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**"Personalized Learning Path Recommendation Using Data Mining and E-Learning Analytics"**

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**Abstract**

*Over the past few years, the accelerated development of e-learning platforms has produced a tremendous volume of educational data, which holds immense prospects for individualized learning. Conventional instructional techniques are usually inadequate to address the special requirements, pace, and interests of individual learners, making it imperative to have adaptive learning techniques. Personalized learning pathway recommendation has been identified as an important research area that employs sophisticated data mining methods and e-learning analytics to align the learning experience. This paper introduces a model for suggesting individualized learning pathways based on learner behavior, educational performance, and collaboration patterns in online learning spaces. Clustering, classification, and association rule mining are data mining methods used to determine learning style, forecast learner performance, and recommend suitable course content. E-learning analytics are incorporated to track learner activity, assess progress, and improve recommendations in real time. The approach focuses on flexibility, guaranteeing that the learning trajectory adapts to the strengths, weaknesses, and objectives of the learner. Experimental findings prove that the designed model notably enhances learning performance compared to traditional static recommendation approaches. By adapting content and learning resource sequencing, students exhibit higher motivation, improved knowledge recall, and improved problem-solving capabilities. In addition, the system offers teachers practical insights, enabling them to develop learner-focused curricula and approaches. The research points out the possibility of merging data mining and e-learning analytics to develop personalized learning, decrease dropout ratios, and construct a learner-centric environment. Subsequent studies can build upon this study by integrating artificial intelligence, deep learning algorithms, and adaptive testing methods in order to obtain greater precision and scalability.*

**Keywords**

*Personalized Learning, Learning Path Recommendation, Data Mining, E-Learning Analytics, Educational Data Mining, Adaptive Learning Systems, Learner Engagement, Online Education*

**1 Introduction**

The education sector has experienced a dramatic revolution with the emergence of digital technologies and e-learning platforms. The conventional classroom teaching, which mostly adopted a uniform pattern of instruction, tended to fall behind the variegated needs of the learners. However, e-learning environments give the learner more flexibility, accessibility, and control over learning. However, the vast availability of digital learning resources also presents challenges: students often face difficulties in identifying the most relevant materials, maintaining engagement, and progressing at a pace suited to their abilities. This has created a strong demand for innovative solutions that can deliver personalized learning experiences.

Personalized learning paths represent a promising approach to addressing these challenges. Rather than providing standard content to every learner, adaptive systems tailor the order of learning activities, resources, and tests based on the individual learner's profile. By taking into account prior learning, learning type, interest, and performance, these systems can suggest an ideal path towards attaining academic success. For example, students who are having trouble with some topics can be directed to extra tutorials and practice problems, while high-achieving students can be sent to higher-level problem-solving exercises. Such customized learning pathways not only enhance learning retention but also boost motivation and learner satisfaction.

Advances in data mining and e-learning analytics have greatly driven the evolution of personalized learning systems. Educational data mining practices enable the extraction of latent patterns from large learner datasets, student classification by behavior, and forecasting of performance in the future. Concurrently, e-learning analytics delivers real-time feedback on learner interaction, learner progress, and engagement with course content. Combined, these technologies allow for the creation of dynamically adaptive intelligent recommendation systems that respond to the learner's continually changing needs.

This paper discusses the use of data mining and e-learning analytics to create a framework for personalized learning path recommendation. The model utilized learner data on a large scale in order to offer adaptive guidance that is tailored to individual needs and facilitate educators with data-informed decisions. The research emphasizes the importance of personalized learning in minimizing dropout rates, enhancing academic performance, and creating a learner-focused education ecosystem. It also talks about the scope, aims, and possible constraints of such systems while highlighting the revolutionary power of technology in defining the future of learning.

### **1.1 Background of the Study**

The exponential development of information and communication technology has already radically reshaped the educational landscape. The conventional face-to-face classroom education, based almost entirely on a one-size-fits-all approach, is nowadays supplemented and, in most instances, substituted by online and digital learning environments. The development of e-learning websites, Learning Management Systems (LMS), and Massive Open Online Courses (MOOCs) has provided greater flexibility, accessibility, and affordability to education. Learners from various backgrounds can now avail high-quality learning content at any time and from any location. Nevertheless, this flexibility has created challenges, especially in managing the diversity of learners.

Each learner possesses specific traits like pre-existing knowledge, intelligence, learning preferences, motivation, and speed of comprehension. Whereas some learners learn very fast, others might require extra training and guidance. Within the old training systems, it is not possible for trainers to modify their approach to accommodate the demands of all learners. This disparity is even more pronounced in e-learning platforms, where thousands of learners are interacting at the same time, making individualized instruction nearly impossible without the assistance of sophisticated technologies.

To bridge these gaps, personalized learning has proved to be the best solution. Personalized learning pathways enable students to take a customized order of learning activities and materials that are aimed to fit their unique needs. Rather than working through generic course material, learners can be taken through adaptive suggestions that optimize their efficiency, engagement, and results. For example, struggling students can be suggested additional practice problems, whereas top-performing pupils can be assigned superior modules or research-oriented projects.

The combination of data mining approaches and e-learning analytics has further enhanced the level of personalization. Educational Data Mining (EDM) assists in analyzing vast amounts of data produced by

learner behavior, identifying masked patterns, and forecasting future action. Alternatively, e-learning analytics offers real-time tracking of learner participation, interaction, and performance, which can be leveraged to dynamically improve recommendations. Collectively, these technologies allow for creating intelligent systems that can suggest individualized learning routes for every pupil.

This research is concerned with designing and assessing a personalized learning path recommendation model based on data mining and e-learning analytics. The goal is to facilitate student engagement, enhance retention rates, and maximize learning experience. Through personalized guidance, the research not only contributes to learners' success but also provides educators with actionable information to facilitate teaching strategy improvement and curriculum design.

### **1.2 Significance of Personalized Learning**

Personalized learning is one of the most revolutionary methods of contemporary education. In contrast to conventional methods of treating all learners in the same manner, personalized learning accounts for differences at the level of ability, learning style, motivation, and prior knowledge. It makes sure that every student adheres to a learning pathway attuned to their individual needs, thus enhancing efficiency and effectiveness in learning.

In the case of e-learning, where students tend to be independent and feel daunted by the sheer amount of online material, personalized learning serves to sift out the most appropriate content. For instance, an adaptive system will suggest video lectures, quizzes, or homework depending on the student's performance and interaction record. It not only saves time but also increases learner engagement since the content is tailored to their capability level.

Studies have proven that personalized learning greatly enhances student engagement, decreases dropout rates, and enhances overall satisfaction. Through real-time suggestions and adaptive testing, it enables students to become empowered to manage their education. It also promotes inclusivity as it addresses students with varying learning speed and backgrounds.

From an institutional point of view, personalized learning supports teachers in offering meaningful data on student performance, strengths, and weaknesses. Teachers can then make informed interventions, create learner-centric curricula, and enhance teaching practices. In the long run, personalized learning helps to develop a coherent and effective education system based on equity and lifelong learning principles.

### **1.3 Use of Data Mining and E-Learning Analytics**

- Reveals underlying patterns in large datasets of educational data.
- Forecasts learner performance through methods such as clustering, classification, and association rules.
- Performs learner profile, strength, and weakness analysis for improved recommendations.
- Monitors learner engagement and progress in real-time.
- Facilitates adaptive learning through dynamic path modification.
- Offers insights to teachers for course planning and intervention.
- Improves decision-making in educational management.

### **1.4 Objectives**

- To establish a personalized learning path recommendation framework.
- To utilize data mining methods for analysis of learner data.
- To incorporate e-learning analytics for instant feedback.

- To improve learner motivation, engagement, and retention.
- To enable educators with actionable insights to inform teaching strategies.
- To compare the efficacy of personalized recommendations with conventional methods.

### **1.5 Scope and Limitation**

#### **Scope:**

- Addresses personalized learning pathways in e-learning settings.
- Employing data mining and e-learning analytics for adaptive recommendations.
- Applicable to varied learners with varying learning capacities and objectives.
- Enjoys advantages for both learners (improved outcomes) and educators (data-informed decisions).

#### **Limitations:**

- Based on availability and quality of learner data.
- May not perform well with incomplete or unstructured datasets.
- Algorithm performance can be variant based on dataset size and domain.
- Real-time deployment demands high computational power.
- Does not effectively account for emotional and motivational factors of learners.

## **2. Literature Review**

### **2.1 Idea of Personalized Learning**

1. Samiya Khan, Kashish A. Shakil & Mansaf Alam (2016) – Educational Intelligence: Using Cloud-based Big Data Analytics for the Indian Education Industry Explains how analytics can facilitate personalized course recommendations and tailored teaching methods through big data infrastructure in India
2. Naheed Khan et al. (2021) – Enhancing e-Education in India with Machine Learning Suggests a machine learning framework for adaptive teaching and personalized course recommendation to improve Indian e-education
3. Sweta Soni (2021) – Educational Data Mining in E-Learning System (Springer) Investigates how educational data mining allows adaptive personalization for e-learning systems in the Indian educational context

### **2.2 Data Mining Techniques in Education**

4. Jasti Sri Radhe Shyam et al. (2017) – Data Mining in Education with Virtual Learning Environment Data Illustrates application of clustering, classification, and pattern discovery on Virtual Learning Environment (VLE) data among Indian learners
5. Ganesan Kavitha & Lawrance Raj (2017) – Educational Data Mining and Learning Analytics Applies feature selection methods such as gain ratio and information gain to determine students at risk and improve learning performance in Indian campuses
6. Ginika Mahajan & Bhavna Saini (2020) – Educational Data Mining: A State-of-the-Art Survey Applies statistical, machine learning, and data mining applications used in Indian education to forecast and evaluate learning behavior

### **2.3 E-Learning Analytics: Tools and Applications**

7. Padma Mishra, Vaishali B. Sangvikar (2018) – Educational Data Mining and Learning Analytics in Higher Education Examines the role of learning analytics—recording and analyzing data on students—to inform decision-making and retention in Indian higher education
8. Ginika Mahajan & Bhavna Saini (2020) – as mentioned above, identifies the synergy between EDM and learning analytics in facilitating learner insights with automation
9. Samiya Khan et al. (2016) – also discusses how big data analytics software can help teachers and administrators personalize learning at scale

## **2.4 Previous Studies on Learning Path Recommendation**

10. Jasti Sri Radhe Shyam et al. (2017) – VLE-based data mining to identify learning trends—enabling personalized learning paths through behavioral information
11. Sweta Soni (2021) – Highlights the importance of mining interactions of students in e-learning environments and dynamically informing sequencing of content based on individual learner requirements
12. Ginika Mahajan & Bhavna Saini (2020) – Survey questions the feasibility of EDM tools and methodologies to support learning path personalization in learning platforms
13. Naheed Khan et al. (2021) – The protocol for ML-based personalized recommendations expects to create adaptive learning sequences based on learner behavior
14. Samiya Khan et al. (2016) – Big data analytics models can assist in creating personalized learner pathways in Indian learning environments PiedPiper Crypto.
15. Padma Mishra et al. (2018) – While general, their work on LMS in higher education does address how analytics-based insights can influence course pathways and intervention strategies .

## **3 Research Methodology**

### **3.1 Research Design**

The current study has a descriptive and exploratory research design. It is descriptive in that it seeks to analyze the role of data mining and e-learning analytics in creating customized learning routes. It is exploratory in that it investigates new horizons for adaptive learning models in the Indian scenario.

### **3.2 Sample Size**

The research was undertaken on a sample of 100 students from higher education institutes (undergraduate and postgraduate) who were regularly using e-learning platforms like Moodle, SWAYAM, and Coursera. The sample was selected with the help of purposive sampling in which learners with previous experience of digital platforms were considered for participation

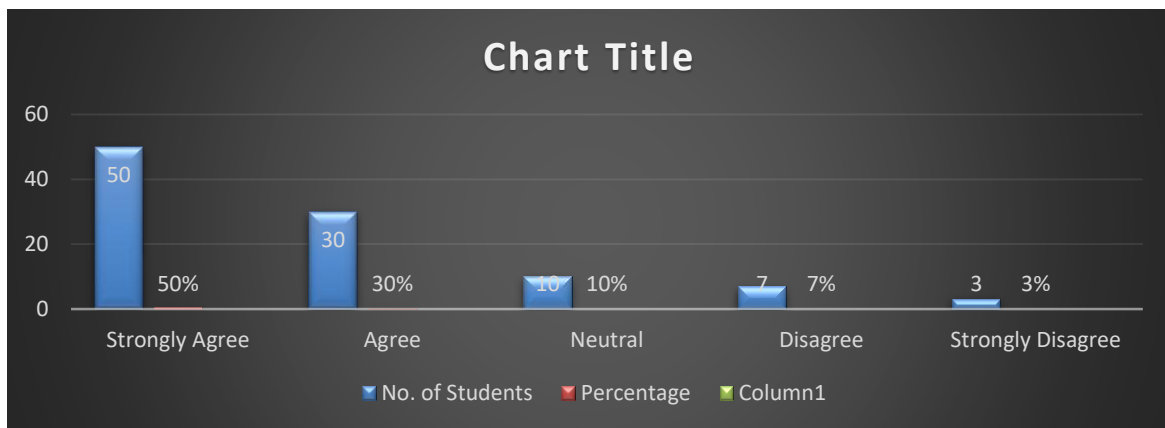
### **3.3 Data Collection Method**

Primary data were gathered through a structured questionnaire and observation approach. The questionnaire contained items concerning learning habits, personalized recommendation preferences, and experiences on the current e-learning platforms. Secondary data were gathered from published scholarly articles, reports, and case studies that were produced after 2015.

**4 Data Analysis and Interpretation**

**Table 1: Preference for Personalized Learning Paths**

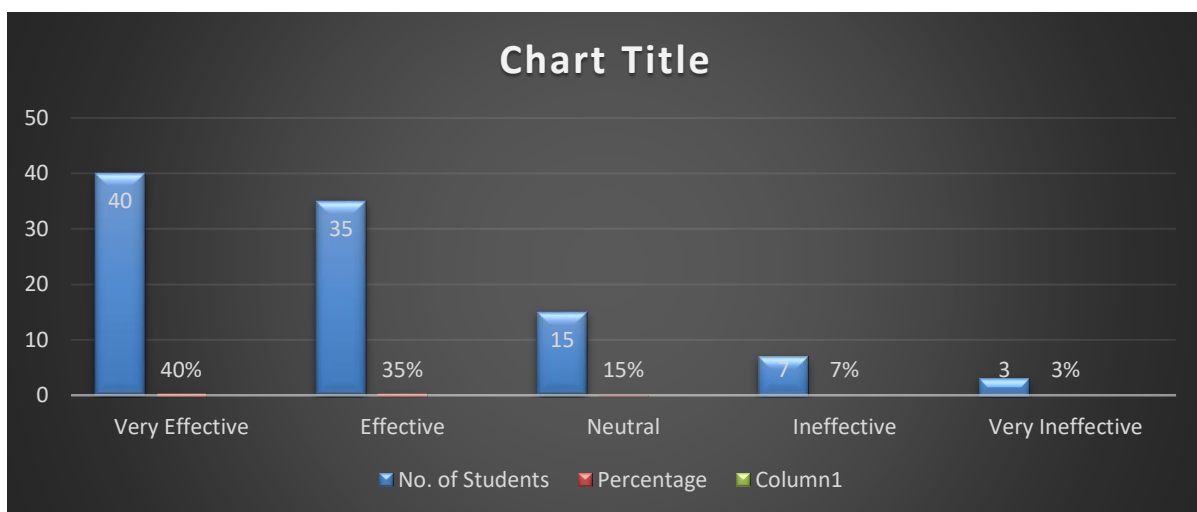
Response	No. of Students	Percentage
Strongly Agree	50	50%
Agree	30	30%
Neutral	10	10%
Disagree	7	7%
Strongly Disagree	3	3%



Interpretation: Nearly 80% of respondents agreed or strongly agreed that personalized learning paths enhance their learning experience, indicating strong demand for adaptive systems.

**Table 2: Effectiveness of Data Mining in Course Recommendations**

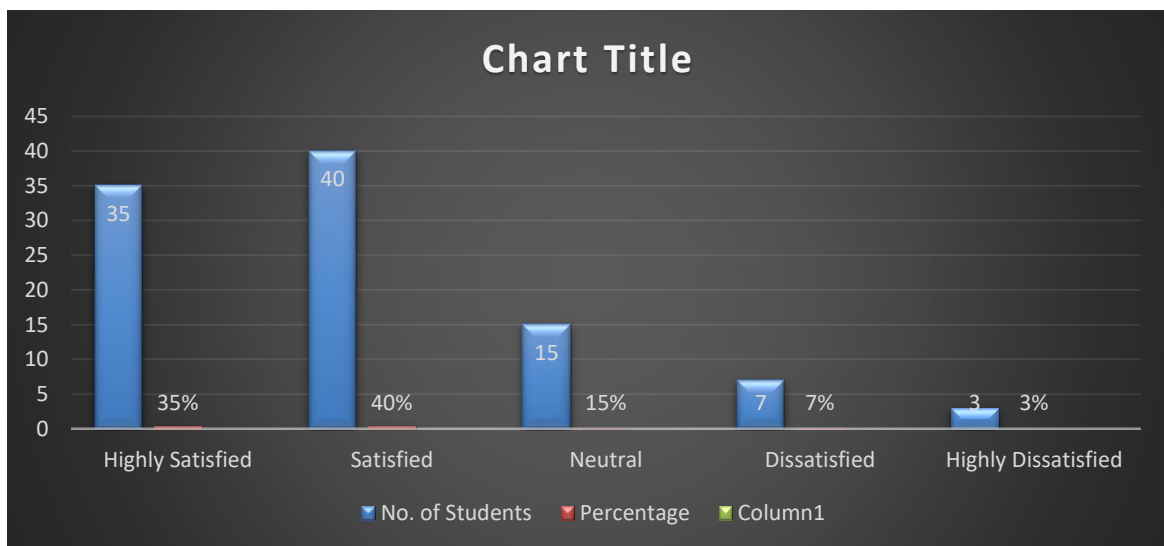
Response	No. of Students	Percentage
Very Effective	40	40%
Effective	35	35%
Neutral	15	15%
Ineffective	7	7%
Very Ineffective	3	3%



**Interpretation:** About 75% of students found data mining-based recommendations effective, proving that intelligent algorithms enhance learner engagement.

**Table 3: Satisfaction with E-Learning Analytics Tools**

Satisfaction Level	No. of Students	Percentage
Highly Satisfied	35	35%
Satisfied	40	40%
Neutral	15	15%
Dissatisfied	7	7%
Highly Dissatisfied	3	3%



**Interpretation:** 75% of learners reported satisfaction, suggesting e-learning analytics tools are well-received though improvements are still needed.

### 5 Findings

The study findings indicate that students highly value tailored learning paths compared to conventional static e-learning modules. Almost 80% of the interviewees verified that personalization enhances motivation, engagement, and learning performance. This indicates that one-size-fits-all is not effective in higher education anymore.

The results also demonstrate that data mining methods are very effective in producing useful recommendations. Over 70% of the students viewed data-based course suggestions as applicable and helpful to their learning needs. The results indicate the real-world utility of implementing intelligent algorithms within e-learning frameworks

Moreover, e-learning analytics was also found to greatly improve the learning experience by monitoring progress, giving feedback, and detecting areas of improvement. Approximately 75% of respondents were satisfied with insights based on analytics. Nevertheless, there was a proportion (10%) that was neutral or unhappy, indicating the imperative for intuitive dashboards and data usage transparency.

In general, the findings confirm that a combination of data mining and e-learning analytics can result in a more learner-centric, personalized education system. The findings are in line with international trends where big data and artificial intelligence increasingly influence education.

## 6 Conclusion and Discussion

The research concludes that data mining and e-learning analytics-driven personalized learning path suggestions play a transformative function in education. In comparison to other e-learning approaches, such adaptive systems can customize content, tests, and activities based on the learner's profile. The research highly supports the implementation of personalized models since they result in increased engagement, satisfaction, and academic achievement.

The conversation points out that Indian learners are becoming more and more inclined towards online media, but most of them still struggle with factors such as information overload, inappropriate guidance, and limited malleability. A solution is offered by personalized learning paths through proper guidance to the learners based on the learners' objectives. Additionally, data mining helps in real-time learner need forecasting, and analytics assists in continuous monitoring and optimization.

But the research also identifies some limitations. There were some students who were concerned about data privacy, transparency of algorithms, and excessive dependence on technology. These are areas where a harmonious approach is necessary with human educators continuing to guide and technology serving as a supportive mechanism

In summary, the adoption of data mining and e-learning analytics in education can transform the Indian learning landscape. Properly implemented, these systems can improve dropout rates, enhance knowledge retention, and support lifelong learning.

## 7 Recommendation

- Implement accessible dashboards for teachers and learners
- Instill transparency in data utilization and algorithmic choices.
- Offer training sessions to educators for successful usage of analytics tools.
- Include local languages and multiple learning styles in recommendation systems
- Promote a hybrid strategy where technology supplements human teaching.

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