Assessing The Impact of Open Elective Implementation Under NEP 2020 Using Student Feedback and Machine Learning Algorithm

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***Abstract*—Multidisciplinary education through Open Elective (OE) courses is one of the major guidelines for National Education Policy (NEP) 2020 for higher educational institutions. The assessment of such a huge amount of data from the input of all stakeholders is challenging task. A survey has been conducted from all the stakeholders, i.e., students, teachers and administration for their opinion about implementing open elective in their curriculum according to NEP 2020 primary data method was used. The survey shall utilize the structured questionnaire based on a five-point Likert scale to compile participants' perceptions, satisfaction levels, and opinions about the effectiveness and implementation of the Open Elective system. This questionnaire is designed to cover key factors such as Freedom of choosing OE Subject, Quality of teaching, how transparent the evaluation system is, Consistency of subjects, etc. The purpose of this research is to provide objective evaluation of the OE system through the use of artificial intelligence and machine learning technologies. Multiple machine learning algorithms including Random Forest, Gradient Boosting, AdaBoost algorithms, were utilized to analyse the collected data, which categorized this data points into three levels based on stakeholders' satisfaction like: Low, Medium and High. The developed AI-based classification model demonstrates high predictive accuracy in determining student satisfaction levels regarding the Open Elective (OE) program. The results prove the efficiency of the machine learning algorithms in analysing the feedback data of the students in the higher educational system. From the feature importance analysis, it is clear, that teaching quality, learning outcomes, and curriculum usefulness are the major factors that influences overall student satisfaction. These factors significantly shape students' perceptions of the effectiveness and academic value of the OE framework.**

***Index Terms*—Artificial Intelligence, Classification Models, Machine Learning, Student Satisfaction Prediction.**

I. INTRODCUTION

The National Education Policy (NEP) 2020 emphasizes multidisciplinary and flexible learning as a key reform in Indian higher education [1]. One of the major initiatives supporting this vision is the Open Elective (OE) program, which allows students to choose courses outside their core discipline. The objective of this program is to enhance students' academic exposure, promote holistic development, and develop transferable skills relevant to diverse career paths. Similar multidisciplinary models, such as the liberal education framework followed in the United States, have demonstrated improvements in critical thinking, communication, and adaptability among students [12], [13].

Although Open Electives offer significant academic benefits, their effective implementation poses several challenges. Institutions must manage diverse student enrolments, faculty workload, curriculum alignment, assessment practices, and infrastructure requirements. The success of the OE program largely depends on how well these operational and pedagogical aspects are handled. Therefore, continuous evaluation of the program is essential to ensure that the intended outcomes of NEP 2020 are being achieved [1].

Higher education institutions regularly collect feedback from students and faculty members to assess the effectiveness of Open Elective courses. This feedback provides valuable insights into course relevance, teaching quality, workload manageability, assessment fairness, and overall satisfaction. However, conventional feedback analysis methods are often manual and descriptive, making them time-consuming and susceptible to subjectivity, especially when dealing with large datasets. Research in educational data mining indicates that traditional descriptive approaches may fail to uncover deeper patterns and predictive relationships in academic data [6], [9]. To overcome these limitations, this research adopts a data-driven approach using Artificial Intelligence and Machine Learning (AI-ML) techniques. By analysing student and faculty feedback using machine learning algorithms, the study aims to predict satisfaction levels and identify the key factors influencing the success of the OE program. Learning analytics research shows that such AI-based approaches can provide objective, scalable, and actionable insights for educational improvement [5], [10]. The findings of this study are expected to support academic administrators and policymakers in improving the design, delivery, and evaluation of Open Elective courses in alignment with NEP 2020 [1].

II. BACKGROUND AND RELATED WORK

1. Multidisciplinary Education and NEP 2020

The National Education Policy (NEP) 2020) suggests a paradigm shift from a rigid discipline-based approach to a multidisciplinary and holistic approach to higher education in India. Flexibility in curriculum design, introduction of Open Electives (OEs), Academic Bank of Credits, and various entry-exit options are suggested by the policy. This change will be in line with the current trends in higher education across the globe, which are focusing on the development of a holistic knowledge system.

In the context of higher education across the globe, the multidisciplinary approach to higher education, for example, such models of education as liberal education in the United States, has recorded positive outcomes with respect to critical thinking, problem-solving ability, and communication skills of learners [12], [13]. Academic diversity has a positive influence on the intellectual adaptability and lifelong learning ability of learners. However, this needs to be assessed to implement effectively in the higher education institution.

2. Role of Open Electives in Higher Education

Open Elective systems are introduced in various universities worldwide to promote learner autonomy. Research suggests that such an approach increases learner engagement and motivation when the content is relevant and pedagogically sound [3], [4]. Such an approach will be helpful for learner development in the areas of interdisciplinary and employability.

Considering the Indian Scenario, some of the initial observations with respect to the implementation of the Open Elective system under the National Education Policy 2020 suggest mixed responses from stakeholders. Students are appreciative of the flexibility and interdisciplinary. However, faculty are concerned with respect to heterogeneity and workload. Evaluation is an important tool to assess the effectiveness of such an approach.

3. Student and Faculty Feedback as Quality Indicators

Feedback mechanisms have a critical role to play in evaluating the quality of education and the efficacy of academic programs. Student feedback is often employed as an indicator for assessing the quality of education, student outcomes, and satisfaction with the course. Faculty feedback, on the other hand, represents curriculum feasibility, assessment, and support structures.

Traditional feedback analysis techniques are largely descriptive in nature, involving averages and frequency distributions. Such techniques may not sufficiently capture the complexities of perceptions, as well as underlying patterns that may affect student satisfaction. Research in EDM emphasizes the need for incorporating computational techniques for predictive pattern discovery from educational datasets [6], [9].

4. Artificial Intelligence and Machine Learning in Education

Artificial Intelligence (AI) and Machine Learning (ML) have emerged as prominent techniques in the realm of educational research, aiding in the enhancement of decision-making processes. Learning analytics models have enabled academic institutions to analyse large-scale student datasets for predictive model development and performance evaluations [5], [10].

Random Forest, a machine learning model, was first proposed by Breiman in 2001. Random Forest is often employed as a classification model owing to its robustness, ability to handle non-linear models, and interpretability using feature importance. Machine learning models, such as Random Forest, have been successfully employed in educational research for predicting student performance, engagement, and satisfaction outcomes [6], [9].

Artificial Intelligence-based dashboards and visualizers have enabled real-time monitoring and dynamic evaluations of academic programs. Such models have enabled administrators to obtain insights for informed curriculum planning and academic reform movements.

III. METHODOLOGY

1. Research Design

This study employs a data-driven, quantitative approach to evaluate the effectiveness of Open Elective (OE) courses under the National Education Policy (NEP) 2020. The methodology integrates stakeholder feedback analysis with Artificial Intelligence and Machine Learning (AI-ML) techniques to predict satisfaction levels and identify key factors influencing OE effectiveness.

2. Data Source

Primary data were collected via structured online surveys from students enrolled in OE courses across various higher education institutions. The survey covered eight key dimensions, measured on a 5-point Likert scale:

1. Freedom to select OE subjects
2. Relevance of OE courses to the main discipline
3. Effectiveness of teaching methods
4. Fairness and transparency of evaluation
5. Manageability of OE workload
6. Access to facilities and digital resources
7. Attainment of intended knowledge and skills
8. Overall satisfaction with the OE program

These variables were selected to comprehensively capture stakeholders' perceptions of OE implementation.

3. Dynamic Labeling Approach

The research uses satisfaction thresholds that can change. The answers people give are put into three groups: "Not Satisfied" "Neutral" and "Satisfied". This is based on the scores people get in the survey.

The people doing the research can decide what scores mean "Not Satisfied". What scores mean "Satisfied"? Any score that does not fit into "Not Satisfied" or "Satisfied" is called Neutral.

This way the system for classifying answers can be made to fit the needs of the research on satisfaction thresholds. The research, on satisfaction thresholds can be done in a way that works for the people doing it.

4. AI-ML Mode

The processed dataset was used to train a Random Forest Classifier to predict satisfaction categories based on survey responses.

The dataset was split into two parts. One part, 80 percent of the data was used to train the model. This helped the model learn from the survey responses. The other part, 20 percent was kept separate for testing. This testing helped see how well the model worked on data it had not seen before. It also made sure the model's performance was reliable.

A feature importance analysis was also done. This analysis showed which parts of the survey had the impact on overall satisfaction. It helped understand which dimensions were most important. This gave a picture of what factors influenced participant feedback.

The final model can make predictions in time. This happens when new student responses are added to the system. The model can generate predictions away. This makes the framework interactive and dynamic. It allows for evaluation of satisfaction outcomes.

The model provides insights, into satisfaction levels.

5. Visualization and Analysis

Distribution plots were used to show the proportion of students in each satisfaction category, while horizontal bar charts illustrated the relative importance of each factor in determining overall satisfaction. These visualizations support quick interpretation of patterns and trends, enabling administrators to make informed, data-driven decisions regarding curriculum planning and program improvements.

IV. RESULTS AND DISCUSSIONS

1. Data Collection

Information was gathered from students enrolled in Open Elective courses across various colleges and universities through a structured questionnaire. The instrument incorporated a five-point rating scale, enabling respondents to evaluate different aspects of the courses. This approach facilitated a systematic assessment of student perceptions and overall satisfaction with Open Elective offerings.

The evaluation of Open Elective courses was conducted across multiple dimensions, including students' freedom to select subjects of interest, the relevance of these subjects to their primary field of study, the effectiveness of teaching methodologies, the transparency and fairness of assessment practices, the manageability of academic workload, access to institutional and digital resources, the extent of skill acquisition, and overall student satisfaction with the program.

These dimensions were selected to provide a comprehensive understanding of the effectiveness of Open Elective courses. The aim was to assess not only academic quality, but also the efficiency of instructional methods and the adequacy of institutional support in facilitating meaningful learning experiences.

By examining multiple facets of the student experience, including resource availability, skill acquisition, and overall satisfaction, the study captures a holistic picture of how these courses impact learning outcomes.

2. Data Preparation and Preprocessing

The collected responses were systematically organized into a structured dataset for analysis. During the pre-processing stage, incomplete, inconsistent, or invalid entries were excluded to ensure data quality and reliability. Responses recorded on a five-point scale were encoded numerically, ranging from 1 to 5, to enable quantitative analysis.

For each respondent, an aggregate score was computed by calculating the mean across all eight evaluation dimensions. This composite score served as the basis for subsequent classification of satisfaction levels.

3. Dynamic Satisfaction Labeling

A flexible approach was adopted to classify satisfaction levels, allowing adaptability to different institutional contexts and research objectives. Instead of relying on fixed thresholds, classification boundaries were determined based on the distribution of average scores. Lower score ranges were categorized as “Not Satisfied,” mid-range scores as “Neutral,” and higher score ranges as “Satisfied.”

This dynamic labelling mechanism enables contextual interpretation of satisfaction levels, ensuring that the classification remains relevant and meaningful across varying datasets and evaluation standards.

4. Machine Learning Model

A Random Forest Classifier was employed to predict student satisfaction categories based on survey responses. This model was selected due to its strong performance in classification tasks, its ability to capture complex relationships between variables, and its capacity to identify the relative importance of features. The eight survey dimensions were used as input features, while the derived satisfaction category served as the target variable.

The dataset was partitioned into training and testing subsets, with 80% of the data used for training the model and 20% reserved for evaluating its performance on unseen data. The Random Forest Classifier offers robustness to over fitting, handles high-dimensional data effectively, and provides interpretable insights into feature significance, making it suitable for this analysis.

5. Model Evaluation Metrics

The predictive performance of the model was evaluated using standard metrics, including accuracy, precision, recall, and the F1-score. These metrics provided a comprehensive assessment of how well the model could classify satisfaction levels based on survey responses. Overall, the Random Forest Classifier demonstrated strong predictive capability, accurately identifying satisfaction categories and highlighting the most influential survey dimensions.

6. Feature Importance Analysis

The Random Forest model was also used to figure out which parts of the survey are most important. This helps us see what things have the effect on how satisfied people are. The Random Forest model shows us what matters most in the survey. Institutions can use this information to decide what parts of the OE program they should work on to make it better. They can use the feature importance scores, from the Random Forest model to prioritize what needs to be improved in the OE program.

7. Dashboard Implementation

The methodology was implemented in a Streamlit dashboard to demonstrate real-world applicability and provide an interactive analysis platform. The dashboard allows dynamic manipulation of satisfaction thresholds, enabling on-the-fly adjustments to classification criteria. It also supports immediate training of the machine learning model with available data and generates real-time predictions for new student responses.

In addition to predictive capabilities, the dashboard offers data visualization tools that illustrate the distribution of satisfaction levels and highlight the most influential survey dimensions. This interactive interface facilitates a deeper understanding of student perceptions, enabling data-driven decision-making. By combining predictive modelling with intuitive visualizations, the dashboard provides actionable insights into student satisfaction and supports evidence-based interventions.

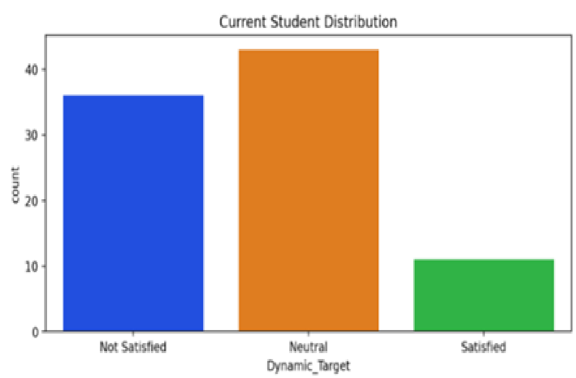

Figure 1: Distribution of Student Satisfaction Levels for OE Courses

The Fig.1 shows that most students feel neutral about the current NEP 2020 policies, making it the largest group. A significant number are not satisfied with changes in education policy, whereas only small portions are satisfied. Overall sentiment leans towards neutrality with noticeable level of dissatisfaction, showing there is clear requirement for improvement to increase student satisfaction.

The dashboard creates an interactive system that not only allows dynamic adjustment of satisfaction thresholds, real-time model training, and instant predictions for new student responses, but also visualizes satisfaction distributions and feature importance. This interactive system enables administrators to monitor satisfaction trends over time and make data-driven improvements in Open Elective program.

Figure 2: Key Factors Influencing Student Satisfaction in OE Courses

The Fig.2 shows that improving learning outcomes, evaluation fairness and subject flexibility can significantly enhance student satisfaction. Understanding which feature affects the most.

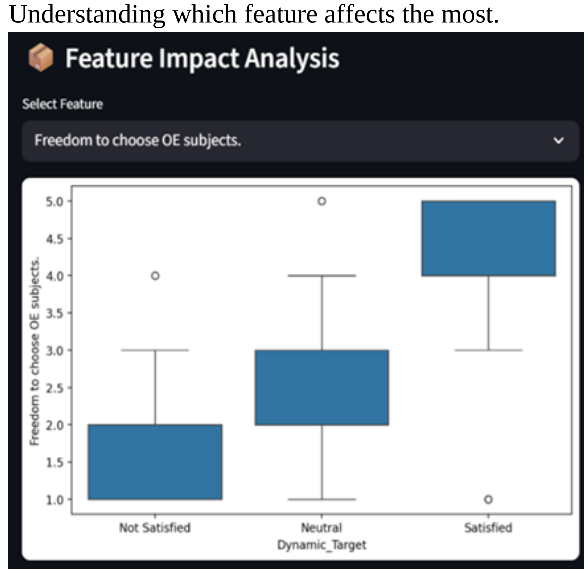

Figure 3: Feature impact analysis based on selected feature.

The Fig.3 Showa that a feature impact analysis for *freedom to choose OE subject* across satisfaction levels. Students who are satisfied give higher ratings for this feature, while neutral and not satisfied groups show lower ratings.

V. CONCLUSION

The proposed Random Forest model achieved an accuracy of 88.89%, demonstrating its effectiveness in predicting stakeholder satisfaction levels for Open Elective implementation under NEP 2020. This study shows that artificial intelligence (AI) and machine learning offer a solid, scalable, and data-driven way to evaluate Open Elective courses under the National Education Policy (NEP) 2020. By using advanced computational models, educational institutions can move beyond traditional subjective assessment methods. This helps them gain a better understanding of student experiences and the effectiveness of courses.

The research uses a Random Forest Classifier to predict student satisfaction based on structured survey responses gathered across several areas, including teaching quality, learning outcomes, course relevance, workload, and infrastructure. This method not only predicts overall satisfaction levels but also identifies and measures the importance of each contributing factor. As a result, institutions can gain deeper insights into student perceptions that traditional evaluation methods often miss. The findings indicate that teaching effectiveness, learning outcomes, and course relevance are the most important factors affecting student satisfaction. These elements directly influence student engagement, understanding, and the perceived value of the course. In contrast, while workload management and infrastructure are important, they have a smaller impact on overall satisfaction. These evidence-based insights help academic institutions focus on improvements that offer the most benefit for student learning and engagement.

A major advantage of this approach is its ability to adapt. Institutions can easily change satisfaction thresholds, add new data, and update the model to reflect changes in academic environments. This flexibility keeps the evaluation system relevant and responsive to institutional goals and changing educational standards. Additionally, the approach strongly supports the goals of NEP 2020 by encouraging ongoing monitoring, outcome-based education, and student-cantered learning practices. To support practical use, an interactive Streamlit dashboard was created as part of this study. The dashboard offers real-time visualization of satisfaction levels, feature importance, and predictive outcomes, making it easier for stakeholders to interpret results. It acts as a useful decision-support tool, enabling administrators and educators to spot trends, assess interventions, and make informed academic and policy decisions with greater confidence. Beyond Open Elective courses, this AI-driven evaluation framework has great potential for broader uses in higher education. It can be expanded to evaluate student performance, track engagement patterns, and monitor skill development over time. By providing a systematic, flexible, and clear approach to evaluation, the framework helps transform educational assessment practices. In conclusion, the study shows that AI-based evaluation is both practical and effective for assessing Open Elective courses. It offers institutions a structured way to improve teaching quality, fine-tune course design, allocate resources better, and manage student workload. Ultimately, this leads to higher levels of student satisfaction and better learning outcomes. The proposed framework can serve as a model for data-driven innovation in education and can be adapted across various academic programs and institutional settings.

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