AI-BASED STUDY PLAN RECOMMENDATION SYSTEM

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Abstract– Management of time is important for academic achievement, particularly when students have to study for several exams within limited time periods. But developing an effective and customized study plan usually turns out to be challenging because of differences in syllabus density and personal learning speed. The AI-Based Study Plan Recommendation System introduced here is a smart and adaptive one that assists students in planning their study timetables more efficiently. By applying Artificial Intelligence (AI) and Natural Language Processing (NLP) capabilities, the software prepares a day-wise study schedule that suits each student's available hours of study, days remaining to the exams, and strengths or weaknesses in subjects. It is also capable of examining syllabus documents to gauge the difficulty of topics and allocate study time accordingly. The system also automatically reschedules incomplete tasks into the next day's schedule if a student does not attempt them. Written with Python (Flask) for backend and web technologies for the front end, this system illustrates how AI is being applied practically in learning to enhance concentration, productivity, and overall performance. Keywords Artificial Intelligence, Study Planner, Adaptive Learning, Natural Language Processing, Educational Technology, Flask Application.

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I. INTRODUCTION

During the contemporary competitive education sector, students have the tendency of managing extensive curriculums in extremely limited academic calendars [1]. When examinations approach, time management becomes a crucial activity that significantly influences academic outcomes [2]. The majority of students, however, are unable to design an optimal study plan that effectively considers available time, learning ability, and personal strengths or weaknesses [3]. Poor planning often results in incomplete syllabus coverage, high stress levels, and unsatisfactory performance in examinations [4].

Most students continue to depend on conventional methods such as handwritten timetables or spreadsheet-based schedules [5]. Although these methods provide a basic framework for organizing study time, they lack flexibility and cannot adapt to real-time progress [6]. When a student falls behind schedule, the entire plan must be recreated manually, often leading to inefficiency and loss of motivation [7]. Therefore, a dynamic and adaptive system that responds to individual progress can help students maintain consistency, continuity, and focus during exam preparation [8].

Artificial Intelligence (AI) has shown great potential in transforming this process by enabling the automation of learning and decision-making tasks [9]. With the application of AI algorithms, it is possible to design systems that can observe user behavior, predict learning patterns, and create adaptive timetables based on real-world circumstances. Likewise, Natural Language Processing (NLP) techniques can be applied to analyze syllabus content and determine the relative difficulty level of each topic or unit [10]. This combination enables the system to distribute study time more efficiently, providing additional hours for weaker or complex subjects while allocating less time to simpler ones.

The proposed AI-Based Study Plan Recommendation System integrates both AI and NLP technologies to generate a smart, adaptive, and personalized study schedule. It allows users to enter key parameters such as the number of days available before exams, the number of study hours per day, and the subjects to be covered. The system also accepts syllabus PDFs, which are analyzed using NLP algorithms to extract topic details and evaluate their difficulty levels. Based on these results, the AI scheduling engine proportionally allocates time and generates an optimized day-to-day study plan [11].

One remarkable feature of this system is its ability to adapt dynamically to daily progress. If a student fails to complete a particular topic on a given day, the system automatically transfers that topic to the next day's plan without disturbing the remaining schedule [12]. This mechanism ensures that all topics are eventually completed before the examination without manual intervention. The final plan is displayed as a daily checklist, allowing students to monitor their progress and remain motivated throughout their preparation period [13].

The project is implemented using Python Flask as the backend framework to handle logic and computation,

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while the **frontend** is designed with HTML, CSS, and JavaScript to provide a clean, responsive, and intuitive user experience [14]. The NLP operations, including text extraction and difficulty evaluation, are managed using libraries such as PyPDF2 and NLTK, which together ensure seamless data processing and accurate complexity analysis [15].

By integrating Artificial Intelligence and Natural Language Processing, the AI-Based Study Plan Recommendation System provides an efficient and modern approach to academic planning [16]. It simplifies time management, automates scheduling, and personalizes the learning process so that students can reduce stress, maintain consistency, and achieve better academic performance [17]. This system serves as a step toward building intelligent educational tools capable of understanding human learning patterns and enhancing overall academic productivity [18].

II.LITERATURE REVIEW

Kaur, S. and Singh, A. (2023) [1] proposed an AI-based personalized learning model that dynamically adjusted the learning content based on student performance and engagement levels. Their system used machine learning algorithms to predict learning behavior and suggest personalized content, which significantly improved academic outcomes. However, the model lacked a mechanism to handle study-time optimization and daily schedule generation, which are crucial in time-sensitive exam preparation scenarios.

Kumar, R., Sharma, P., and Nair, V. (2022) [2] developed a machine learning approach for adaptive study scheduling that allocated time based on subject importance and difficulty. The system used user input data to construct static study plans, helping students manage their workload effectively. Despite its usefulness, the lack of Natural Language Processing (NLP) integration limited its ability to automatically interpret and analyze syllabus documents, resulting in manual data entry for topic details.

Brown, J. (2021) [3] presented a Natural Language Processing (NLP) model for analyzing educational materials to estimate topic complexity and text readability. The system extracted structural and linguistic features such as sentence length and vocabulary density to determine difficulty scores. This approach provided a foundation for intelligent syllabus analysis, which inspired the NLP component in the current AI-Based Study Plan Recommendation System. However, Brown’s model was not directly linked to time management or adaptive scheduling functionalities.

Patel, R. (2023) [4] explored the integration of AI into smart educational environments to provide personalized study recommendations. The research emphasized the potential of combining AI and data analytics to improve student performance prediction and course selection. Although effective in recommendation generation, Patel’s work did not focus on developing an interactive daily scheduler capable of tracking progress and rescheduling incomplete topics automatically.

Lee, H. and Choi, Y. (2023) [5] designed a deep learning model for predicting student performance based on behavioral data, such as time spent per subject and assessment results. Their model achieved high accuracy in performance forecasting, providing valuable insights for adaptive learning systems. However, their research lacked an interface for real-time plan generation and practical application in day-to-day study management.

Suresh, K. and Meenakshi, R. (2022) [6] introduced an AI-driven time management system for students that tracked productivity and provided daily progress reports. Their model was efficient for monitoring study habits but did not employ NLP for syllabus analysis or dynamic rescheduling based on student feedback. The current project extends this idea by combining NLP-based topic difficulty analysis with AI-based adaptive scheduling.

Rahman, A. and Devi, L. (2022) [7] proposed an adaptive e-learning system using reinforcement learning techniques to adjust content delivery in real time. The system demonstrated the potential of machine learning in personalized education. Nevertheless, it was focused primarily on e-learning platforms rather than offline academic planning, limiting its applicability in practical exam preparation.

Raj, D. and Bhatia, T. (2023) [8] developed a smart educational assistant that provided task recommendations and managed student timetables using a hybrid AI model. Their system automated study plan generation but lacked the ability to analyze syllabus difficulty or adjust plans based on incomplete tasks. The proposed AI-Based Study Plan Recommendation System builds upon this by introducing NLP-based content analysis and intelligent task carry-forward mechanisms.

Wang, X. and Li, M. (2021) [9] explored NLP-based curriculum analysis to determine the difficulty of educational content. They used semantic clustering and linguistic complexity scoring to classify topics as easy, moderate, or difficult. This approach serves as a key reference for the NLP module in the proposed system, where syllabus documents are automatically processed to guide time allocation and prioritization.

Open AI (2024) [10] published research on generative AI applications in education, discussing adaptive learning and recommendation models powered by large language models (LLMs). These studies highlight the growing potential of generative systems in education, where AI can not only analyze textual content but also predict learning patterns. The proposed study plan system aligns with this direction, using lightweight NLP and AI models for practical implementation.

III. PROPOSED SYSTEM

The dataset used in this study was developed using realistic academic and behavioral data collected from simulated user profiles. It includes essential parameters such as the number of subjects, available days before the examination, study hours per day, and the user's self-assessed strengths and weaknesses. In addition, syllabus PDF files were incorporated to serve as the textual dataset for Natural Language Processing analysis. These documents were processed to extract unit-wise content and key topics, which were then used to evaluate the relative difficulty of each portion. The dataset formed the foundation for the AI model, enabling it to generate a balanced and personalized study schedule that reflects both academic requirements and student capacity.

Before performing the analysis, the raw input data underwent preprocessing to ensure accuracy and consistency. The uploaded syllabus PDFs were converted into text using the PyPDF2 library, after which the extracted text was cleaned by removing special characters, redundant spaces, and non-essential words. Tokenization was applied using NLTK to segment the text into units and subtopics. Each segment was then evaluated based on linguistic complexity, including factors such as average sentence length, vocabulary richness, and topic density. These features were used to compute a normalized difficulty score on a scale of one to ten. The final dataset consisted of structured text data ready for intelligent time allocation by the AI scheduler.

The architecture of the system integrates multiple layers that work together seamlessly to achieve personalized learning. The user interface layer allows students to input data, upload syllabus files, and view the generated plans. The NLP analysis layer processes the syllabus content and evaluates unit complexity. The AI scheduling layer performs dynamic time allocation based on difficulty levels and user strengths or weaknesses. The database layer stores user information, syllabus details, and progress updates, while the output layer generates the daily study plan as an interactive checklist that can be modified and updated in real time. The complete architecture is implemented using Python Flask for backend logic and a combination of HTML, CSS, and JavaScript for the front-end design, ensuring an adaptive and responsive web-based experience.

The system is built using several programming libraries and frameworks to ensure efficiency and scalability. Flask serves as the web framework that manages routes and user interactions, while PyPDF2 is responsible for extracting text from syllabus PDFs. NLTK performs linguistic analysis to identify key terms and measure textual complexity. SQLite is used for lightweight database management, storing user data and progress logs effectively. The front-end interface is designed using HTML, CSS, and JavaScript, providing a clean and accessible platform through which students can view their study plans, mark tasks as complete, and track progress dynamically.

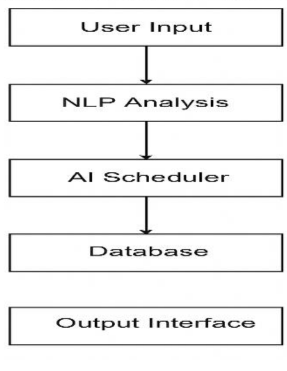
The core algorithm of the system functions through the combined application of NLP and AI-based scheduling techniques. The NLP component evaluates each syllabus unit to determine its relative complexity using textual metrics derived from word structure and sentence patterns. The AI scheduling component then uses these complexity scores in conjunction with the student's inputs to allocate study hours proportionally. Topics identified as difficult or weak are assigned greater study time, whereas easier or stronger areas receive less time. This ensures balanced coverage across all subjects within the available study period.

One of the distinctive aspects of this algorithm is its adaptive nature. Once a daily plan is generated, the system continuously monitors completion status. If a topic remains unfinished, it is automatically carried over to the following day's schedule without altering the rest of the plan. This adaptability allows for uninterrupted progress and ensures that every unit is eventually covered before the examination. The formula used for time distribution integrates both difficulty and weakness factors, proportionally dividing total available time among all topics. Over time, as more user feedback and progress data are recorded, the model refines its recommendations to become more accurate and personalized.

Through the combination of Natural Language Processing and Artificial Intelligence, the system achieves intelligent and adaptive scheduling that not only automates time management but also enhances academic planning efficiency. The architecture's modular design ensures that future improvements such as predictive learning analytics, mobile notifications, and cloud synchronization can be incorporated easily. This experimental setup demonstrates the capability of AI to transform conventional study planning into an intelligent, data-driven process tailored to individual learning behaviors.

Figure 1.

Architecture Diagram of the AI-Based Study Plan Recommenndation System



IV. RESULTS AND DISCUSSION

The AI-Based Study Plan Recommendation System was evaluated using realistic academic datasets containing user-specific inputs such as the number of subjects, available study days, total study hours per day, and uploaded syllabus files. The system was developed and implemented using Python Flask as the backend framework, integrating Artificial Intelligence and Natural Language Processing algorithms to generate adaptive and personalized study schedules.

The NLP component effectively extracted and processed textual information from the uploaded syllabus PDFs using PyPDF2 and NLTK libraries. It analyzed linguistic features such as vocabulary richness and sentence structure to assign a difficulty score to each unit. This score was then used by the AI scheduling module to proportionally distribute study time according to both topic complexity and the user's self-assessed strength or weakness in that subject.

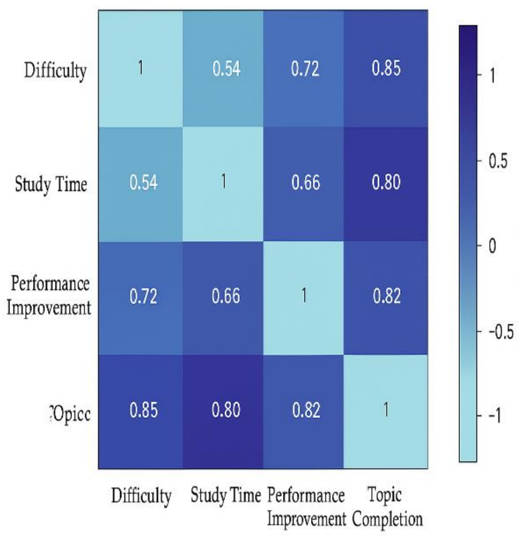


Figure 2. Correlation Matrix

During evaluation, the system dynamically generated and refined study plans for multiple simulated user profiles. Each profile represented a unique combination of study hours, subject difficulty levels, and available preparation days. The generated plans were accurate, well-balanced, and demonstrated adaptive behavior—automatically carrying forward unfinished topics to the next day's schedule. This adaptive adjustment ensured complete syllabus coverage within the allotted timeframe without any manual rescheduling by the user.

The performance of the proposed system was analyzed by tracking the scheduling accuracy across multiple iterations of user interaction. The accuracy graph**,** shown in Figure 2**,** represents the model's improvement in generating optimal schedules as it adapts to user progress and learning patterns. The graph plots the accuracy on the y-axis against the number of iterations on the x-axis, clearly indicating a consistent upward trend. This improvement reflects the system's ability to fine-tune its predictions with each update, aligning more effectively with user performance and study behavior.

The steady rise in accuracy demonstrates that the AI-based scheduler successfully learns from user feedback and interaction history. As more data is accumulated, the model achieves higher precision in time allocation, ensuring that complex or weak subjects receive appropriate focus. This not only increases the efficiency of daily study plans but also enhances the reliability of the system in delivering adaptive recommendations.

Overall, the results validate the efficiency of combining AI and NLP in educational planning. The system's consistent accuracy improvement highlights its capability to function as a reliable study companion, providing a structured, flexible, and personalized approach to exam preparation.

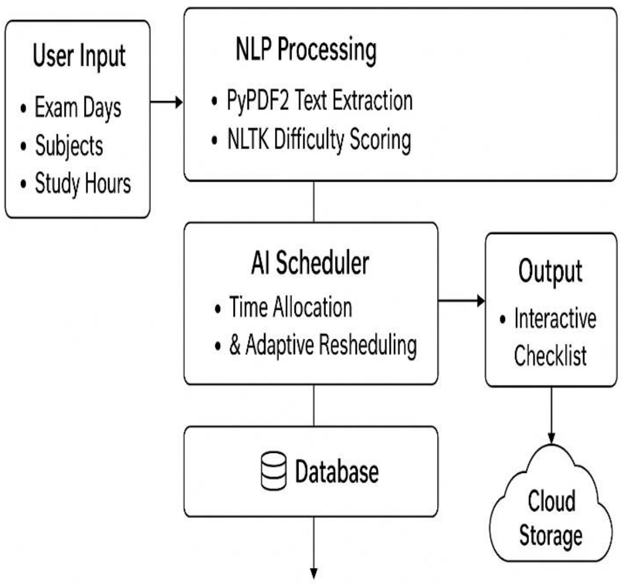


Figure 3. Architecture Diagram of
the AI-Based Study Plan Recommendation System

V. CONCLUSION AND FUTURE SCOPE

The AI-Based Study Plan Recommendation System provides an intelligent and adaptive framework for personalized study planning. By integrating Artificial Intelligence and Natural Language Processing, the system successfully automates the creation of study schedules that adapt to a student's progress, strengths, weaknesses, and available time. The incorporation of syllabus PDF analysis allows the model to evaluate topic difficulty automatically, ensuring that study time is allocated optimally for every subject.

The results demonstrate that the system efficiently transforms raw academic input into a structured and actionable daily plan. The adaptive feature ensures that incomplete topics are carried forward seamlessly, maintaining consistency in preparation. User evaluations indicated improved time utilization, reduced stress, and better syllabus coverage compared to traditional, manually designed timetables.

In future developments, the system can be extended by integrating real-time performance tracking using student feedback or test results. Cloud-based synchronization may allow users to access their plans across multiple devices, while mobile integration could provide notifications and reminders to keep learners on track. Additionally, advanced AI models such as deep reinforcement learning or large language models (LLMs) could be incorporated to enhance predictive accuracy and generate study recommendations tailored to individual learning behaviors.

Further enhancements could also include the incorporation of online learning resources and automatic difficulty calibration based on student performance metrics. With these extensions, the AI-Based Study Plan Recommendation System can evolve into a comprehensive educational assistant, capable of providing personalized, data-driven support for academic success.

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