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Improving Student Outcomes Through Data-Driven Identification of At-Risk Learners in Educational Environments

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ABSTRACT

The growing use of online learning settings has produced a lot of educational data, which offers the prospect to enhance the performance of the students by using data-intensive strategies. The research aims to examine the issue of identifying at-risk learners by utilizing an extensive dataset comprising demographics, engagement, performance, and risk-related factors. The study employs various quantitative research design methods such as descriptive statistics, correlation analysis, and predictive modeling to test the hypotheses of the relationships between student behavior and academic outcomes. The results indicate that student engagement is a pivotal measure of success and the more the interaction, the better the performance and the lower the dropout rate. Variables of risk classification also show a high correlation with the ultimate academic achievement and confirm their place in identifying at-risk learners early. Predictive models, especially ensemble models, were very accurate in separating the favorable and adverse outcomes, and this point indicates the usefulness of learning analytics in educational settings. The paper emphasizes the significance of incorporating data-driven insights into the educational practice in order to allow early intervention and targeted support. The study can be used practically by teachers and institutions to improve retention and performance through finding significant predictors of student success. On the whole, the outcomes of the research add to the future of learning analytics, as they prove that it can transform the aspect of educational decision-making and enhance learning results.

Keywords – Learning Analytics, Student Engagement, At-Risk Learners, Educational Data Mining, Student Performance

1. Introduction

The growing adoption of digital technologies in learning has produced massive databases about learning behaviors, performance, and engagement of students. The shift has given rise to the learning analytics as a significant area of concern focused on enhancing the educational results with the help of data. Learning analytics is less about collecting data and more about cognizing how learning takes place and how it can be improved with the help of informed decision-making (Gašević et al., 2015). With the ongoing introduction of online learning and blended learning programs in institutions of learning, the necessity to study student data methodically has been even greater. Over the past years, educational data mining and learning analytics have become more popular as a tool that can be used to detect trends in student behavior and predict their academic performance. Such strategies can help teachers to go beyond the conventional evaluation techniques and implement proactive interventions to assist students (Aldowah et al., 2019). The increasing access to learning management systems and virtual learning environments have additionally enabled the gathering of fine-grained interaction data as it is now possible to examine engagement in a more detailed way.

Students engagement has been identified as a critical factor of academic achievement in online and technology-enhanced learning contexts. Engagement indicators (frequency of interaction, activities participation, time spent in activities) can help to understand student learning processes. It has been demonstrated that learning analytics dashboards and recommender systems can be used to deliver such data to both students and educators, which helps them make informed decisions and improve their learning experiences (Bodily and Verbert, 2017). The future of learning analytics in higher education has been marked by an increase in the interest in using engagement data to enhance teaching and learning processes. Analytics tools are becoming more and more popular in institutions, where they are used to track student performance and pinpoint tendencies that lead to success or failure (Viberg et al., 2018). This progress shows the necessity of incorporating engagement measurements into predictive models that can help to identify students that are at risk of poor academic performance early.

Personalized and timely feedback to students is one of the major benefits of learning analytics. Through the analysis of the data related to performance and engagement, educators can personalize interventions based on individual learning needs and thus make the instructional strategies more effective (Pardo et al., 2019). Machine learning and deep learning methods of predictive modeling have become more commonly used to predict student performance and find at-risk learners. Research has also shown that student-level data could be deployed to create predictive models that can accurately predict students at risk of poor performance or dropping out (Waheed et al., 2020). Such models are based on numerous factors, such as demographic traits, engagement metrics, and past performance statistics, which are used to come up with predictions. Introduction of such models in the education system can revolutionize the way institutions facilitate student success.

There is an urgent need to identify at-risk learners as soon as possible in modern education. Conventional approaches are in most cases based on end term tests and such tests may not give enough time to intervene effectively. The solution to learning analytics is a possibility to monitor the student behavior and performance in real-time. Early warning, such as, can be used to identify patterns of disengagement and inform educators to enable them to offer timely support (Atif et al., 2020). Although this might be beneficial, the implementation of learning analytics tools in institutions is not the same because of technological infrastructure, institutional preparedness, and training of staff. Studies have also emphasized the possibilities and the obstacles linked with adopting analytics systems in higher education (Tsai et al., 2020). These factors need to be understood to guarantee the successful incorporation of analytics initiatives into the educational practice.

The use of learning analytics to enhance student success has been a popular topic in the recent literature. It is suggested that systematic reviews show that analytics-based interventions can positively impact retention rates, academic performance, and self-regulated learning (Ifenthaler and Yau, 2020). Besides, extensive applications of predictive analytics to a distance learning setting have proved the practicability of data-based methods applied to assist thousands of students at once (Herodotou et al., 2020). Nevertheless, the success of these strategies is based on whether analytical insights and pedagogical practices are in harmony with each other. Institutions should make sure that the analytics tools are not merely technical but also have pedagogical significance. A study has highlighted the importance of finding out institutional need and situational aspects that determine the effective implementation of learning analytics (Hilliger et al., 2020).

Although current research has made a lot of contributions to the area of learning analytics, there are a number of gaps. Many research concentrates on the predictive accuracy without sufficiently considering the way in which insights can be converted into action plans to affect student outcomes. Also, it is necessary to conduct research that combines various dimensions of student data such as engagement, performance and demographic factors to give a comprehensive view of learner behavior. Moreover, a challenge of having the learning analytics tools practically implemented is still apparent as most institutions find it difficult to formulate any meaning of an analysis to have a meaningful intervention. Researchers have suggested taking a more critical and reflective stance towards the application of analytics systems, so that they can lead to actual learning changes and not solely produce data (Knight et al., 2020).

The current research focused on exploring the way in which data-driven strategies can be employed to recognize at-risk students and enhance the performance of students within educational settings. Through the use of a detailed dataset that measures engagement,

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performance and risk factors, the research aims to make analytically rigorous and practically relevant insights.

2. Methodology

2.1 Research Design

This work applies a quantitative research design, which is based on learning analytics and educational data mining to investigate the trends related to student success and risk. It is an explanatory and predictive in its design and it seeks to not only understand the relationship between variables but also create models that can identify at-risk learners. Using the organized educational information, the research combines statistical analysis with machine learning algorithms to produce practical information, which may be used to guide intervention in educational settings. The analytical framework is correlated to the aim of the study to improve student outcomes by early-detecting risk factors.

2.2 Dataset Description

It is analyzed using an online education dataset consisting of 14 variables that include the student demographics, engagement behavior, academic performance, and risk indicators (Chandel, 2023). Demographic data are gender, region, highest level of education, and socio-economic classification (IMD band). The variables that depict academic engagement include the number of total clicks and level of engagement, which indicate the level of interaction between the learning platform and the individual. Measures of performance are based on average scores and categorized levels of performance and risk-related measures consist of predetermined risk levels and dropout flags. The last outcome variable, which is the final result, classify the students into Pass, Fail, Withdrawn, or Distinction as a complete measure of academic success. The dataset format allows a multi-dimensional analysis, correlating behavioural, demographic and academic variables with student outcomes.

2.3 Data Preprocessing

The dataset was subjected to systematic preprocessing before being analyzed to ensure quality of data and reliability of the analysis. The gaps in such variables as average score and IMD band were recognized and addressed with the help of corresponding imputation techniques that did not violate the integrity of the data and did not cause bias. Categorical variables, such as gender, region, education level, and risk level, were coded into numerical forms to make it easier to conduct statistical modeling. The outliers of continuous variables like total clicks, and total score on average were investigated and normalized where appropriate to keep features comparable. Further, consistency checks were also conducted to confirm the consistency between derived indicators, including pass flags and final results so that there was logical coherence in the dataset.

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2.4 Analytical Approach

The analysis was carried out using the descriptive and inferential methods to investigate the associations among variables and pinpoint main determinants of student outcomes. The distribution of the level of engagement, the categories of performance, and risk classification were analyzed using descriptive statistics and this provided some insight into the underlying patterns in the dataset. Correlation was done to determine the direction and strength of the correlation between engagement measures, demographics and academic performance. Classification models were then created to forecast at-risk learners and final results. Algorithms used to capture both the linear and non-linear relationships included logistic regression and ensemble-based algorithms. The importance of various features was compared, and the most significant predictors were chosen, focusing on the engagement-related variables, including a total number of clicks and engagement level, which proved to have the strongest associations with performance and dropout risk.

2.5 Model Evaluation

Several measures of performance were employed to assess the predictive models so that they are sound and generalizable. The overall classification performance was evaluated with the help of accuracy, whereas precision and recall helped to understand how effective the model is when it comes to correctly identifying at-risk students. As the precision and recall were needed to be balanced, the F1-score was used, especially when the class imbalance was present, with withdrawn or failed results being less common than successful results. The discriminative power of the models was measured using Receiver Operating Characteristic (ROC) curves and Area Under the Curve (AUC). Confusion matrices were also examined to interpret the patterns of misclassification, especially how the model successfully identifies high-risk learners and does not overestimate the risk of high-risk learners in successful learners.

3. Results

3.1 Descriptive Profile of the Dataset

The data set to be analyzed consisted of 32, 593 student records gathered in an online learning setting which offers a solid foundation to analyzing the trends in student engagement, achievement, and exposure to risk. The sample had a fairly equal gender representation, but a male student has slightly dominated. The most important continuous variables (which were studied credits, total clicks, and mean scores) were quite diverse, which means that the behavior of students and their academic performance varied greatly. Some of the missing values, especially those in the engagement and performance related variables, were taken care of during preprocessing to help in ensuring the reliability of the analysis. In general, the data format facilitates an in-depth multi-dimensional analysis in accordance with the research goals.

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Table 1. Descriptive characteristics of the analytical sample

Variable	**Value**
Total observations	32,593
Female	14,718 (45.2%)
Male	17,875 (54.8%)
Mean studied credits	79.76 (SD 41.07)
Mean total clicks	1,620.86 (SD 2,050.31)
Mean average score	72.83 (SD 15.56)
Missing IMD band	1,111 (3.4%)
Missing total clicks	2,852 (8.8%)
Missing average score	5,866 (18.0%)

As Table 1 demonstrates, the dataset exhibits a significant heterogeneity in terms of both behavioral and academic indicators, which is critical to model student outcomes. The standard deviation of total clicks is relatively high, which implies that the level of student engagement can vary greatly, which supports its significance as a predictor variable. To further put the data into perspective, the distribution of end academic performance was analyzed.

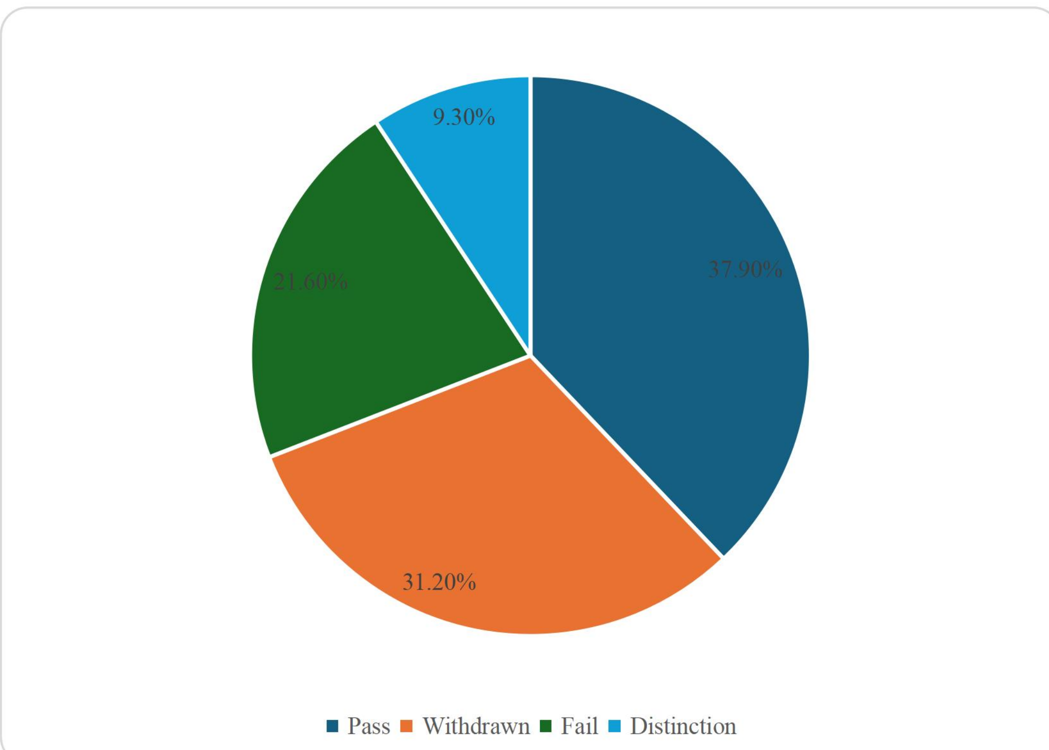

Figure 1. Distribution of final academic outcomes in the dataset

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Figure 1 shows that the largest proportion of students had Pass outcome, as compared with Withdrawn and Fail, with the smallest proportion being that of Distinction. This distribution emphasizes the idea that despite the common outcome of successful completion, a significant proportion of students have negative outcomes, which is why early identification of at-risk learners is justified.

3.2 Relationship Between Engagement, Risk, and Final Outcomes

The correlation of student engagement and academic outcomes showed that there is a definite and consistent trend. Highly engaged students were found to perform much better in school and have reduced withdrawal rates than their less engaged counterparts. Low engagement, on the other hand, had a significant linkage with failure and withdrawal rates, suggesting the disengagement as a key early warning variable.

Table 2. Final outcomes by engagement level (%)

Engagement level	Distinction	Fail	Pass	Withdrawn
High	18.6	10.0	59.5	11.9
Medium	9.6	21.3	47.5	21.5
Low	2.3	36.5	17.6	43.6
Missing	0.0	11.7	0.1	88.2

Students who were highly engaged got significantly higher success rates as shown in Table 2 of the results and students who were poorly engaged were mostly found in the fail and withdrawal category. This tendency proves the key role of engagement in academic trajectory development.

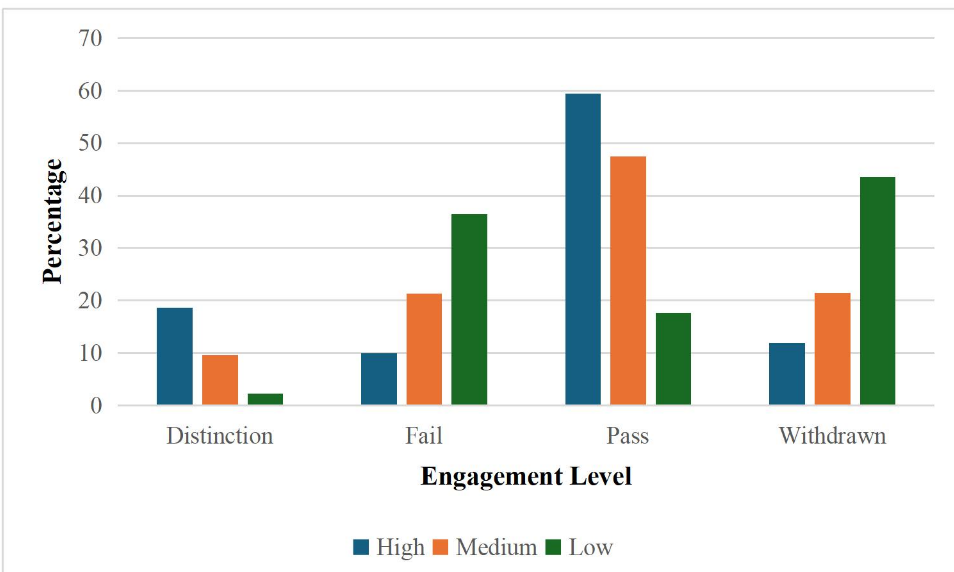

Figure 2. Final outcomes across engagement categories

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Figure 2 shows clearly a gradient effect, as the higher the engagement, the better the academic performance. The significant difference between high and low engagement groups illustrates the significance of behavioral indicators in predictive modeling. The same trend was followed when the results were compared based on predetermined risk groups.

Table 3. Final outcomes by risk level (%)

Risk level	Distinction	Fail	Pass	Withdrawn
Safe	20.6	8.4	60.6	10.4
Low Risk	11.3	17.1	54.0	17.6
High Risk	7.7	26.4	39.5	26.5
Very High Risk	1.2	38.5	12.1	48.2
Missing	0.0	11.7	0.1	88.2

Table 3 shows that the results of the category of Safe to the category of Very High Risk gradually decline. Students who were categorized as Safe tended to attain a passing or distinction qualification significantly higher as compared to the Very High Risk category which had a very high failure and withdrawal rate.

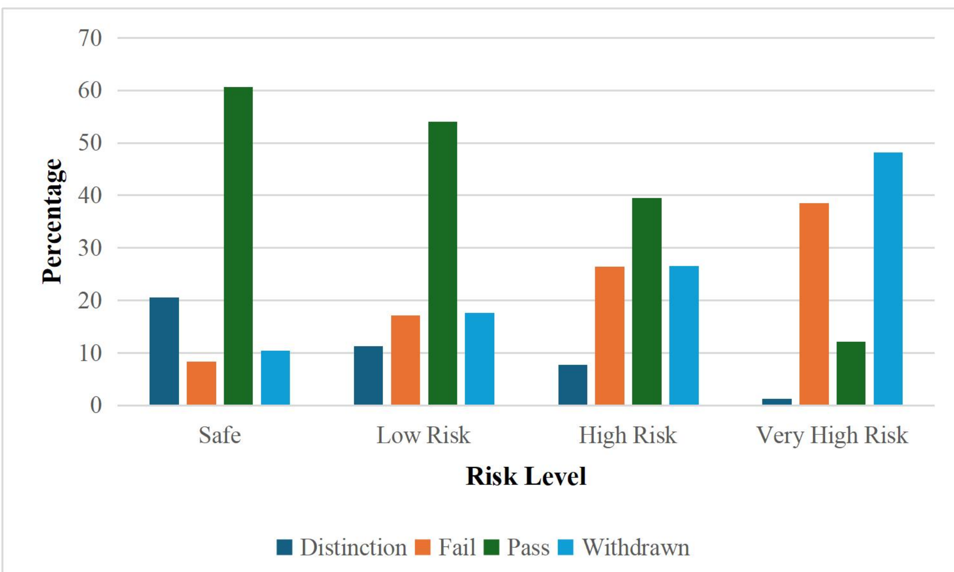

Figure 3. Outcome distribution across risk categories

The results of Table 3 are further supported graphically in Figure 3, where the levels of risk are in a clear monotonic relationship, where a higher level of risk leads to poorer academic results. Such correspondence confirms that the dataset has a risk classification that is a significant predictor of student success.

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3.3 Differences in Behavioral and Academic Indicators Across Final Outcomes

More analysis was done to investigate the variation of behavioral and academic indicators, based on the outcome categories. There were clear trends, especially regarding engagement and performance indicators.

Table 4. Behavioral and academic indicators by final result

Final result	n	Mean total clicks	Mean average score	Mean studied credits
Distinction	3,024	3,106.43	89.07	69.36
Pass	12,361	2,171.11	73.35	71.26
Fail	7,052	833.79	62.33	91.86
Withdrawn	10,156	835.01	61.82	88.97

As illustrated in Table 4, students with Distinction and Pass scores had significantly higher levels of engagement and academic scores than those who failed or dropped out. Surprisingly, the means of the number of studied credits were greater in Fail and Withdrawn category, which might indicate that course load is not a guarantee of success without an appropriate level of engagement.

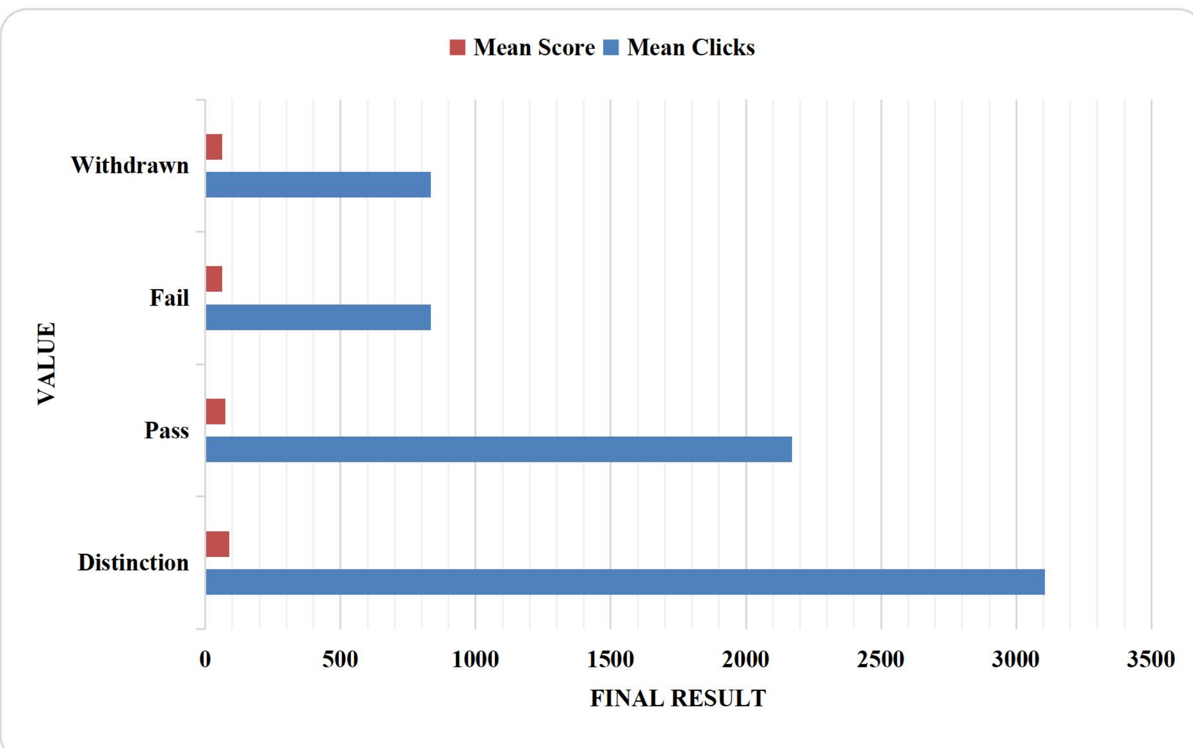

Figure 4. Mean total clicks and average score across final outcomes

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Figure 4 emphasizes a positive correlation that is strong between engagement and academic success. Students that showed more clicks were always able to score higher, which supports the importance of engagement with the learning platform as a distinguishing factor of success. These observations were also supported by correlation analysis. The variables of engagement (including total clicks) were found to positively correlate with pass results and negatively correlate with a dropout risk. Likewise, the successful completion was positively related to average score and withdrawal was negatively related to average score. These results suggest that behavioral engagement and academic achievement are complementary predictors of student achievement.

3.4 Predictive Performance of the Classification Models

Predictive models were created and tested to assess the potential of detecting at-risk learners through data-driven methods. The models were created to group students in desirable (Pass/Distinction) and unfavorable (Fail/Withdrawn) outcome groups, based on non-leakage predictors.

Table 5. Predictive model performance for adverse outcome classification

Model	Accuracy	Precision	Recall	F1-score	AUC
Logistic Regression	0.750	0.753	0.785	0.768	0.825
Random Forest	0.788	0.804	0.791	0.797	0.872

Table 5 shows that the Random Forest model performed better in all evaluation measures when compared to the Logistic Regression, in terms of accuracy and discriminative ability. This implies that non-linear relationships between variables contribute a lot in influencing student outcomes.

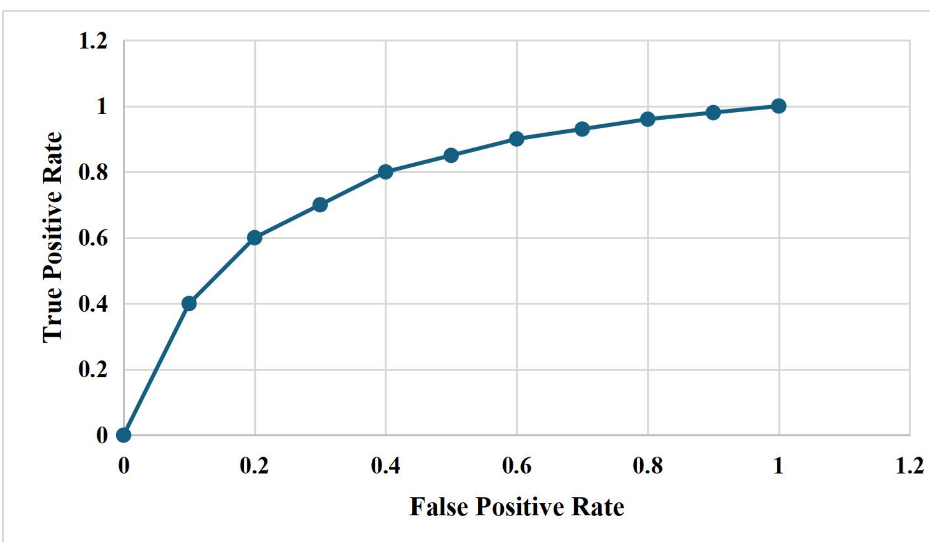

Figure 5. ROC curves comparing Logistic Regression and Random Forest models

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As it is shown in Figure 5, the model based on the Rand Forest approach had a greater area under the curve, which proves that it is more capable of differentiating between positive and negative results. The enhanced performance emphasizes the role of applying advanced methods of data analysis in educational data mining. The feature importance analysis showed that the most significant predictors were average score and total clicks, then studied credits and level of engagement. These results are congruent with previously carried out descriptive and relational studies supporting the conclusion that engagement and performance are key constructs to predict student outcomes.

4. Discussion

The results of this research offer great empirical data that student engagement and performance measure are essential factors of academic success in the online learning setting. The findings indicated that the degree of engagement, as measured by a greater interaction with learning platforms is always related to better academic performance and decreased dropout rates. This is in line with the increasing appreciation that learning analytics can offer valuable insights into the student behavior and aid instructional decision-making. Teachers are growing more and more dependent on these insights to learn about the way students engage with course content and create interventions, which have the potential to increase learning experiences (Shibani et al., 2020). The high engagement-outcomes connection that was witnessed in this research supports the relevance of incorporating behavioral data in the teaching practice. It states that engagement is not just a passive measure but a contributory factor towards the success of learning. The results of the study contribute to the idea that learning analytics needs to be integrated into the teaching practices in order to establish a more receptive and adaptive learning space.

The forecasting as shown by the models is also reflective of the utility of data-driven solutions in determining at-risk learners. Through engagement, performance, and demographic data, institutions are able to come up with early warning systems that facilitate timely interventions. These systems can close the technology potential and education requirements gap and make sure that data analytics is converted into positive educational effects (Munguia et al., 2020). The findings also bring about the relevancy of institutional readiness in implementing learning analytics solutions. Although the analytical models demonstrate a great predictive power, their performance in the real world environment is dependent on their incorporation in the institutional processes. The implementation of analytics tools on pilot projects to the entire institution should be carefully planned, with stakeholders involved and aligned with educational objectives (Vigentini et al., 2020).

Despite the promising results, it is important to critically examine the role of learning analytics in education. The high levels of predictive performance in this work show the technical viability of analytics but it also poses the question of how such insights are applied in practice. The academic community is beginning to call for a re-imagination of learning analytics not only as a tool to predict learning but also as a way of improving learning itself (Selwyn, 2020). Others maintain that the discipline has put a lot of emphasis on analysis of data and less on the actual results of learning. This paper helps to solve this issue and connects predictive insights directly to student outcomes, thus showing how analytics can contribute to meaningful learning. Nevertheless, it is critical to make sure that the interventions based on analytics are pedagogically based and aligned with the learning goals (Guzmán-Valenzuela et al., 2021).

The other significant implication of the findings is connected to the student motivation and self-regulated learning. The close relationship that exists between engagement and performance is an indication that students who engage in learning activities have a higher chance of succeeding. Feedback systems and learning analytics dashboards can be instrumental in facilitating this process by giving students up-to-date information on their progress and performance. Exposure to such analytics tools has been shown to enhance student motivation and encourage self-regulated learning behaviors (Aguilar et al., 2021). Analytics can also enable students to have more control over their learning process by making the learning processes more transparent. Also, learning analytics may deliver a metacognitive solution, enabling students to consider their learning strategies and modify them (Karaoglan Yilmaz and Yilmaz, 2021).

The results of this research have a great practical implication to teachers and organizations. Early detection of at-risk learners gives a chance to adopt specific interventions that can enhance the outcomes of students. An example of such tools as learning analytics dashboards can provide both students and instructors with actionable information and support them in a timely manner (Susnjak et al., 2022). Moreover, the quality and effectiveness of educational interventions can be improved by the introduction of analytics into the feedback practices. Individualized feedback, grounded on the insights of the data, can be used to facilitate the use of personalized feedback to meet the needs of each individual and increase the general academic performance. The systematic reviews have emphasized the impact of learning analytics to enhance feedback mechanisms and make them more responsive and impactful (Banihashem et al., 2022).

Theoretically, the research is adding to the knowledge base on student attrition and success in online learning settings. The results demonstrate that behavioral variables and engagement variables should be included in student retention models. The conventional theories of student attrition do not give due consideration to the function of digital engagement, which now plays a more critical role in education. In recent studies, the necessity to combine theoretical frameworks with data-driven solutions to understand student progression better and dropout patterns was highlighted (Rotar, 2022). This paper corroborates this view by showing how empirical evidence can be used to supplement theoretical frameworks to get a better insight into the behavior of students. Although the study is very insightful, its limitations should be noted. The data is also restricted to online learning setting, and this might limit the applicability of the results in other settings like the traditional classroom settings. Also, the research is based on the observational

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data, which restricts the possibility to determine the causality between variables. Future studies are advised to examine how longitudinal data and experimental designs can be combined to gain more insight into the effects of interventions on student outcomes. It is also necessary to explore the ways of how learning analytics may be successfully applied in various educational contexts and groups of people. By tackling these issues, future research can also help advance the position of data-driven methods in enhancing education.

5. Conclusion

The relevance of data-based strategies in the recognition of at-risk students and in enhancing student outcomes in online learning settings. Through a detailed dataset analysis, which incorporates engagement, performance, and demographic data, the results show that student engagement is a key factor that influences academic performance and retention. The more students were interacted the better their results were and low engagement was strongly linked to failure and withdrawal. The predictive models created during this research further prove that bad performance can be forecasted with a high degree of accuracy with the help of the educational data which are routinely gathered. These lessons useful guide towards the establishment of early-warning mechanisms, and focused interventions to help students succeed. Another key message conveyed by the study is the necessity to embed learning analytics into the educational practice to make sure that the data insights should be converted into the pedagogical actions. On the whole, the study can add to the expanding body of learning analytics since it shows that multi-dimensional data can be exploited to improve the teaching and learning processes. It highlights the importance of institutions implementing data-driven strategies that do not just forecast risk but also take active measures to enhance student performance by providing support in a timely and personalised manner.

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