally, qualitative research may be undertaken to explore emerging themes and sub-themes to identify potential additional variables.

REFERENCES

1. Abdolrezapour, P., Jahanbakhsh Ganjeh, S., & Ghanbari, N. (2023). Self-efficacy and resilience as predictors of students' academic motivation in online education. *PLOS ONE*, 18(5), e0285984. <https://doi.org/10.1371/journal.pone.0285984>
2. Anandhi, P., & Nathiya, E. (2023). Application of linear regression with their advantages, disadvantages, assumption and limitations. *International Journal of Statistics and Applied Mathematics*, 8(6), 133–137. <https://doi.org/10.22271/math.2023.v8.i6b.1463>
3. Asadpour, M., Bakhshi, M. H., Mirzapour, P., & Shahabi, M. (2025). The motivational role of teachers: A systematic review of key factors influencing students' academic motivation. *European Journal of Psychology of Education*, 40(4), Article 133. <https://doi.org/10.1007/s10212-025-01039-0>
4. Berdida, D. J. E. (2023). Resilience and academic motivation's mediation effects in nursing students' academic stress and self-directed learning: A multicenter cross-sectional study. *Nurse Education in Practice*, 69, 103639. <https://doi.org/10.1016/j.nepr.2023.103639>
5. Blbas, H. T. A. (2024). Descriptive statistics. *IntechOpen*. <https://doi.org/10.5772/intechopen.1002179>
6. Brand, A., Sachs, M. C., Sjölander, A., & Gabriel, E. E. (2023). Confirmatory prediction-driven RCTs in comparative effectiveness settings for cancer treatment. *British Journal of Cancer*, 128, 1278–1285. <https://doi.org/10.1038/s41416-023-02144-x>
7. Cassidy, S. (2016). The Academic Resilience Scale (ARS-30): A new multidimensional construct measure. *Frontiers in Psychology*, 7, 1787. <https://doi.org/10.3389/fpsyg.2016.01787>
8. Cubero, G. D., & Villocino, R. E. (2024). Student engagement, academic motivation, and school climate: A structural equation model on academic self-efficacy in state colleges and universities in Region XI. *University of Mindanao Journal of Research and Technology*, 4(7). <https://uijrt.com/articles/v4/i7/UIJRTV4I70020.pdf>
9. Dong, Y. (2023). Descriptive statistics and its applications. *Highlights in Science, Engineering and Technology*, 47, 16–23. <https://doi.org/10.54097/hset.v47i.8159>
10. Ekmekci, A., & Serrano, D. M. (2022). The impact of teacher quality on student motivation, achievement, and persistence in science and mathematics. *Education Sciences*, 12(10), 649. <https://doi.org/10.3390/educsci12100649>
11. Fortus, D., & Tuitou, I. (2021). Changes to students' motivation to learn science. *Disciplinary and Interdisciplinary Science Education Research*, 3(1), 1–15. <https://doi.org/10.1186/s43031-020-00029-02>
12. García-Pérez, N. M., & Peñaloza, G. (2025). A scoping review of interventions on middle school students' attitudes towards science. *PLOS ONE*, 20(1), e0315757. <https://doi.org/10.1371/journal.pone.0315757>
13. Glynn, S. M., Brickman, P., Armstrong, N., & Taasobshirazi, G. (2011). Science motivation questionnaire II: Validation with science majors and nonscience majors. *Journal of Research in Science Teaching*, 48(10), 1159–1176. <https://doi.org/10.1002/tea.20442>
14. Gonzalez-Nucamendi, A., Noguez, J., Neri, L., Robledo-Rella, V., & García-Castelán, R. M. G. (2023). Predictive analytics study to determine undergraduate students at risk of dropout. *Frontiers in Education*, 8, 1244686. <https://doi.org/10.3389/feduc.2023.1244686>
15. Goodfellow, L. T. (2023). An overview of survey research. *Respiratory Care*, 68(9), 1309–1313. <https://doi.org/10.4187/respcare.11041>
16. Guo, W., Wang, J., Li, N., & Wang, L. (2025). The impact of teacher emotional support on learning engagement among college students mediated by academic self-efficacy and academic resilience. *Scientific Reports*, 15, 3670. <https://doi.org/10.1038/s41598-025-88187-x>

17. Jara Cerdan, A. S., Medina Sanchez, R. J., & Arbulú Ballesteros, M. A. (2025). Resilience and work stress in educational institutions: Mediation of motivation and time moderation. *Behavioral Sciences*, 15(7), 888. <https://doi.org/10.3390/bs15070888>
18. Khan, E. (2023). Regression analysis: An overview of techniques for modeling relationships between variables. *Journal of Statistics and Mathematical Sciences*, 9, 1–6.
19. Khatoon, A., Daud, A., & Amjad, T. (2024). Categorization and correlational analysis of quality factors influencing citation. *Artificial Intelligence Review*, 57, 70. <https://doi.org/10.1007/s10462-023-10657-3>
20. Legault, L. (2017). Self-Determination Theory. In V. Zeigler-Hill & T. Shackelford (Eds.), *Encyclopedia of Personality and Individual Differences*. Springer. https://doi.org/10.1007/978-3-319-28099-8_1162-1
21. Mullis, I. V. S., Martin, M. O., Foy, P., Kelly, D. L., & Fishbein, B. (2020). TIMSS 2019 international results in mathematics and science. International Association for the Evaluation of Educational Achievement. <https://timssandpirls.bc.edu/timss2019/international-results/>
22. Pössel, P., Rudasill, K. M., Adelson, J. L., Bjerg, A. C., Wooldridge, D. T., & Black, S. W. (2013). Teaching behavior and well-being in students: Development and concurrent validity of an instrument to measure student-reported teaching behavior. *Journal of Psychoeducational Assessment*, 31(3), 317–330. <https://doi.org/10.1177/0734282912464422>
23. Potvin, P., & Hasni, A. (2021). Interest, motivation and attitude toward science and technology at K–12 levels: A systematic review of 12 years of educational research. *Studies in Science Education*, 57(1), 1–38. <https://doi.org/10.1080/03057267.2020.1865287>
24. Punzalan, C. H. (2022). STEM interests and future career perspectives of junior high school students: A gender study. *International Journal of Research in Education and Science*, 8(1), 93–102. <https://doi.org/10.46328/ijres.2466>
25. Schunk, D. H., Meece, J. L., & Pintrich, P. R. (2020). *Motivation in education: Theory, research, and applications* (5th ed.). Pearson Education.
26. Sutradhar, A., Adhikari, A., Sutradhar, S. M., & Sen, S. (2023). Use of correlation analysis in educational research. *International Research Journal of Education and Technology*, 5(5), 731–737.
27. Teppo, M., Soobard, R., & Rannikmäe, M. (2021). A study comparing intrinsic motivation and opinions on learning science (Grade 6) and taking the international PISA test (Grade 9). *Education Sciences*, 11(1), 14. <https://doi.org/10.3390/educsci11010014>
28. Van Vo, D., & Csapó, B. (2022). Exploring students' science motivation across grade levels and the role of inductive reasoning in science motivation. *European Journal of Psychology of Education*, 37(3), 807–829. <https://doi.org/10.1007/s10212-021-00546-w>
29. Veneracion, E. (2023). Students' motivation and learning strategies on academic performance in science in the new normal. *Psychology and Education: A Multidisciplinary Journal*, 15(3).
30. Wolniak, R. (2023). The concept of descriptive analytics. *Scientific Papers of Silesian University of Technology: Organization and Management Series*, 172. <https://doi.org/10.29119/1641-3466.2023.172.42>
31. Zapf, A., Rauch, G., & Kieser, M. (2024). Regression analyses and their particularities in observational studies. *Deutsches Ärzteblatt International*, 121(5), 149–156. <https://doi.org/10.3238/arztebl.m2024.0032>
32. Zhao, B., & Jiang, X. (2023). Correlation analysis of regional education, finance and economic development in China. *Biomedical Journal of Scientific & Technical Research*, 53(5).
33. Zimba, O., & Gasparyan, A. Y. (2023). Designing, conducting, and reporting survey studies: A primer for researchers. *Journal of Korean Medical Science*, 38(48), e403. <https://doi.org/10.3346/jkms.2023.38.e403>