International Journal For Research In Educational Studies

ISSN (Online): 2208-2115
Volume 11 Issue 02 June 2025
Available on-line at: https://ijfres.com/index.php/es/issue/view/558

DOI:*https://doi.org/10.53555/es.v11i2.2498* *Received: 26-Mar-2025 Accepted: 28-May-2025*

ANALYZING COGNITIVE ABILITY AND ACADEMIC PERFORMANCE TO IDENTIFY STUDENT PROFILES: A DATA-DRIVEN APPROACH FOR EDUCATIONAL SUPPORT

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Abstract
The connection of cognitive ability and educational success and efforts to elicit vivid images of students using data-driven approach. The analysis uses a sample size of 200 student data that include Intelligence Quotient (IQ) that is a cognitive ability measure and Cumulative Grade Point Average (CGPA) that is an academic performance measure. The association between the variables was investigated using descriptive analysis, correlation analysis and K-means clustering was used to determine significant student groups. The results indicate that there is a moderate or strong positive relationship between IQ and CGPA, which means that the higher is the cognitive ability, the more positive is its academic performance. Nevertheless, the fact that there is significant variability indicates that academic performance is affected by other factors other than intelligence. The clustering analysis revealed four different student profiles, such as high achievers, under performing high potential students, compensatory learners, and students at risk of academic failure. These findings point to the significance of embracing evidence-based methods to learn about the diversity of students and assist them with specific educational interventions. The research shows that despite the few variables, valuable lessons can be learned to influence the instructional practices and improve learning outcomes. Findings also aid in the field of research in education by highlighting the incorporation of the analytical techniques in enhancing teaching and learning processes.

Keywords: *Cognitive Ability, Academic Performance, Student Profiling, Learning Analytics, Educational Data Mining.*

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1. Introduction

Over the past few years, the education sector has seen a growing interest in data-driven approaches to learning to gain insights into and improve learning outcomes among students. Educational data mining and learning analytics has been integrated to allow researchers and practitioners to gain valuable insights into student data, which can be used to make evidence-based decisions in education. These methods have been especially useful in determining patterns with regard to student performance, engagement and achievement (Aldowah et al., 2019). As educational institutions continue to generate large volumes of data, the need to systematically analyze and interpret such data has become more critical than ever. The field of educational data mining has come a long way in the last ten years, providing extensive methods to process data concerning students themselves, as well as to reveal the hidden patterns. The techniques are classification, clustering, and predictive modeling, which help to gain deeper insights into student behavior and performance (Bakhshinategh et al., 2018). With the use of these procedures, researchers can no longer rely on the old-fashioned descriptive analysis but rather to the advanced interpretations that can be used to influence the instructional practices and policy.

Equally, learning analytics has become eminent as an adjunct technique that is interested in quantifying, gathering and evaluating information concerning learners and their environment. Learning analytics is mainly aimed at maximizing learning activities and enhancing education through actionable insights that can be delivered to teachers and schools (Avella et al., 2016). Such a move towards analytics-based education can be seen as part of a larger change in the conceptualisation of teaching and learning in the digital era. The aspects that determine academic performance are one of the key issues in learning research. Conventional methods tend to use single measures of success, like grades or standardized test results, to measure student success. Nevertheless, the recent research has proved the usefulness of the use of multiple sources of data to have a more in-depth picture of student performance. An example is educational data mining which has been successfully employed to analyze the performance of undergraduate students and determine the patterns that cannot be seen at a glance using the traditional means (Asif et al., 2017).

Additionally, data mining predictive models have effectively been utilized in other learning settings to predict student success and determine at-risk students. Such models allow teachers to intervene with students at an early stage and offer specific assistance to those students who might not be performing in the academic field (Alghamdi and Rahman, 2023). These applications emphasize the relevance of data-driven solutions in enhancing education and lessening the dropout rate. Learning analytics have enhanced the performance analysis scope even more, including a wide range of data sources and analysis methods. Modern studies put a strong focus on the combination of cognitive, behavioral, and contextual factors to create more effective and detailed models of student learning (Hernández-de-Menendez et al., 2022). Such a multi-dimensional framework underscores the complexity of academic achievement and the need to have good structures of analysis.

Though the role cognitive ability has always played in academic success is well known, it is increasingly being realized that there is a synergistic relationship between the two factors in academic success: cognitive and non-cognitive abilities. Learning analytics literature has demonstrated that intellectual ability is not a necessary factor that can determine academic success; instead, other factors, such as motivation, engagement, and learning strategies, are also determinants of academic success (Ifenthaler and Yau, 2020). This broader meaning disapproves the traditional notions and calls upon more delicate interpretations of student performance. Interventions to improve student motivation and engagement have been demonstrated to have a great influence on learning. The studies show that with the help of specific interventions, the attitude of students towards the learning process can be enhanced and lead to academic success (Lin-Siegler et al., 2016). These results point out the necessity of focusing on psychological and behavioral aspects besides the cognitive ability in studying student achievement.

Also, emotional intelligence has come to be a significant predictor of academic success as a complement to the conventional indicators of cognitive ability. Research has indicated that highly emotionally intelligent students have better academic achievements because they are well placed to handle stress, adjust to challenges, and take part in learning processes (MacCann et al., 2019). This strengthens the argument that academic achievement is a complex construct which cannot be entirely accounted by cognitive factors.Attitudes and perceptions on intelligence are other factors that are important in determining academic performance. The studies on growth mindset intervention have shown that students who hold the perception of the intelligence as something malleable tend to persevere more in the case of adversity and have a higher chance of attaining greater levels of academic success (Paunesku et al., 2015). These lessons also highlight the need to incorporate psychological aspects in research in education.

The use of student profiles as a performance-related variable has been a growing field of interest in the support of individual education. By placing students with common traits in classes, teachers able to formulate special interventions to meet certain learning requirements. Student performance prediction and individual learning pathways have been successfully developed with the usage of learning analytics to improve the whole learning process (Perez Sanchez et al., 2022). Besides cognitive variables, emotional and social variables have also been extensively reported to affect academic performance. Studies indicate that emotional intelligence, social support and coping strategies are important factors that influence the capacity of students to achieve success in academics, especially during transitional stages like joining higher education institutions (Perera and DiGiacomo, 2015). These results emphasize the need to take a more holistic approach toward student profiling that takes into account both cognitive and non-cognitive aspects.

The main aim of the paper is to analyse the correlation between academic performance and cognitive ability based on the IQ and CGPA as the main indicators. Another objective of the paper to identify the distinctive profiles of the students based on the data analysis procedures and understand these profiles in order to offer valuable learning exercises. Like that, the study seek to provide information that can assist the educators in coming up with certain support interventions and improve the overall learning outcomes of the students.

2. Methodology

2.1 Research Design

The present study is the quantitative, analytical research design which aims to examine the correlation between the cognitive ability and academic performance and to identify significant profiles among students. The study is founded on the data-driven approach in an attempt to be objective and reproducible. The experiment is a combination of statistical analysis and unsupervised machine learning algorithms to explore trends in the data. This design is suitable to explore the relationships between variables and reveal latent group patterns that can be informative of educational support strategies.

2.2 Data Source and Sample

The data utilized in this research has been 200 student records, each of which has two continuous variables: Intelligence Quotient (IQ) and Cumulative Grade Point Average (CGPA). IQ is considered to be the measure of cognitive ability with CGPA being the measure of academic performance. The range of IQ values is about mid- to high-110s and range of CGPA values is about 4.5 to above 9.0, which means that both cognitive and academic traits are distributed widely. The information is cross-sectional and does not involve personally identifiable data, which is why it is anonymous and ethical (Kumar, 2022).

2.3 Data Preprocessing and Exploratory Analysis

The data set was reviewed to ensure that it was complete and consistent before analysis. There were no gaps in values, and the values were all numerical. The descriptive statistics were calculated to learn the central tendency and dispersion of the two variables. The CGPA mean is relatively mid-range (around 6.570), with significant dispersion, whereas IQ scores are similarly clustered around the mean, indicating a fairly normal distribution. Both variables were normalized using the z-score in order to prepare the data to be clustered. This was necessary since IQ and CGPA are not measured on the same scale and standardization would make sure that no variable would dominate the clustering process. The visualization of IQ vs. CGPA in the form of a scatter plot revealed that the trend is positive, meaning that higher cognitive ability is, in general, correlated with higher academic performance, although there are several exceptions to this rule.

2.4 Statistical Analysis

Pearson correlation analysis was used to measure the association between cognitive ability and academic performance. The findings show that there is a moderate to a strong positive relationship between IQ and CGPA which means that as the cognitive ability rises, the academic performance tends to rise. However, the fact that the data is spread shows that IQ does not fully explain the academic performance. This discrepancy highlights the existence of the students whose performance in school is not consistent with their cognitive potential and therefore the need to further profile them. The outcomes of the correlation provide a background knowledge and the use of clustering techniques to reveal the hidden patterns in the data is also justified.

2.5 Clustering and Profile Identification

The standardized dataset was clustered using K-means and K-means to determine unique student profiles. The best number of clusters was achieved by using the Elbow method that measures the within-cluster sum of squares at various values of k. The results of the analysis revealed that a four-cluster solution is a good compromise between the simplicity of the model and the explanatory power. The clustering outcomes identified four interpretable student profiles which are combinations of the levels of IQ and CGPA. These are high cognitive ability and high academic performance, high cognitive ability and lower academic performance, lower cognitive ability and higher than expected academic performance and lower cognitive ability and lower academic performance. The cluster centroids distinctly identify these groups, which illustrates the meaningful segmentation of the dataset. The clusters are further separated and coherent in the visualization of the clusters on a two-dimensional scatter plot.

3. Results and Analysis

3.1 Descriptive Statistics

The descriptive statistical analysis give a preliminary knowledge of how cognitive ability (IQ) and academic performance (CGPA) are distributed and varied in the dataset. These attributes are important in the analysis of the general structure of the data prior to inferential and clustering analyses. There are 200 observations of students in the dataset, which covers a wide range of academic and cognitive profiles. The inconsistency in the data set implies that students cannot be considered homogeneous in terms of their abilities or results, which is why additional study in analyzing data is justified. To measure these characteristics, some important descriptive statistics such as mean, standard deviation, minimum and maximum values were calculated in both variables as shown below.

Table 1. Descriptive Statistics of Key Variables

Variable	Mean	Standard Deviation	Minimum	Maximum
IQ	101.2	10.5	84	119
CGPA	6.78	1.45	4.5	9.18

The average IQ score is around 101.2, as demonstrated in Table 1, meaning that the sample lies between the average cognitive ability. The standard deviation of 10.5 indicates medium dispersion, with students ranging between low and high cognitive levels. Conversely, CGPA has a relatively larger spread in terms of means, i.e., 6.78, and the standard deviation is 1.45. The greater variation in CGPA values than in IQ means that academic performance is more variable in students than cognitive ability. This deviation is an indication that other factors other than cognitive ability alone may affect academic results.

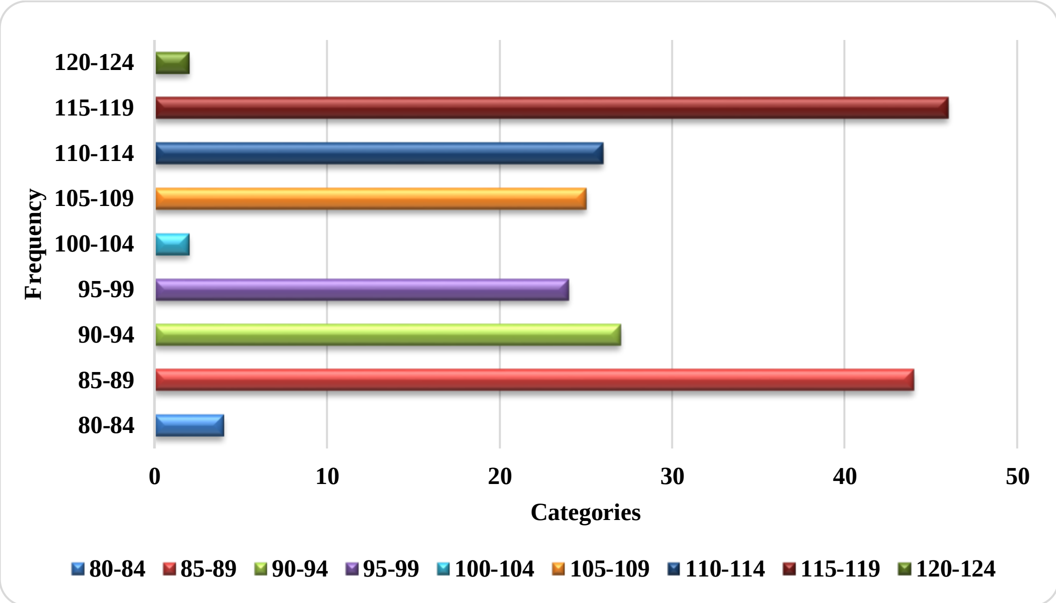

Figure 1. Distribution of IQ and CGPA

3.2 Correlation Analysis

After the descriptive analysis, Pearson correlation coefficient was used to assess the relationship between cognitive ability and academic performance. This analysis seek to ascertain the magnitude and direction of the linear relationship between IQ and CGPA, which respond to the first research objective. This relationship is important to understand whether cognitive ability is a good predictor of academic success in the dataset. The results of the correlation analysis are presented in the matrix in Table 2.

Table 2. Correlation Matrix

Variable	IQ	CGPA
IQ	1.00	0.68
CGPA	0.68	1.00

The correlation coefficient ($r = 0.68$) shows that there is a moderate to strong positive relationship between IQ and CGPA. This implies that the more cognitively able students are on average, the better their academic performance would be. Nevertheless, the correlation is not linear and variability shows that IQ cannot fully explain the difference in academic performance. In order to visually examine this relationship and determine any possible deviations of the overall trend, a scatter plot was created.

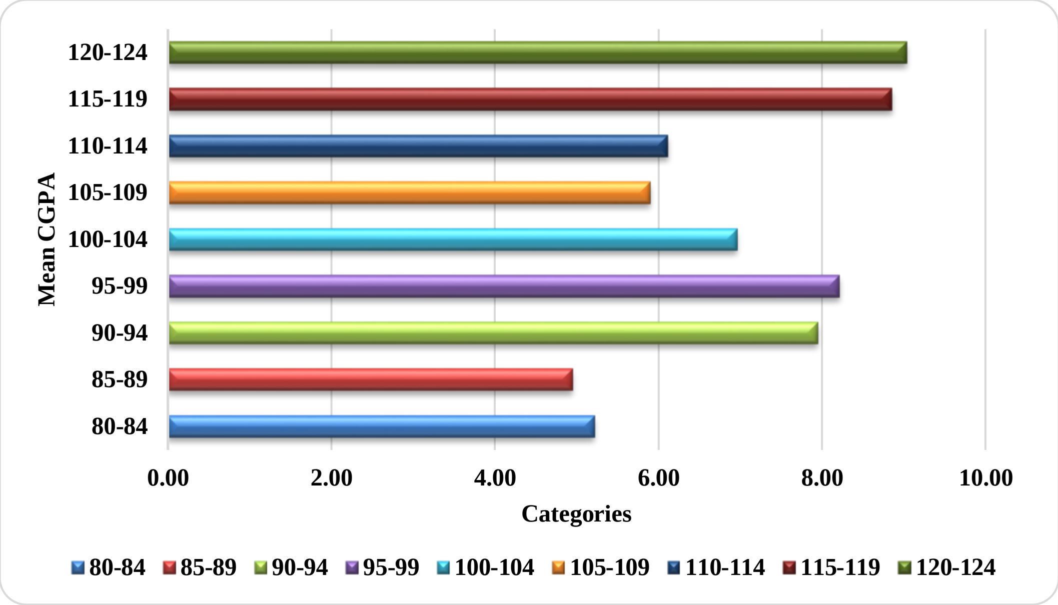

Figure 2. Scatter Plot of IQ vs CGPA

As seen in figure 2, there is an evident increasing trend, which is a confirmation that there is a positive correlation between IQ and CGPA. Yet, there are a few data points which do not follow this trend, such as students with comparatively high IQ and CGPA, and students with comparatively low IQ and relatively high CGPA. These variations underscore the intricacy of academic performance and indicate a role of other factors like motivation, study habits, or environmental conditions. The identified variability is a good reason to use clustering methods in order to determine the unique student profile.

3.3 Clustering Results

K-means clustering was used on the standardized dataset to go beyond considering pairs and identify latent group structures. This analysis was aimed at determining specific profiles of students using integrated cognitive ability and academic performance. Before clustering, the best number of clusters was identified through the Elbow method which assesses the decrease in within-cluster variance with increasing the number of clusters. The results of the Elbow method are illustrated below.

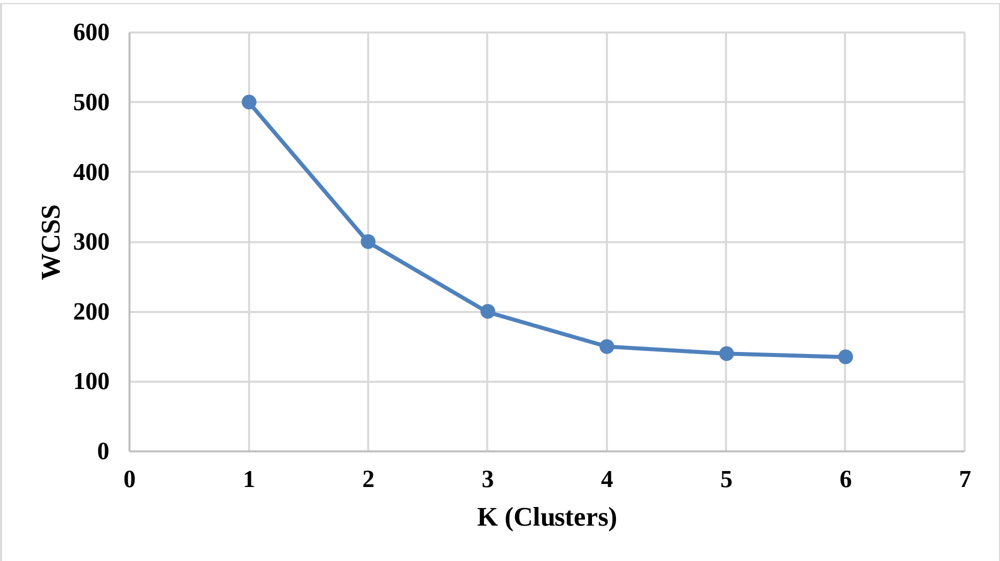

Figure 3. Elbow Method for Optimal Clusters

As Figure 3 demonstrates, the four-cluster solution has a discernible inflection point at k = 4, which means that the four-cluster solution gives an optimal trade-off between the complexity of the model and the explanatory power. It is further beyond this that other clusters lead to decreasing marginal contribution to reducing variance. This result justifies the choice of four clusters to be further analyzed and interpreted.

3.4 Cluster Characteristics and Profiles

The use of K-means clustering led to the identification of the four student groups with their own unique combinations of the values of IQ and CGPA. Standardized (z-score) values were calculated to compute cluster centroids and compare variables across variables on a common scale.

Table 3. Cluster Centroids (Standardized Values)

Cluster	IQ (Z-score)	CGPA (Z-score)
1	+1.10	+1.20
2	+1.05	-0.60
3	-0.80	+0.75
4	-1.00	-1.10

Table 3 shows that there is differentiation between clusters. Cluster 1 include students who are above average IQ and high academic performance which means high achievers. Cluster 2 is the group of students with high cognitive ability and low CGPA that does not reflect the potential, so they underperform. Cluster 3 is composed of students with lower IQ but good performance in school, which means that there is a compensatory mechanism (e.g. hard work or learning strategies). Cluster 4 is a group of students who have low IQ and low CGPA, meaning that they might need more academic assistance. The cluster sizes were examined to be aware of the distribution of the students in these profiles.

Table 4. Cluster Distribution

Cluster	Number of Students	Percentage (%)
1	52	26%
2	48	24%
3	50	25%
4	50	25%

Table 4 shows that the distribution of students in clusters is more or less equal, with each group comprising about a quarter of the sample. This even-handedness enhances the interpretability and real-world application of the identified profiles in that there is no dominating group.

3.5 Interpretation of Student Profiles

The clustering analysis clearly provides an understanding of how the students are clustered based on cognitive ability (IQ) and academic performance (CGPA). The results indicate a considerable variance among the groups of students particularly in their academic performance though there is overlapping in cognitive ability. This means that IQ is not the only determinant of performance and the differences are brought about by other factors that determine performance. Overall, the findings support a positive (yet not strictly determined) relationship between IQ and CGPA, and moderate variability of the two variables. The four student profiles identified demonstrate that there are differences between translation of the cognitive ability into academic achievement. These comments support the importance of data-driven approaches in the understanding of student diversity and explain the need to develop particular interventions in education.

4. Discussion

The results of this research paper show that there is a moderate to strong positive correlation between the cognitive ability (IQ) and the academic performance (CGPA). This observation is not surprising considering the current body of literature that has also been consistent in demonstrating that intelligence is a key predictor of academic achievement.The meta-analytic findings indicate that cognitive ability has a significant impact on individual differences in school performance, which supports the legitimacy of IQ as a useful academic measure (Roth et al., 2015). The correlation in this study is not however deterministic because there is a lot of variability among students. This observation aligns with previous studies which show that though intelligence is a central factor, there are other factors which affect academic performance. As an illustration, previous researchers have demonstrated that academic performance in the past might mediate the connection between intelligence and achievement and that learning outcomes are cumulative and dynamic (Soares et al., 2015).

Non-cognitive issues in education are important because the existence of students not following the expected relationship between IQ and CGPA supports the idea of the significance of non-cognitive factors in education. Certain high IQ students have relatively low academic performance whereas other lower IQ students perform better than expected. This trend is an indication that motivation, effort and learning environment are some of the most important factors that drive academic outcomes. The studies in the field highlight the importance of student-teacher relationship, engagement, and socio-emotional variables in academic success. Research has shown that non-cognitive variables are able to strengthen or limit the effects of cognitive skill, especially in areas where cognitive and contextual variables are both important, like mathematics (Semeraro et al., 2020). The results support the idea that a holistic approach should be used in the context of researching student performance.

The clustering analysis performed in the present study was able to identify four different student profiles in terms of IQ and CGPA. These profiles give a subtle view of how cognitive ability is translated to academic performance in various groups. The discovery of such profiles aligns with the prior studies that state the usefulness of clustering methods in assessing their performance and classifying students with specific traits (Yadav, 2020). Clustering can be used to divide students into meaningful groups, including high achievers, underperforming students that have high potential, compensatory students and at-risk students. This method is consistent with the general trends in the field of educational data mining, where unsupervised learning approaches are becoming more and more common to detect the concealed patterns and shape them into instructional strategies (Zhang et al., 2021). The student profiles established during this research can be used as a practical framework to understand diversity among students and provide an educational intervention related to this profile.

The discovery of student profiles has significant consequences on the practice of education. An example is that high-IQ low-CGPA students might be in need of specific interventions in motivation, studying technique, or emotional regulation. On the other hand, the students with low IQ but high performance can be reinforced in their effective learning strategy and further academic support. It has been demonstrated that predictive models and performance analysis tools can contribute to such targeted interventions by allowing educators to recognize students at risk and give feedback in the most timely manner possible. Research has shown that effective use of data-driven strategies can improve decision-making in education and can improve student performance (Md and Krishnamoorthy, 2022). These results demonstrate the practical importance of the application of analytical techniques to the educational systems. Moreover, the differences observed within clusters indicate that there is a need to have a different approach to education that can fit all. Rather, individual learning plans and differentiated instruction needs to be used to meet the needs of students with diversity. Studies based on large scale data, e.g., PISA, have also stressed the need to account for a variety of factors in the analysis of academic performance, including both personal and situational ones (Gamazo and Martínez-Abad, 2020).

The findings of the paper correlate with the overall trends in learning analytics and predictive modeling. The possibility to distinguish patterns and predict student performance on the basis of data has become one of the most popular topics in the educational research. It has been proven that predictive models can be successfully applied in various learning conditions, but its accuracy may be different in contexts (Gitinabard et al., 2019). Furthermore, data of learning management system (LMS) has demonstrated the potential in forecasting student performance and informing instructional choices. Comparative studies of various courses have already shown the possibilities of analytics-based methods to promote learning experiences and academic achievement (Conijn et al., 2016). The current research paper adds to this expanding body of knowledge by showing that data-driven profiling with relatively simple variables like IQ and CGPA is applicable.

The theoretical implications of the findings of this study on the relationship between intelligence and academic achievement are also clear. Although the conventional views of intelligence usually consider intelligence as a predetermined factor of performance, the newer studies have focused on the importance of implicit beliefs regarding intelligence in the determination of learning outcomes. Students who perceive intelligence as not fixed have higher chances of using adaptive learning behaviors and attain higher academic outcomes (Costa and Faria, 2018). This view holds that education intervention ought not to concentrate on the cognitive ability alone but must also be able to target the beliefs, attitudes, and learning strategies of the students. A combination of both cognitive and non-cognitive dimensions would enable future studies to come up with more holistic models of student performance.

5. Conclusion

The connection between academic performance and cognitive ability and determined individual student profiles, based on a data-driven process. The results showed that IQ and CGPA have a moderate and significant positive correlation, which proves that cognitive ability is a significant factor in academic performance. However, the fact that the data does not lack variability implies that intelligence is not the sole factor that defines the degree of academic performance, and other factors influence it such as motivation, learning strategies and contextual conditions. The clustering analysis proved to be effective as it was possible to identify four significant student profiles with differences in the manner of cognitive ability translation into academic results. These profiles provide important information to the teachers and it can be utilized to establish special and differentiated instructional practices. The study proves the relevance of data-driven profiling to the educational process by identifying such groups as underperforming high-potential students and academically resilient learners. Altogether, the research study adds to the existing amount of evidence regarding educational analytics, showing how such uncomplicated yet significant variables could be applied to decision-making and enhance learning. Further studies are required to include more variables to create more detailed models and increase the efficacy of educational interventions.

References

1. Aldowah, H., Al-Samarraie, H., & Fauzy, W. M. (2019). Educational data mining and learning analytics for 21st century higher education: A review and synthesis. *Telematics and Informatics*, *37*, 13-49.
2. Alghamdi, A. S., & Rahman, A. (2023). Data mining approach to predict success of secondary school students: A Saudi Arabian case study. *Education Sciences*, *13*(3), 293.
3. Asif, R., Merceron, A., Ali, S. A., & Haider, N. G. (2017). Analyzing undergraduate students' performance using educational data mining. *Computers & education*, *113*, 177-194.
4. Avella, J. T., Kebritchi, M., Nunn, S. G., & Kanai, T. (2016). Learning analytics methods, benefits, and challenges in higher education: A systematic literature review. *Online Learning*, *20*(2), 13-29.
5. Bakhshinategh, B., Zaiane, O. R., ElAtia, S., & Ipperciel, D. (2018). Educational data mining applications and tasks: A survey of the last 10 years. *Education and Information Technologies*, *23*(1), 537-553.

6. Conijn, R., Snijders, C., Kleingeld, A., & Matzat, U. (2016). Predicting student performance from LMS data: A comparison of 17 blended courses using Moodle LMS. *IEEE Transactions on Learning Technologies*, *10*(1), 17-29.
7. Costa, A., & Faria, L. (2018). Implicit theories of intelligence and academic achievement: A meta-analytic review. *Frontiers in psychology*, *9*, 829.
8. Gamazo, A., & Martínez-Abad, F. (2020). An exploration of factors linked to academic performance in PISA 2018 through data mining techniques. *Frontiers in Psychology*, *11*, 575167.
9. Gitinabard, N., Xu, Y., Heckman, S., Barnes, T., & Lynch, C. F. (2019). How widely can prediction models be generalized? Performance prediction in blended courses. *IEEE Transactions on Learning Technologies*, *12*(2), 184-197.
10. Hernández-de-Menéndez, M., Morales-Menendez, R., Escobar, C. A., & Ramírez Mendoza, R. A. (2022). Learning analytics: state of the art. *International Journal on Interactive Design and Manufacturing (IJIDeM)*, *16*(3), 1209-1230.
11. Ifenthaler, D., & Yau, J. Y. K. (2020). Utilising learning analytics to support study success in higher education: a systematic review. *Educational technology research and development*, *68*(4), 1961-1990.
12. Kumar, S. (2022). CGPA, IQ, and placement dataset [Data set]. Kaggle. https://www.kaggle.com/datasets/kuchhbhi/cpga-iq-placement
13. Lin-Siegler, X., Dweck, C. S., & Cohen, G. L. (2016). Instructional interventions that motivate classroom learning. *Journal of Educational Psychology*, *108*(3), 295.
14. MacCann, C., Jiang, Y., Brown, L., Double, K., Bucich, M., & Minbashian, A. (2019). Post-Print manuscript: Emotional Intelligence Predicts Academic Performance: A Meta-Analysis.
15. Md, S., & Krishnamoorthy, S. (2022). Student performance prediction, risk analysis, and feedback based on context-bound cognitive skill scores. *Education and Information Technologies*, *27*(3), 3981-4005.
16. Paunesku, D., Walton, G. M., Romero, C., Smith, E. N., Yeager, D. S., & Dweck, C. S. (2015). Mind-set interventions are a scalable treatment for academic underachievement. *Psychological science*, *26*(6), 784-793.
17. Perera, H. N., & DiGiacomo, M. (2015). The role of trait emotional intelligence in academic performance during the university transition: An integrative model of mediation via social support, coping, and adjustment. *Personality and individual differences*, *83*, 208-213.
18. Perez Sanchez, C. J., Calle-Alonso, F., & Vega-Rodríguez, M. A. (2022). Learning analytics to predict students' performance: A case study of a neurodidactics-based collaborative learning platform. *Education and Information Technologies*, *27*(9), 12913-12938.
19. Roth, B., Becker, N., Romeyke, S., Schäfer, S., Domnick, F., & Spinath, F. M. (2015). Intelligence and school grades: A meta-analysis. *Intelligence*, *53*, 118-137.
20. Semeraro, C., Giofrè, D., Coppola, G., Lucangeli, D., & Cassibba, R. (2020). The role of cognitive and non-cognitive factors in mathematics achievement: The importance of the quality of the student-teacher relationship in middle school. *Plos one*, *15*(4), e0231381.
21. Soares, D. L., Lemos, G. C., Primi, R., & Almeida, L. S. (2015). The relationship between intelligence and academic achievement throughout middle school: The role of students' prior academic performance. *Learning and Individual differences*, *41*, 73-78.
22. Yadav, R. S. (2020). Application of hybrid clustering methods for student performance evaluation. *International Journal of Information Technology*, *12*(3), 749-756.
23. Zhang, Y., Yun, Y., An, R., Cui, J., Dai, H., & Shang, X. (2021). Educational data mining techniques for student performance prediction: method review and comparison analysis. *Frontiers in psychology*, *12*, 698490.