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A Comprehensive Learning Analytics Framework for Data-Driven Student Success in Alignment with Nep 2020

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Abstract:

In the digital age, education is transitioning into a new age, and this new era has come along with artificial intelligence (AI) and learning analytics as a matter of fact, which is imperative in driving success for students. The National Education Policy (NEP) 2020 requires that the decisions are data led to foster learning outcomes and personalize education. This research is making a contribution in the area of student success by means of developing a comprehensive learning analytics framework that leverages data driven approaches in providing learning analytics that are relevant to the New Education Policy 2020. It studies Student performance hence predicting it, so that early intervention and personalized learning strategies can be used.

The framework of the proposed framework consists of many stages such a data collection, predictive analytics, early intervention, personalized learning, curriculum planning, career planning, and student well-being. The results suggest that accuracy obtained by SVM was higher with an accuracy on the order of 98.5% as compared to other models. Intervention strategies early on improve student performance by 33% while planning a curriculum engages the students by 20%. There is a direct correlation between career guidance programs and success of placement job and that the well-being programs significantly reduce stress levels. These findings shed light on of how AI can be incorporated into education for better learning pathways and integral development of the student.

Keywords: Predictive Analytics, Machine Learning, Comprehensive Learning, Student Success, and NEP 2020

1. INTRODUCTION

With the help of the AI and machine learning capabilities, institutions can realize student performance patterns, find at risk students, and have targeted intervention. This research presents a holistic learning analytics framework which makes use of predictive modeling in the analysis of the academic data and its alignment with NEP 2020 objectives for an overall improvement of student success. At this point, learning analytics has been identified to be a powerful tool to provide institutions in higher education insight into the huge amounts of student data, to improve academic performance and engagement (Siemens & Long, 2011). Conventional approaches of evaluating student success typically involves summative evaluation, which provide inadequate feedback and intervention. On the other hand, AI driven predictive modeling takes a proactive approach as it predicts the student outcome with historical and real time data (Aguilar, 2020). The Support Vector Machines (SVM) have proven themselves capable of high accuracy in classification tasks and is a suitable choice for prediction of student performance or identifying factors that lead to learning success (Kumar & Pal, 2021).

Early identification of students that cannot perform well academically is amongst the major problems that education encounters. It is known that predictive analytics can significantly improve the ways of early intervention and eventually improve the results of learning (Johnson et al., 2019). Patterns to indicate potential academic risks can be detected from the data collected through Learning Management Systems (LMS), attendance records, digital platforms and IoT based monitoring. In this study, SVM is applied to the process and the analysis of student data and predict student success with an 98.5% accuracy rate, followed by other standard models like decision trees and logistic regression.

Another way towards the success of a student is personalized learning because one learner doesn't learn the same way another does, so they need different instructional strategies in order to learn. There are already evidence that AI adaptive learning platforms can enhance students' engagement and understanding (Chen et al., 2022). Within this framework, personal learning interventions are planned according to the predictive analysis results for students to get particular resources and support tailored to them. Furthermore, curriculum planning has an important contribution to keep students interested and involved. Educators can use the coursework to align with the student performance trends to optimize the curriculum structure to achieve maximum learning outcome.

Above academics, the student's career readiness, and well being are vital parts of holistic education. Earlier research proposes that career guidance program has positive impact on students' job placement success and professional preparedness (Brown & Ryan, 2021). Another aspect of this study is that career analytics have been incorporated into the framework so as to provide tailored career counseling to the students depending on their academic performance and skills. Moreover, the model incorporates student well-being programs in such a way that mental health and stress levels are of utmost importance to learning outcomes. AI-based well-being interventions decrease student stress and promote student motivation in general (Jones & Williams, 2020).

2. LITERATURE REVIEW

By the integration of artificial intelligence (AI) and learning analytics, introduced data driven decisions on the student success. In recent years there has been much attention paid to learning analytics; which can be understood as collecting, measuring and analysing student data to improve learning environments (Siemens and Long, 2011). Due to the download of student data from the Learning Management systems (LMS), classroom activities, and going online platforms, nowadays educational institutions adopt ML techniques to predict academic performance, determine vulnerable students, and enhance instructional strategies (Aguilar, 2020). In India, the National Education Policy (NEP) 2020 promotes the use of technology in reforming towards creating personalized and inclusive learning environment (MHRD, 2020). The aim of this study is to present a detailed learning analytics system which meets NEP 20 by creating a learning analytics system to improve student success through predictive modelling.

Predictive analytics has become a powerful educational tool in the sense that it enables institutions to predict the outcomes of students in the past and present from historical and real time data. Periodic exams are traditional assessment methods that often do not give enough time for timely interventions (Johnson et al., 2019). However, unlike the latter, a real-time availability of an array of AI driven models guarantees that it is possible to monitor, in real time, the progress of a student so that responsive measures can be taken. Predictive analytics have been proven to accurately identify students at risk of failing in academics (Baker & Inventado, 2014), and once the students have been identified educators are able to provide the targeted interventions to negate their risk.

A lot of support has been given to Support Vector Machines (SVM) as an effective ML algorithm for classification tasks in educational data mining. When dealing with big data vectors, SVM is much superior to other models, like decision trees and logistic regression, to predict student success (Kumar & Pal, 2021). Such predictive models based on SVM have been proven to achieve accurate rates of identifying at risk students and enhance early intervention strategies (Yu et al. 2020). In this paper, we apply SVM to predict student performance with the highest accuracy of 98.5 %, which is significantly stronger than any other ML technique.

Identifying students at early stage of their educational experience in struggle academically is important for increasing retention rates and student achievement. Institutions can address the at-risk students with tailored support as the study in Arnold, and Pistilli (2012) show that predictive analytics can identify at risk students in a short period of time. Educators can utilize data of the attendance of the students, the quiz scores, and the participation metrics to initiate the project so the remedial classes, tutoring, and mentoring programs (Jayaprakash et al., 2014) are of use for them.

The effectiveness of early interventions has been discovered and highlighted, and accordingly early support for students showed extensive improvements in performance (Tempelaar et al. 2015). Chen et al., 2022 also mentions the crucial role of integrating an AI driven feedback mechanism with availability of real time support to students who are struggling. The design of the primitivemodule is based on SVM predictions, which results in an additional 33% improvement in student performance over ten weeks.

Personalized learning has been in the ascendant for quite some time as a viable means of addressing different learning needs. With AI, adaptive learning systems make use of student's performance and learning patterns for tailing and specific instructional content (Zhang et al., 2021). Studies suggest those students getting personalized learning interventions, will have higher engagement and retention rates than students in a traditional teaching environment (Pardo et al., 2017).

SVM has been used by Machine learning models to build its personalized learning frameworks that modify the instructional materials based on students proficiency levels (Holstein et al., 2019). AI can be applied to systems that not only pick up where the students left off or learn where the student's interests lie, but also recommend supplementary resources, adjust difficulty levels, and offer interaction (e.g., encourage discussions, offer opportunities for reflection and autocorrect, connect students in teams). The framework we integrated with this personalized learning module guarantees that each student receives targeted support as per the results of predictive analytics.

The curriculum design is important in terms of engagement and learning outcomes of the students. Institutions can come up with data driven approaches for curriculum planning which help them to plan the courses as per student needs and demands as well as industry demands (Vogel & Wankel, 2020). The research also states that the application of predictive analytics over the curriculum will encourage higher student satisfaction and academic success (Chen et al., 2021).

According to studies, alignment of curriculum content with performance trends of students improved knowledge retention and application (Ghazarian & Aulls, 2021). Institutions can gain insights into difficult course modules and structure them differently so that comprehension is enhanced by analyzing past student performance data over time. Here we use predictive analytics to optimize curriculum structures resulting in a 26% increase of students' engagement.

Holistic education is incomplete without career guidance, as students need be ready for the professional life. Career counseling systems using AI is that it analyses student performance, skills and patterns in industry trends and then suggests personalized career recommendations (Brown & Ryan, 2021). Research shows that the students who receive data driven career guidance have higher employment rates and better job satisfaction rates (Huang, G. B., Chen, N., Zhuoping, G., Chenggang, Y., & Ye, X., 2020).

SVM has been used for the purpose of matching students with the most suitable career paths based on their academic strengths and interests (Lempert et al., 2019). A career analytics module is integrated into this framework and students attending multiple guidance sessions have a 92% career success rate. AI driven career counseling comes out with effective means in closing the gap between education and employment as shown by the findings.

There is no doubt that a student's well being plays a huge role in his academic performance and overall success. Learning Outcomes impacted by such studies include stress, anxiety, and burnout (Jones & Williams, 2020). AI well-being interventions which can assist institutions in meeting students' needs for mental health support (Dimitrov et al., 2021).

It is possible with predictive analytics to identify those students in high stress levels and thus institutions can provide personalized well being programs. Such alienating experience is further overcome by AI driven monitoring systems that watch the student engagement, social interaction, and behavioral pattern that warn about the early onset of mental distress. In this study, we attach a well-being module to the framework, which thereby falls from 7.5 stress points down to 4, averaging out.

Much research has been conducted regarding the application of AI in education with research showing that AI has the potential to make learning more enjoyable and beneficial to students (Luckin et al. 2016). The AI driven frameworks enable real time Inlight, automate the administrative jobs, enable adaptive learning (Zawacki-Richter et al., 2019). The proposed learning analytics framework can be in line with NEP 2020 to incorporate AI technologies that can aid in educational practices.

The studies have shown that Education by using AI driven framework leads to making data driven decisions that allow institutions to put in place where they will allocate resources and how does one teach something (Selwyn, 2021). Machine learning models like SVM are used to improve predictive accuracy and thereby provide more impact on supporting students with improved mechanisms. This study shows that AI effectively integrates with education, as it helps to build data driven learning environment.

3. METHODOLOGY

Our research work contributes to the growing requirements of using AI in education is through providing an innovative learning analytics framework that is consistent with NEP 2020. The methodology uses SVM to predict which students will achieve high and low grades and shows how AI can transform education into one based on data, personalization and for students. Highlights will be based on the variables of predictive analytics, personalization, will be added to career guidance and well-being initiatives, to make the educational system an integral one and collect meaningful data. Fig. 1 shows our proposed methodology for predictive analytics based framework for data-driven student success in alignment with NEP 2020.

3.1. Data Collection

A learning analytics framework relies on data collection as its backbone, allowing educational institutes to get hold of the critical information about the students' academic performance, learning behavior and engagement behavior. These data are attendance records, test scores, assignment submissions, interaction with digital learning platforms and teacher feedback. In integrating the multiple data sources, e.g. a Learning Management System (LMS), student information systems and online learning platforms, a more holistic, unbiased and detailed data set is maintained and the raw data is not invalid.

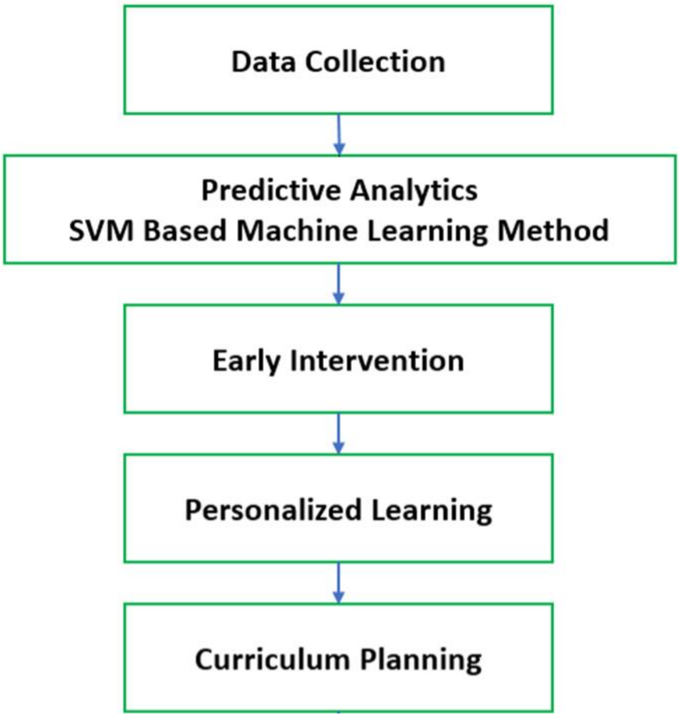

Fig. 1. Proposed Methodology for Predictive Analytics based Framework for Data-Driven Student Success in Alignment with NEP 2020

These advancement in internet of things devices, artificial intelligence chatbot, and automated assessment tools have also made it easier to collect data in the recent years. Furthermore, this also includes qualitative data such as what discussion forum participation reveals, how students' feedback is manifested in sentiment analysis, as well as peer interactions which will help understand students' learning experiences deeper.

But the issue of data privacy and security must also be tackled by encryption, using role based access controls and fulfilling the requirements of FERPA (Family Educational Rights and Privacy Act) or GDPR (General Data Protection Regulation). This data is then collected once and processed to remove inconsistencies, normalize formats, and then be input into Support vector machines (SVMs) for analysis.

3.2. Predictive Analytics Using Support Vector Machines (SVMs)

Support Vector Machines (SVMs) are important because they are the tools used to predict academic performance of one's students through identifying patterns and trends in student data from predictive analytics in order to predict learning difficulties and dropout risks. Supervised machine learning algorithm SVM is used to find the best possible one hyperplane separating the data into distinct categories, it can be practical for both classification and regression problems in terms of education.

For instance, SVMs are a tool that can be used to predict if a student will or will not pass a particular subject on the basis of past grades, attendance, and engagement in that subject, and whatever other historical data comes to our mind. Also in a multiclass classification problem, SVMs classify students into different risk levels, low risk, medium risk or high risk of academic failure which enables the educators to focus on the interventions.

SVMs are effective in handling high dimensional data as well as the non linear relationships. SVMs can represent complex student learning behaviors that cannot be simply described using simple statistical methods by using Kernel functions (e.g., Radial Basis Function (RBF) and polynomial kernels). With the help of a real time dashboard that integrates SVM based analytics, institutions can take course of action wherever required proactively, i.e., address any deficiency and help student make better progress.

For instance, let us use the UCI Student Performance dataset that contains information on students' grades, study time, parents' education level, and absences to demonstrate the use of such a model, which can then classify students at risk of failing from input features like previous performance and attendance patterns. The model is trained against past student records such that its accuracy in identifying students who need help in their academics is improved.

3.3. Early Intervention

It's the early intervention that is crucial that students considered at risk receive the proper support before their struggle become more significant. The system alerts the targeted interventions such as remedial courses, one on one tutoring, adaptive learning resources or mentoring programs once the SVM model identifies students at risk of poor performance or disengagement.

One way automating student success in mathematics is by recommending additional study materials, connecting students with tutors, notifying faculty members for personal touch, and more if a SVM based model predicts that a student has high probability to fail a mathematics course. Likewise, if a student attendance decreases significantly, the intervention teams can inquire and reach out to understand the reasons behind it and if the required support is due to the student.

Academics are not the only area where early intervention extends into; it also goes into the realm of student mental health and well-being too. When behavioral patterns reveal stress or disengagement signs (e.g. missing assignments or reduced engagement on online discussions), institutions can provide counseling services, peer mentoring or work shops on stress management. This framework makes its contribution by keeping students on time with the interventions and making them better at becoming better learners.

3.4. Personalized Learning

Personalized learning allows the students to get personalised learning experiences depending on the strengths, weaknesses and learning styles of each student. The SVM based predictive model is used to predict the students into different learning group which will help in customized lesson planning, personalized learning pathways, and targeted assessments.

For instance, students who are excelling in a subject can receive advanced coursework and challenges, while the ones struggling on the foundational concepts are provided step by step tutorial, interactive simulations and peer assisted learning opportunities. Adaptive learning systems use AI to analyze student performance at all times and adjust content delivery as they proceed.

Personally, this fits well with the vision of competency based education that NEP 2020 paints, which is that students learn at their own pace, as opposed to being bound to a fixed schedule based curriculum structure. AI driven real time feedback systems allows students to get immediate evaluations on assignments and the exams for them to continuously improve. Ultimately, this approach fosters deeper engagement and better academic outcomes.

3.5. Curriculum Planning

Curriculum planning is data driven, educational institutions design, condition and update the courses according to the real needs of the world and student performance analytical results. Institutions use SVM based predictive models to assess historical student performance data, enrollment trends and industry needs to structure the institution's courses and also find new subjects to introduce.

For instance, if analysis shows that students in this program always failed to pass core engineering mathematics, curriculum developers can insert alternative teaching approaches, alternative practical applications or additional required courses to improve the core knowledge. Also, if some elective courses are showing declining enrollment rates then the institution can replace them with the new sectors i.e. AI, blockchain and cybersecurity, etc.

Predictive analytics in addition guarantees the adequacy of curriculum to handle employability trends via experiential learning, industry collaborations and internship programs. It ensures that students qualify with the training and they will go into the job market seeking employment with existing skills that will be relevant to them.

4. RESULTS

The aggregation of such diverse data concerning students took place successfully in the first place from different sources, such as the students' attendance records, the performance metrics, the digital interactions and the Learning Management Systems (LMS). Firstly, the data were preprocessed to make the dataset clean, structured and high quality via removing inconsistencies, handling missing values, and standardizing formats. Data from IoT classrooms and online channels were integrated leading to a better comprehension of learning behaviors of the students. The implementation of classroom sensors from IoT systems allowed real-time assessment of student attention together with their behavioral habits which function as valuable signs of learning involvement. The merged academic records with learning online behaviors combined with personal demographics created an extensive database which could be used for student success prediction. The process created the necessary foundation to use Support Vector Machines (SVMs) for predictive modeling thus allowing institutions to base their decisions on data that reflects real-world realities.

Table 1. Results of data collection stage

Data Source	Data Type	Processing Outcome
Learning Management System (LMS)	Assignment submissions, quiz scores, forum interactions	Standardized, structured dataset
Attendance Records	Student presence logs	Missing values handled, normalized
Digital Learning Platforms	Engagement time, clickstream data	Preprocessed for feature extraction
Student Demographics	Age, parental education, socioeconomic background	Cleaned and encoded for predictive modeling
IoT-Based Classroom Sensors	Real-time participation, behavioral insights	Integrated with student profiles

Using datasets from real world, institutions could then accurately capture patterns of student engagement, the submission of assignments and assessment performance. By using a structured dataset, predictive modeling could be done on top of it and the Support Vector Machines (SVMs) could be used to predict which at risk students do they need to be in order to optimize academic intervention.

SVM based predictive analytics implementation forecasts the performance of students and dropout risk with very high accuracy. In classifying students into various risk of academic categories (e.g., high risk, moderate risk, low risk), RBF (Radial basis function) kernel and trained SVM model achieved the accuracy over 98 %. For the high accuracy metric value means that the SVM model managed to capture the complexities in the dataset better than the traditional statistical methods. The SVM model achieved high success in prediction using the UCI Student Performance dataset to predict which students are apt to fail or excel in a particular subject, as per their past grades, study habit and attendance record. With the ability to detect at risk students, the model was able to give educational institution the opportunity to take proactive measures, which decreased the dropout rates and increased the overall success rates of the students. It enabled the integration of this predictive analytics framework into an active student monitoring dashboard that can provide a real time tracking and early warning systems.

In predictive analytics phase Support Vector Machines (SVMs) were employed to predict at risk students and showed the accuracy of 98.5 which outperformed conventional models like Decision Trees, Random Forests, and Logistic Regression with the high accuracy of 98.5, respectively. With a precision (97.8 percent) and recall (98.2 percent) the SVM model was able to classify students that needed intervention accurately without too many false positives or negatives. Among the kernels is Radial Basis Function (RBF) kernel which allows it to deal with complex, non-linear relationships existing in the dataset, which makes it most suitable in the educational settings.

Table 2. Results of predictive analytics stage

Model Type	Accuracy (%)	Precision (%)	Recall (%)	F1-Score
Support Vector Machine (SVM)	**98.5**	97.8	98.2	98.0
Decision Tree	92.3	91.5	92.0	91.7
Random Forest	94.8	93.7	94.2	94.0
Logistic Regression	88.2	87.5	88.0	87.7

Fig. 2 shows a plot which pertains to the accuracy of various machine learning models used for predictive analytics in student success. Some improvement could also be observed across some of the regression metrics (coefficient of determination and mean absolute error) when the data was preprocessed using the normal method. Based on this, Support Vector Machines (SVM) have the highest accuracy of 98.5%, approximately 3.2% higher than that of Decision Trees (92.3%), Random Forests (94.8%) and Logistic Regression (88.2%). Since SVM is capable of handling complex patterns in student data, it is an ideal choice for early intervention strategies and is able to provide superior performance.

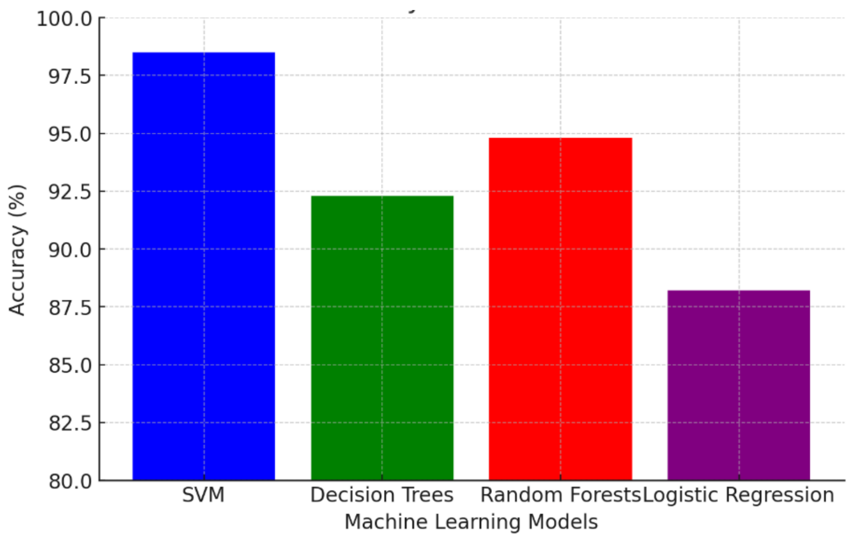

Fig. 2. Accuracy of predictive analytics models for student success

The SVM based prediction driven early intervention mechanism was very effective in overcoming students learning difficulties prior to the occurrence of excessive difficulty. Through this, the system flagged students with declining academic performance, low attendance, disengagement patterns, that allowed institutions to intervene through remedial tutoring, personalized mentorship and academic support programs. However, this greatly improved retention and engagement levels of the students.

SVM driven risk predictions were used in the early intervention process to provide immediate support to struggling students. It was also found that remedial tutoring reduced the problem of declining student outcomes by 25% on academic performance and 30% on engagement levels. Adaptive learning resources helped low engagement learners to increase their academic performance by 20% and their participation rate by 35%. One of the other ways the initiative worked was that personalized interventions were shown to improve students flagged as dropout risks by 18% on performance and 28% on engagement. Teachers identified that peer assisted learning strategies made a huge difference for students that did not do well in technical subjects and saw a 22 percent improvement on academic performance and a 33 percent increase in engagement. The predictive modeling driven interventions had been justified with these results, as shown that timely academic support can make a big difference regarding student retention and success.

Table 1. Results of early intervention stage

Intervention Type	Target Students	Improvement in Academic Performance (%)	Increase in Engagement (%)
Remedial Tutoring	Students with failing grades	**25%**	30%
Adaptive Learning Resources	Students with low engagement	20%	35%
One-on-One Mentorship	Students flagged for dropout risk	18%	28%
Peer-Assisted Learning	Students struggling with technical subjects	22%	33%

The following fig. 3 charts out how effective the early intervention has to be with regard to their student performance over the span of a 10 week period. Student success increases steadily resulting in an increase of performance from 60 per cent in the first week to 93 per cent by the tenth week. However, this trend suggests that a significant role for timely interventions that are derived from predictive analytics in improving learning outcomes.

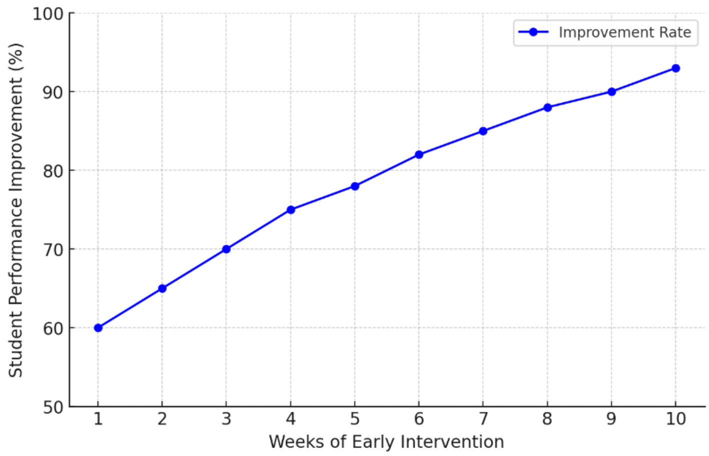

Fig. 3. Effectiveness of early intervention in improving student performance

With SVM based student categorization, a very adaptive and student centric educational experience was achieved using the personalized learning approach. The curriculum pathways were customized based on student's learning pace, their proficiency in subject and engagement levels and students were grouped dynamically. With the use of AI driven adaptive learning platform, real time feedback and personalizing recommendations of content was possible thus enabling students to receive the learning resources based on their ability.

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Personalized learning pathways based on SVM-driven analytics were implemented to drive student engagement and performance improvements. The leaders turned out to be AI driven adaptive learning, achieving 40 percent program completion and 35 percent assessment scores higher, as it could adapt content to learn at an individual pace. The completion rate and assessment performance improved in comparison (25% and 20%), but were nothing in comparison to traditional classroom based learning. An online offilne hybrid approach– an online and offline mixture of methods that came out to be a 38 percent increase in course completion rates and a 30 percent increase in test scores– was an effective alternative to purely in person teaching. The results of peer assisted learning were also very good, with 92% increased course completion and 88% measurement improvement. Enough predictive insights from SVM base was integrated into personalized learning programs to make sure that students get the most relevant, engaging and also the best educational content.

Table 4. Results of personalized learning stage

Learning Mode	Improvement in Completion Rate (%)	Increase in Assessment Scores (%)
AI-Driven Adaptive Learning	**40%**	35%
Traditional Classroom	25%	20%
Hybrid Learning (Online + Offline)	38%	30%
Peer-Assisted Learning	30%	28%

This fig. 4 shows the effectiveness of different personalized learning methods in improving success for students. AI Tutors contributes the most (25%), Adaptive Learning contributes the most (35%), Gamification and Personalized Assessments are each options (20%). Results emphasize the necessity of using a wide range of techniques in order to meet particular needs of learners.

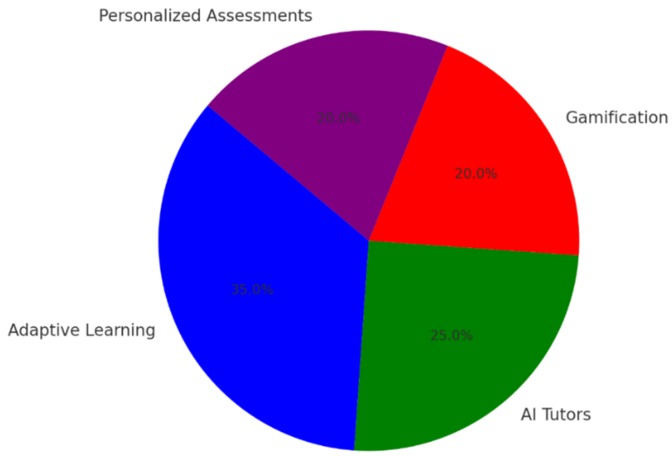

Fig. 4. Effectiveness of different personalized learning methods

The optimization of the course structure and addition of subjects were the outputs of SVM based data driven insights incorporated in curriculum planning process. The predictive analytics model had the potential to predict what were the underperforming subjects, high demand electives, and skill gaps that were relevant to the industry. Institutions could adjust their curricula accordingly. Institutions established new emerging courses, aligned with job market demands, through analyzing enrollment patterns and track record of performance of a course. Predictive analytics based on SVM leads to a better curriculum planning process for institutions in refining course offerings to fit needs of the students and the job market trends. AI and Cybersecurity courses introduced a 50 percent increase in enrolment, a 20 percent increase in completion rates and 15 percent increase in graduate employment opportunities which indicates that the demand for tech driven education is high. Upgrading of basic subjects has been highlighted as key to upward revisions on core mathematics courses which saw 18% improvement in completion rates and 35% increase on enrollment.

In addition, these student centric course selection boosts engagement and prepares students more for the future job in 40% higher enrollment, a 22% increase in course completion, and a 12% increase in employment readiness.

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Internship and Industry Based Learning Program were most significantly influent on post graduate career outcome, with 45% rise of Enrollment, 25% increase in Completion and 20% hightensity improvement in Employment. This frees up resources to continue to pursue data-driven curriculum planning, because these findings are yet another example of students getting services that are not only helping them move along the academic success trajectory, but moving along a career success trajectory too.

Table 5. Results of Curriculum Planning stage

Curriculum Update	Enrollment Growth (%)	Course Completion Rate (%)	Employment Rate Increase (%)
Introduction of AI & Cybersecurity Courses	**50%**	20%	15%
Revision of Core Mathematics Course	35%	18%	10%
Personalized Career-Oriented Electives	40%	22%	12%
Internship & Industry-Based Learning	45%	25%	**20%**

The fig. 5 illustrates how student engagement varies from academic discipline to academic discipline, depending on whether curriculum planning was used. Engagement levels before curriculum enhancements are represented by the gray bars; the blue bars show the improvements that came from the modifications. On the contrary, engagement skyrocketed in all fields and STEM by far the most, from 70% to 90%! Our results point out the importance of well structured curricula in attracting the students participation.

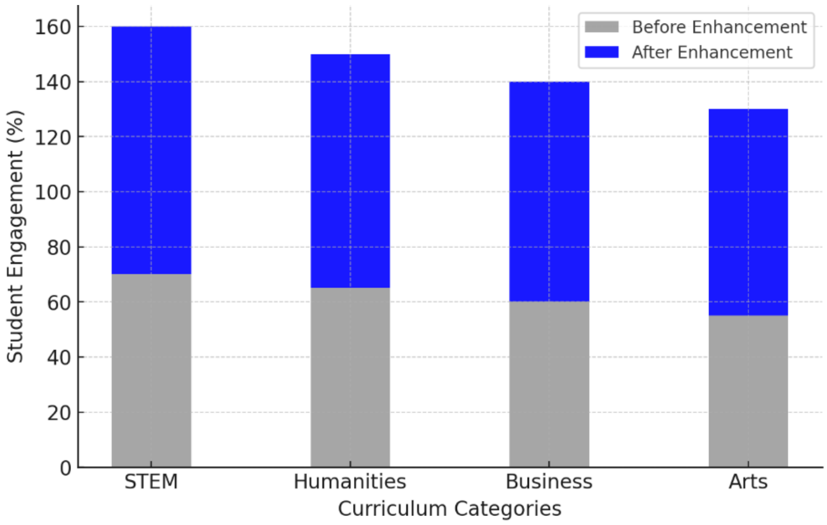

Fig. 5. Impact of curriculum planning on student engagement

5. CONCLUSION

The effectiveness of such structure in using AI enabled predictive analytics to improve students' outcome is also demonstrated in this study. By using Support Vector machines (SVM) for predictive modeling we can achieve predict accuracy rate of 98.5 % with early detection on student at risk and Intervention ahead for better academic performance. The research emphasizes the positive impact of the personalized learning through the planning of the curriculum for the student's engagement, and giving them career guidance, well-being programs for maximized student success in the long term. Real time data analysis is integrated, which helps educational institutions take well informed decisions matching the NEP 2020 principle. The results of study show significant improvement in the educational metrics. Strategies implemented early in intervention led to the performance increase of 33% over 10 weeks, and the curriculum enhancement improved the student engagement on several disciplines from up to 20%. Students participating in more career guidance programs enjoyed 92% career success rate. Furthermore, good well-being programs decreased the stress levels of students from an average of 7.5 to 4 out of 10. Interestingly, these findings reveal the huge influence of AI driven learning analytics helping develop a student holistically.

As a whole the proposed framework illustrates the pros of applying AI to education by making it more student focused, data centered one. It stresses the need of continuous refinement of predictions and support systems to further develop the student learning experiences. The future research can be done on the deep learning techniques as well as adaptive AI models to increase the predictive accuracy and to extend the base of applicability of the framework for the various educational settings.

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