Adaptive Learning System with Educational Data Mining and Learning Analytics

A Thesis submitted in the fulfillment of the requirements for the award of the degree of

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in

Computer Science and Engineering Department

submitted by

Anika
(Registration No. 951503004)

Under the supervision of

Dr. Parteek Kumar
Professor, TIET

Dr. Deepak Garg
Professor, Bennett University

THAPAR INSTITUTE
OF ENGINEERING & TECHNOLOGY
(Deemed to be University)

Thapar Institute of Engineering and Technology

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Certificate

I hereby certify that the work which is being submitted in this thesis entitled "*Adaptive Learning System with Educational Data Mining and Learning Analytics*", in fulfillment of the requirements for the award of the degree of DOCTOR OF PHILOSOPHY submitted in Computer Science and Engineering Department, Thapar Institute of Engineering and Technology, Patiala, is an authentic record of my own work carried out under the supervision of *Dr. Parteek Kumar* and *Dr. Deepak Garg* and refers work of other researchers which are duly listed in the reference section. The matter presented in this thesis has not been submitted for the award of degree in any other University.

(Anika)
Regd. No. 951503004

This is to certify that the above statement made by the candidate is correct and true to the best of my knowledge and belief.

Parteek Kumar

(Dr. Parteek Kumar)
Professor, Computer Science and Engineering Department,
Thapar Institute of Engineering and Technology, Patiala-147004 (INDIA)

Deepak Garg

(Dr. Deepak Garg)
Professor, School of Computer Science Engineering and Technology,
Bennett University, Greater Noida-201310 (INDIA)

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(Anika)

Abstract

As per the 21^{st} *century educational trends, there is increase in the size of the cohort of students in the present classrooms. Further, present COVID pandemic situation, switching the modes of learning from offline to online, and inclusion of technology in the existing learning environments, the fields of educational data mining, learning analytics and adaptive learning systems have gained much attention worldwide. These help in optimizing the educational environments in various ways like providing personalized learning support, improving student learning outcomes, instructor performance and curriculum, identifying career learning pathways etc. This research study aims to develop an adaptive learning system with educational data mining and learning analytics, for the blended learning environments. To develop the proposed system, the distinguishment between the knowledge level of the students is supported. Since the study is performed for blended learning environments, the viewpoints, characteristics, behavioural analysis and identification of probable parameters for different category students (high versus low performers) is necessary.*

This research study helps to build an understanding of low performer and at-risk (failure or dropout) students' behaviour by interviewing low performer, at-risk students of fifth semester undergraduate engineering students. It focuses on the underlying reasons behind their low performance, at-risk behaviour for blended learning environments. This study explores their learning behaviour and perceptions, reasons for being low performers and objectives behind studying the courses. The research findings reveal that majority students belonging to the at-risk, low-performer category are found to be well-aware about their present academic state. They intentionally devote a minimal time to the courses, as they are focusing on their other prioritized aspects like building of new skills-set for making themselves market ready. Through these research findings, this study also proposes flexible design and reflections for blended learning environments.

For further exploring the reliability, behavioural analysis of acquired feedback, this research work also addresses the question of whether gender and socio-economic differences affect students' opinion of their teachers in higher education, across a number of disciplines. The research analyzed the differentials in students' ratings of *their teachers in five disciplines in the field of education. Data was drawn from student responses to the surveys conducted in a large Indian university at the end of each course unit. This study analyzes 112919 and 16354 complete sets of student ratings, to study the gender and socio-economic diversity based effects respectively. Statistical multivariate and univariate general linear models were used to derive the relevant results and graphs. The study reveals the existence of socio-economic status bias, gender-typical behaviour, gender-atypical behaviour, and same-gender and cross-gender biases; these resulted in differential ratings in the disciplines examined.*

For efficient designing of the proposed system for blended learning environments, this research study also focusses on exploring the workable parameters for available online environments. This study explores two types of logs (activity and performance) for identification of reliable parameters. For first study, it contributes towards efficient at-risk student identification by proposing a generalized sequential deep learning model for learning behaviour identification, built upon temporal 3-dimensional clickstream data. The model is trained and validated on two big public datasets: KDD Cup 2015 and OULAD. The results on the unseen test data achieve a classification accuracy ranging from 87.6%-92% and AUC from 0.881-0.961 and outperform other existing baseline models. For performance parameters based study, it proposes a modelling methodology for deploying interpretable Hidden Markov Model for mining of the sequential learning behaviour from light-weight assessments. The public OULAD dataset having diversified courses and 32,593 student records is used for validation. The results on the unseen test data, achieve a classification accuracy ranging from 87.67%-94.83% and AUC from 0.927-0.989, and outperforms other baseline models. For implementation of early warning systems the study also predicts the optimal time period, during the first and second quarter of the courses. With the outcomes, this study tries to establish an efficient generalized modelling framework that may lead the higher educational institutes towards sustainable development.

After the identification of performance parameters as reliable inputs, the research work focusses on checking the effectivity of these for blended learning environments. This research work utilizes lightweight formative assessments for blended learning environments. It discusses their implementation and effectiveness in early identification *of at-risk students. This study validates the usage of lightweight assessments for three core pedagogically different courses of large computer science engineering classrooms. It uses voting ensemble classifier for effective predictions. With the usage of lightweight assessments in early identification of at-risk students, accuracy range of 87%–94.7% have been achieved along-with high ROC-AUC values. The study also proposes the generalized pedagogical architecture for fitting in these lightweight assessments within the course curriculum of pedagogically different courses. With the constructive outcomes, the light-weight assessments seem to be promising for efficient handling of scaling technical classrooms.*

At the end, as an outcome of this research work, it presents an adaptive learning system with educational data mining and learning analytics. The proposed system is built upon topic based learning management system with various basic functionalities. The web interface provides support for student and teachers in effective management of the course. For research purpose, the topics are mapped with the course knowledge components. These are used to trace the student knowledge level. The adaptive interface with dashboard helps to judge the knowledge level of the student and provides adaptive educational content recommendations. For support of educational data mining and learning analytics, it is integrated with a machine learning portal. This portal helps the instructors in easy analysis. The instructors can train, test course specific models. They can also make early predictions regarding the student at-risk behaviour and can provide timely intervention to the respective students. This proposed system has the capability to embed effectiveness in the blended learning environments and can be used for the benefits of the society in the educational field.

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List of Abbreviations

ADS	Advanced Data Structures & Algorithms
ALS	Adaptive Learning System
APSU	Austin Peay State University
AS	Assessment Skills
AUC	Area Under the Curve
AVD	Analysis & Visualization of Data
BED	Big Educational Datasets
BPL	Below Poverty Line
CC	Content Coverage
CCw	Constructing Courseware
CEQ	Course Experience Questionnaire
CFIN	Context-aware Feature Interaction Network
CGPA	Cumulative Grade Point Average
CIE	Civil Engineering
CM	Concept Maps
CMS	Content Management System
COE/CSE	Computer Science and Engineering
CSV	Comma Separated Values
DBMS	Database Management Systems
DM	Data Mining
DS	Data Structures
DT	Decision tree
EDM	Educational Data Mining
ELE	Electrical Engineering
EM	Ensemble Model
ESE	End Semester Examination
EWS	Early Warning System
FDP	Faculty Development Programme
FN	False Negative
FP	False Positive

FSI	Feedback for Supporting Instructors
GBM	Gradient Boosting Machine
GEN	General
GLM	Generalized Linear Models
GS	Generic Skills
GrS	Grouping Students
HMM	Hidden Markov Model
HSS	Humanities and Social Sciences
iLIME	Learning Interaction Mentoring Evaluation
ICT	Information Communication Technologies
IIM	Indian Institute of Management
IISc	Indian Institute of Science
IIT	Indian Institute of Technology
IOHMM	Input-output Hidden Markov Model
ISB	Indian School of Business
ITS	Intelligent Tutoring System
IV	Information Visualization
kNN	k-Nearest Neighbour
KDDCUP15	KDD Cup 2015 Dataset
LA	Learning Analytics
LACE	Learning Analytics Community Exchange
LMS	Learning Management System
LR	Logistic Regression
LSES	Low Socio-economic Status
LSTM	Long Short-Term Memory
LWA	Light Weight Assessment
MHRD	Ministry of Human Resource Development
ML	Machine Learning
MLP	Multi Layer Perceptron
MLR	Multiple Linear Regression
MOOC	Massive Open Online Courses
MS	Motivational and Supportive

MSE	Mid Semester Examination
NB	Naive Bayes
NGO	Non-Government Organization
NMC	New Media Consortium
NN	Neural Network
NPTEL	National Programme on Technology Enhanced Learning
OULAD	Open University Learning Analytics Dataset
OBC	Other Backward Classes
PDF	Portable Document Format
PI	Peer Instructions
PS	Practical Skills
PSc	Planning and Scheduling
RB	Rule Based
RF	Random Forest
RNN	Recurrent Neural Network
ROC	Receiver Operating Characteristic
RS	Recommendation for Students
SA	Statistical Analysis
SC	Scheduled Castes
SM	Student Modelling
SMS	Short Message Service
SOFA	Short-lightweight Online Formative Assessments
SOM	School of Mathematics
SP	Student's Performance
SPSS	Statistical Package for Social Sciences
SRS	Student Response System
ST	Scheduled Tribes
STDEV	Standard Deviation
STEM	Science, Technology, Engineering & Mathematics
SVM	Support Vector Machine
SWAYAM	Study Webs of Active-Learning for Young Aspiring Minds
TN	True Negative

TP	True Positive
UNIR	Universidad International De La Rioja
USB	Undesirable Student Behaviour
VLE	Virtual Learning Environment
XGB	eXtreme Gradient Boosting

List of Publications

1. Anika Gupta, Deepak Garg, Parteek Kumar. "Analysis of Students' Ratings of Teaching Quality to Understand the Role of Gender and Socio-Economic Diversity in Higher Education". In: *IEEE Transactions on Education* 61.4 (2018), pp. 319–327. DOI: 10.1109/TE.2018.2814599 (*Impact Factor: 2.116*)

2. Anika Gupta, Deepak Garg, Parteek Kumar. "An ensembling model for early identification of at-risk students in higher education". In: *Computer Applications in Engineering Education* (2021). pp. 1–20. DOI: 10.1002/cae.22475 (*Impact Factor: 1.532*)

Chapter 1
INTRODUCTION

1.1 Overview

With the introduction of Information Communication Technologies (ICT) in education, the classrooms are going digital. Interactive whiteboards, social media interactions, online discussion boards, lectures, quizzes, and tests *etc.* all are part of today's ICT based classrooms. This major shift in the higher education paradigm is because of the changing needs of today's environment concerning the 21^{st} century skill requirement as opposed to the industrial age's factory model. As per the New Media Consortium (NMC) Annual Horizon Report's educational predictions, *Learning Analytics* and *Adaptive Learning* are the significant role players that will highly influence the future of the forthcoming technology-enabled learning environments [208].

1.1.1 Introduction to Educational Data Mining (EDM)

With the introduction of online learning and collection of "Big Educational Data" (BED) at the backend of these systems, Educational Data Mining emerged as a major research area. It comprises of computational, psychological, research methodologies and approaches for having a basic knowledge of how students learn. Computer-supported interactive learning systems and environments have opened opportunities for the collection and analysis of student data for discovering of the patterns and trends. This can lead to new discoveries and predictions and also for test hypotheses about how students learn. Figure 1.1 represents the major milestones in the field of EDM and LA.

Educational data collected via different online learning systems can be integrated at a larger scale for students. They can further be explored for its variables by various data mining algorithms for model building.

EDM is concerned with "*developing, researching and applying computerized methods to detect patterns in large collections of educational data that would otherwise be hard or impossible to analyze due to the enormous volume of data within which they exist*" [168].

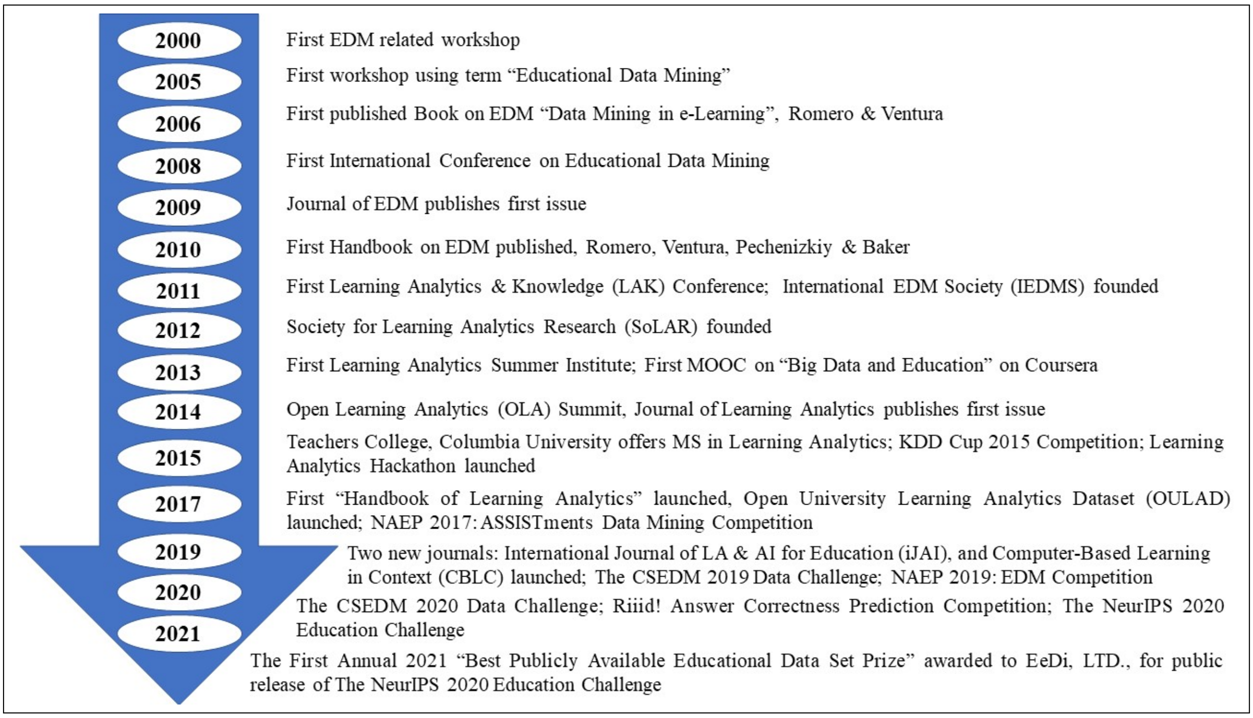


Figure 1.1: Timeline of milestones in EDM and LA [165, 299, 307]

Features of educational data can be clubbed into the following points [170].

- **Hierarchical:** The collected data is nested inside one another starting from keystroke level, answer level, session-level, student level, classroom level, teacher level, and institute level.

- **Time:** Time captures important data like the length of practical sessions or total time taken to learn.

- **Sequence:** Sequence deals with the ordering of the concepts and practice tutorials offered to the students for learning.

- **Context:** It helps in providing explanations of the outcomes and deals with the know-how of where a particular model works or fails.

1.1.2 Introduction to Learning Analytics (LA)

Learning analytics being a branch of web analytics and a sister field of EDM aims to keep track of the learner's profile by collecting and analyzing the learner's details with respect to its online interactions. This technology finds its way because of its student enrollment management, tracking student progress, student degree planning, tracking time to degree, and assessing student learning outcomes.

LA has three levels of functioning, *i.e.*, student, instructor, and institutional level. For students, it can act as a personalized assistant and can provide a lifelong learning experience. For an instructor, it acts as an assistant for better class management and for better productivity. It helps in the timely identification of outlier students too. At the administration level, it enhances the student retention rates, course completion rates, optimization of resources, and helps to improve the service quality.

Overall, LA is defined as "*measurement, collection, analysis and reporting of data about the learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs*" [142].

The general reference model of LA consists of four dimensions. These four dimensions are data and environments, stakeholders, objectives, and methods [143]. LA approaches derive educational data from a variety of sources at the backend, which can be either centralized educational systems or distributed learning environments. The application of LA can be comprised of different stakeholders, including students, teachers, educational institutions, researchers, and system designers. These all stakeholders can have their different perspectives, goals, and expectations from the LA application. However, the main objectives of LA are found to be monitoring, prediction, mentoring, and assessment *etc.* as per the requirements of these stakeholders. Different methods involved in the detection of interesting patterns hidden in educational data sets and their analysis are Information Visualization (IV), Data Mining (DM), Social Network Analysis (SNA), and Statistics.

1.1.3 Learning Analytics Process

LA, with its glorifying characteristics of tracking student progress, timely student's risk behaviour identification, improving retention and completion rates, adaptive and predictive analysis, is identified as a complete process in itself. Its implementation process involves the following steps.

- First step is to identify the major challenges that need to be addressed by LA, identify concerned resource persons and develop an action plan.

- Next step is to determine the major inhibitors in the way of implementation.
- After this, the tools need to be identified, which may include predictive analysis, degree mapping tools, early-alert system, and reporting tool *etc.*
- Finalizing the high-level analytics strategic plan and sharing it with the institution's stakeholders form the final step before implementation and analysis.

1.1.4 Difference between EDM and Learning Analytics

EDM and LA have certain differences. EDM mainly focuses upon development of new tools and algorithms to discover the hidden data patterns whereas LA focuses on application of existing tools and techniques at scalable instructional systems for knowledge extraction and creation of the actionable data for proper human judgement. Figure 1.2 and Table 1.1 show the major differences between EDM and LA.

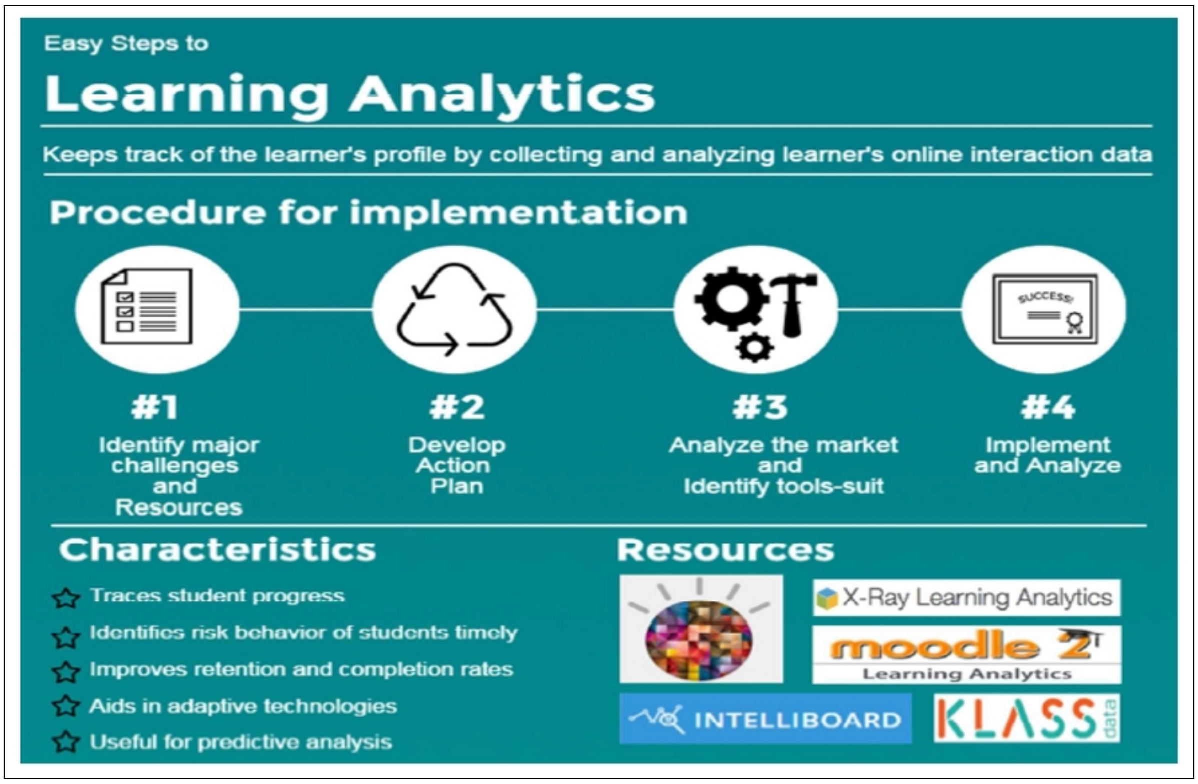


Figure 1.2: Learning analytics process and characteristics

1.1.5 Adaptive Learning through Learning Analytics

One of the specialized branches of LA, Adaptive learning systems, aim to provide more customized educational content delivery for individual students' performances and interests. These systems are specifically designed to adjust themselves dynamically and deliver the level and type of course content according to the learner's skill acquirement and abilities. It aims at determining the exact knowledge of the learner accurately. It logically moves the course learners through a sequential learning path set by the instructor, to prescribed learning outcomes and skill mastery. It mainly focuses on student-centric learning designs. This helps to accelerate and boost the learner's performance along with the help of automated as well as instructor's timely interventions. The adaptive systems achieve the above-mentioned automated content adjustment by keeping track of students' learning pathways and sequential control of the course learning tracks. It also tracks the pace as well as the level of the learner's skill attainment throughout the course.

Table 1.1: Major questions answered by EDM and LA

Educational Data Mining	**Learning Analytics**
Focus Point	
It focuses mainly on identifying patterns within the data through the development of new tools and algorithms.	Focuses on the application part. It applies the tools and techniques for the large designed educational systems and thus helps in human decision-making.
Different Examples of Questions tackled by EDM and LA	
What sequence of topics is most effective for a specific student?	When are students ready to move on to the next topic?
Which student actions are associated with better learning and elevated grades?	When will a student be at-risk for not completing a course?
Which actions represent student satisfaction and engagement?	If no intervention is provided, what grade is a student likely to receive?
What features of a specific learning environment lead to better learning?	Is student in such a state that he should be referred to a counsellor for help?

1.1.6 Adaptive Learning System (ALS) Model

Basic ALS consists of methods that organize modular educational content, systems for assessment purposes that track the learner's progress and evaluate their ability. It also assists through techniques that match the presentation of content to individual learners based on their possessed skill set dynamically and in personalized ways. The researchers at the Action Lab, EdPlus of Arizona State University, have constructed the ALS framework that integrated three areas of content, assessment, and competency frameworks, as shown in Figure 1.3.

Table 1.2: Main differences between EDM and LA [150]

	Educational Data Mining	**Learning Analytics**
Discovery	The key idea is automated discovery. Leveraging upon the human judgment is just a tool to accomplish the goal of automated discovery.	The key idea is leveraging upon the human judgment. Automated discovery is used as a tool to accomplish this goal.
Reduction and Holism	Main emphasis is on reducing the whole system into components and analysis of the individual component along with their relationships.	Main emphasis is on studying and understanding of the systems as whole and in their full complexity.
Origins	EDM has strong origins in educational software, student modelling along with the prediction of course outcomes.	LA has stronger origins in semantic web, intelligent curriculum, outcome prediction, and systemic interventions.
Adaptation and Personalization	The main focus is on automated adaption	The main focus is to provide relevant information as well as empower the instructors and learners.
Techniques and Methodologies	Classification, clustering, Bayesian modelling, relationship mining, discovery with models, visualization	Social network analysis, sentiment analysis, influence analytics, discourse analysis, learner success prediction, concept analysis, sense-making models.

The researchers at the Action Lab, EdPlus of Arizona State University, have constructed the ALS framework that integrated three areas of content, assessment, and competency frameworks. Content modules form an important part of the adaptive systems as they index the critical concepts, which are presented in the form of a series of multistep problem. This helps learners to synthesize concepts that are new to them. As suggested by Arizona researchers, "*Competencies are defined units of knowledge, skills, and abilities used to evaluate skill mastery and the demonstrated application of those skills.*" Competencies and identified skills are further defined as sub-competencies. These sub-competencies collectively complete a particular skill or competency structure. Prior learning assessments help to validate the learning and provide credit to the learners for what they already know. They place the learners at the floor or starting of the next viable competency level that needs to be learned in the path of knowledge building throughout the course [215].

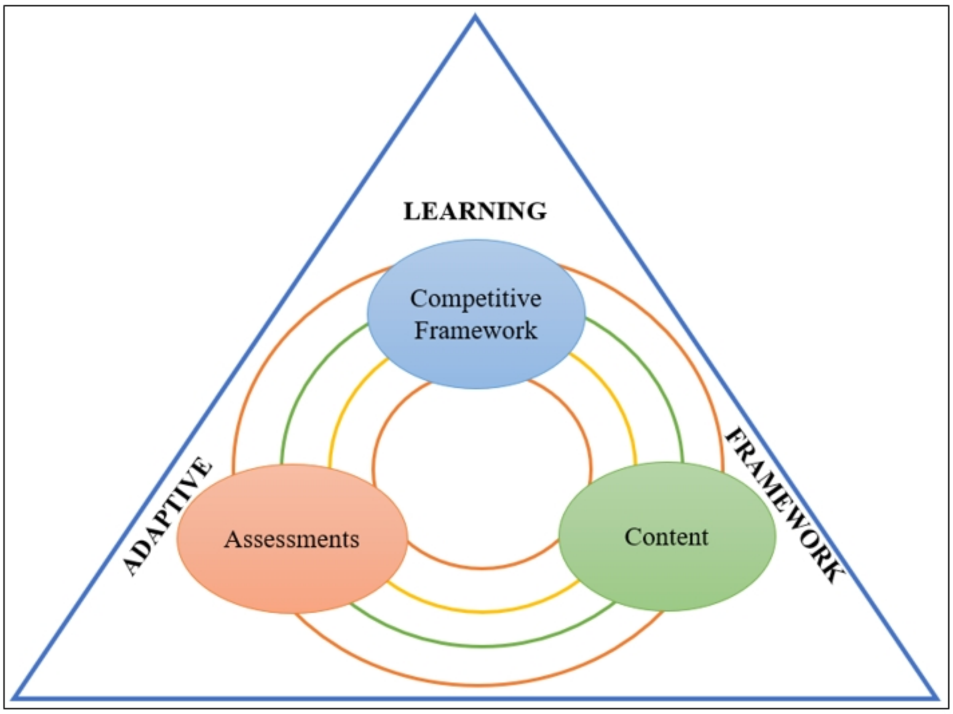


Figure 1.3: Adaptive learning model [8]

As ALSs are one of the specialized branches of LA, these, along with LA, automatically possess all the benefits of LA. Additional advantages of ALS include complete automation of learner's assessments, predictive analysis, addressing the different levels of prior knowledge and content progression, automated feedback without the instructor's intervention. This helps in reducing instructor's workload. These systems help to solve the problem of learning skills mastery amongst the increasing diversification of the students. Student-centered design makes the students owner and controller of their own learning journey. Real-time response, automated interventions, and timely feedback helps in better course coverage and learning outcomes and that too at student learning pace. The instructor gains insights into individual learners' needs, their learning pathways, and progress so that instructor can timely allocate time to students who need remediation. ALS empowers faculty by providing rich educational data analysis of their course learners' progression, which can help in better course design. If effectively created and implemented, ALSs have the capability to track every student's learning trajectory providing the instructor a better insight into the students learning progression, leading to timely interventions when and wherever needed.

1.1.7 Blended Learning Environments

In the field of education, 21^{st} century has been embraced with massification of education. Embedding and equipping students of large classroom with the required skills like problem solving, critical thinking, collaboration, and teamwork, seems to be a daunting task. The academic drifts and diversification due to varying possessed skill-set, differential learning abilities, pose major challenge. In consideration with the present COVID scenario, online and blended leaning has become the norm.

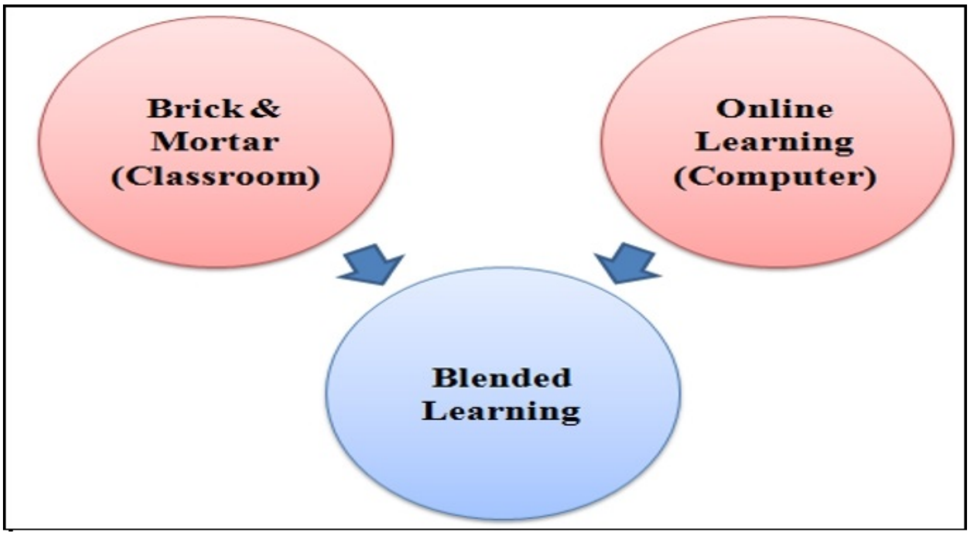


Figure 1.4: Blended learning model

Blended learning is the educational practice that combines digital tools with traditional classroom face-to-face teaching. Blended learning environment, as shown in Figure 1.4, is a learning environment that combines face-to-face instructions with computer-assisted technology-mediated instructions. Traditional classroom based face-to-face interactions involve direct communication between instructors and learners, whereas online computer-assisted technology-mediated instruction uses communication technologies for interacting with the learners, which can be located anywhere around the world. Researchers give three basic reasons for the adoption of blended approaches as these improve learning effectiveness, increase access and convenience, and provide greater cost-effectiveness [100].

Blended learning methods score over traditional and online environments as they help to improve the learning effectiveness, increase access and learning convenience, and are also cost-effective. Some of the benefits of blended learning are it results in high levels of student achievement by providing students to work on their own with new concepts, provides a personalized educational experience for students, on behalf of an instructor it makes sure, that the students fully understand new concepts before moving on. Improve communication between instructors and part-time students via the incorporation of information technology in the course content delivery methods. Through this students can better evaluate their understanding of content via computer based qualitative and quantitative assessment modules.

It also has the potential to lessen the educational expenses using e-content in the form of e-textbooks and e-notes. Data compilation and modification of instruction and assessment are easy in the case of blended learning environments. As software involved in this process automatically collects learner data and assess academic progress, providing better insight to the teacher as well as the students.

This research work proposes an adaptive learning system with EDM and LA for blended learning environments. This research work proposes an ALS with EDM and LA for blended learning environments. For this, behavioural analysis of blended learning environment students is performed, for identification of probable parameters. It then looks for effective parameters for practical online learning environments through public datasets. Once the effective parameters are identified, the pedagogy and model are proposed, for adopting them in blended learning environments. Then, an ALS is proposed with integrated machine learning interface for personalized learning for students and analytics interface for instructors. It utilizes the generated data for assisting the instructors of blended learning environments, through its timely predictions of at-risk students. The next section discusses about the need of these adaptive learning systems in present learning environments.

1.2 Need for Adaptive Learning System

As we are advancing in this 21^{st} century, there is increase in the size of the cohort of students in the present offline classrooms. Further, present COVID pandemic situation, switching the modes of learning from offline to online, and inclusion of technology in the existing learning environments, the fields of LA and ALS have gained much attention worldwide. The major benefits of these fields are given below.

- **Identification of Target Courses:** LA help institutions in identifying those target courses/disciplines that align themselves along with the needs and preferences of their students by examining the student enrolment rates and their interests towards specific disciplines.

- **Curriculum Improvement:** It helps in designing the new curriculum through strategic planning and analyzing the weak points and strengths of the existing curricula for achieving maximum learning outcomes.

- **Student learning outcomes, behaviour and process:** From the available educational data, with the help of data mining, useful information can be mined. Instructors can get a better insight regarding their student's learning paths, behaviour *etc.* They can also adjust their educational content accordingly.

- **Improved instructor performance:** LA can help the educators in the identification of the areas needing improvement for better facilitation of the interactions with students. This can be done via activity logs and interaction with the students in technology-enabled environments.

- **Post-educational employment:** The LA can also assist in identifying the post-educational opportunities for the graduates and thus helps to keep the target education more closely aligned to the employment market needs.

- **Personalized Learning:** LA can also help in providing personalized learning environments. They can help in largely determining the student success rate through real-time reviewing, action, and timely feedback to the students.

- **Learning analytics practitioners and research community:** Researchers and practitioners can also leverage from the LA, as they can easily share information and collaborate. They can do so by identifying the gaps existing between the industry market skills requirements and academia and working on overcoming the existing problems.

LA, despite its various uses and advantages, is still said to be in its nascent stage. Its actual advantages vary and very much depends upon its type of implementation and on the learning environments in which it is implemented.

1.3 Applications of Adaptive Learning System

The main aim of EDM and LA is to improve the learning process, guiding student learning as well as side by side developing a deeper understanding of the educational phenomenon. These areas, when quantified, can be divided into several categories, each of which is discussed below [127].

- To highlight the useful information for making it noticeable and support decision making [118, 123].
- To support the instructors/administrators by providing them timely information (regarding the organization of learning material resources, improve student's learning *etc.*) for taking proactive and appropriate measures and thus help in better decision making [62].
- Provide students with personalized recommendations for links to visit, next assignment to attempt *etc.*, with respect to their personal activities [103].
- Help in estimating the unknown value of learning variables for students like performance, knowledge, marks or score, success rate *etc.* [98].
- Development of cognitive models, based on learner's characteristics which includes modelling of their skills as well as declarative knowledge [86].
- To identify the unusual behaviour of the learners like misuse, erroneous activities, playing games, lower motivation levels, dropping out and failures *etc.* [39].
- Identification of the common traits, features, characteristics amongst the learners such that further successful personalized and adaptive systems that promote effective group learning can be implemented [105].
- Structural Analysis of the learner's network, targets to study relationships amongst the learners rather than as a learner's individual properties [57].
- To construct concept maps that help to automate the educational process. Text mining is also used, in the educational domain, for automatically constructing academic articles [90].

- To exchange, reuse and organize learning contents or resources automatically and develop the courseware [78].

- To improve the traditional educational process by planning for the future courses and their scheduling, developing curriculum *etc.* [91].

1.4 Open Challenges

Here, the open challenges with respect to the different fields like EDM and LA, ALS, and blended learning environments are discussed.

1.4.1 EDM and Learning Analytics Challenges

Irrespective of the numerous advantages of the LA, there are various challenges faced during the adaptation of this process that can be represented in the following points.

- **Data collection:** The major challenge when looking for LA is data collection and tracking. It forms the very basis of the whole LA process's success. Availability of resources, the establishment of social platforms for educational interactions, and the pre-requisite knowledge of the learning environments are some of the major steps in its data acquisition.

- **Evaluation process:** LA helps the instructor's evaluation to function appropriately. Appropriate educational content is demanded to be delivered to the students in a timely and accurate way, whereas due to the unprecedented explosion of available online data, it becomes critical for the ever-developing evaluation process.

- **Learning environment optimization:** Due to the expanded boundaries of the Learning Management System (LMS) into open learning environments, discovery of new problems faced by students can be there. A different set of challenging data and parameters can exist, which need to be researched over for determining the success from learner's perspectives and thus optimizing the respective learning environments.

- **Emerging technology:** For leveraging the full potential of the LA, learning and technology are required to go hand-in-hand, which remains a challenge as technology continues to develop constantly. The research on LA and pedagogy is still believed to be in their beginning stages.

- **Ethical and privacy issues:** The ethical, legal, and risk are the major considerations while dealing with LA. How much data is being captured, how and where it is used poses major privacy concerns, and that is why LA ethical and legal complexities challenge the institutions for its usage.

While implementation of the LA system in different learning environments, the above-mentioned challenges need to be addressed at the initial level itself. Complete data collection, data tracking, and privacy concerns need to be handled, and in place, evaluation procedures must be properly refined, proper data analysis methodologies and interpretation along with their appropriate presentations must be properly dealt with to achieve better learning environment optimization.

1.4.2 Adaptive Learning System Challenges

Although developing an effective adaptive system is a big challenge, the challenge lies in implementing the created system in present learning environments. Other significant challenges apart from basic LA challenges that exist for these systems can be clubbed as given below [215].

- Intelligent adaptive systems require a high amount of big educational data regarding the learner's actions, their learning behaviour information, and content interaction for effectively mapping the optimal learning path for the learner and are data-intensive.

- Smart content repositories need an appropriate amount of metadata to be created and kept. This presents challenges like the source of metadata, its amount, the resource responsible for creating as well as maintaining the metadata libraries. As and otherwise, if this metadata foundation is inappropriate, the entire personalization intent is affected and compromised.

- ALS research and development is expensive and needs early-stage funding for developing market prototypes and software involved.

- Instructor's proficiency for the successful adoption of these systems, their usage, and implementation stand as another major challenge.

While creating and implementing an adaptive system in the learning environments, the above-mentioned challenges need to be addressed along with the basic challenges of the LA for successful usage implementation of these systems.

1.4.3 Blended Learning Challenges

Designing an effective blended learning environment seems to be quiet challenging. It requires lot of efforts from the instructors as well as students, as they are expected to acquire new skills and update themselves for the classrooms. Below are some of the specific challenges.

- Decision regarding what concepts to deliver through mediated technology and which ones to reserve for one-to-one personal interaction, seems to be a daunting task.
- Usage of information technology as a part of pedagogical ecosystem is not consistently accepted by all regions and institutions.
- Lack of sufficient training and experience in the technological tools, often leads to sub-optimal results with lower teaching satisfaction rates.
- Students' dependence on instructors for guidance, despite of the usage of technologically advanced tools, sometimes proves in an overhead.
- Student's data privacy is a major concern, as the technologically advanced classrooms are being integrated with their personal lives.

The technologies discussed here are said to be in their nascent stage in the field of education. These are predicted to have vast potential in changing the higher education scenario that matches the level of today's learning environment concepts of personalized and lifelong learning. Different and multiple ways of involvement of these technologies in higher education are left to be explored on the part of the user as these fields in education still need time for their stability.

1.5 Motivation

As evidenced in this COVID era, the online educational systems have played a very important role within the lives of the students as well as instructors. With the onset of the large use of online education due to the current COVID pandemic and Massive Open Online Courses (MOOCs) for distance education, the traditional era of education has been revolutionized. Online education has posed strong challenges and is the cause of various new resulting pedagogical designs like blended learning, *etc.*

Educators are trying to tap the potential of online resources and pedagogies for the effective delivery of online education by tackling tech-crazy learners. However, despite the tremendous efforts made, one major hindrance in the path is the "distance". As opposed to the traditional classrooms where instructors can identify the real-time mental and behavioural states of the learners and modify their content delivery accordingly, this identification seems to be difficult in the case of online learning. Due to lack of eye-to-eye contact, diversified learning rates, and backgrounds of the learners, this has further elevated the problems like higher dropout rates, lower retention rates, *etc.* for the online courses. As the need of the hour and to tackle the above-mentioned issues for online education, some effective strategy in the form of the smart and personalized learning system, acting as a teaching assistant, must be in place for bridging this gap of distance for providing a real-time learning environment.

This research work proposes an ALS that first traces the topic based knowledge level of the students and then helps them to provide appropriate topic-wise educational content based on their knowledge level. The proposed system works on the concept of topic based LMS implemented with the basic functionalities. Along with the necessary educational content distribution and assessments, it also assists the instructors in effective early identification of at-risk students.

The proposed system is designed with respect to the blended learning environments. It helps to deliver quality education to the students through its early at-risk identification functionality for the instructors and its personalized learning functionality for the students. This may further help in increasing the student course retention rates and decreasing the course or program dropouts.

1.6 Research Gaps

As per the increase in the cohort of students in the classrooms, the ever-increasing craze for online and mobile learning environments, enhanced technical advancements, and outdated one-size-fits-all notion in educational scenarios, there still exist multiple research gaps which hinder the delivery of quality education in 21^{st} learning environments. In lieu of the above characteristics and their adaptation, the following research gaps have been identified.

- It is very hard to find public, complete and strong datasets for educational purposes. The educational datasets have sensitive information associated with them. So, various ethical and privacy concerns need to be addressed before making them available for public usage. Also, as the educational level of the learners and delivery models vary from country to country, the same acquired dataset cannot be used in multiple contexts to draw fruitful inferences [168, 201, 252].
- With the increase in the cohort of students in the classrooms, lack of special focus on outstanding, weak, and outlier students, their learning progression tracking, emotional support, timely feedback, and remediation is seen. Individualized proper guidance for students, regarding the educational carrier pathways to choose aligned with industry and market needs, area of research *etc.* based on their past and present performance and skill-set attainment is lagging far behind in present educational scenarios [168, 201].
- For blended learning environments, models like flipped classrooms exist, but concrete proofs concerning the experimentation and implementation of adaptive learning models, distributed and networked student learning models for Indian educational learning environments is still lacking [190].
- Although various Intelligent Tutoring System (ITS), adaptive systems for completely online environments exist in the literature, but most of them are found to be domain-specific. There is a great need for a generalized system model/architecture whose scope is not limited to a particular subject or domain [127, 168].
- No strong evidence of machine learning techniques like classification and

clustering techniques, sequential pattern mining, context-awareness and student's behaviour, applicable for Indian educational environments, is found. Qualitative research methods yielding significant results are still lacking [168].

- There is a need for a teaching assistant system for blended learning environments which supports personalized learning for the students that adapt itself according to the learning style and pace of the student. The system automatically detects the student's weak points by tracing the student's learning history timely and display appropriate content and assessments. It also identifies the extra-ordinary as well as bottom-line students timely for better insight, direction, and skill-building. In parallel, this system can also help the instructors in the early identification of at-risk students for timely intervention. Thus, it can help in increasing the retention rate of the students for blended learning environments.

1.7 Research Objectives

To develop an ALS for blended learning environments, which first capture and then create the actionable data with the help of EDM and LA. Uses it further for embedding adaptiveness in the learning environments for providing personalized learner-friendly course pages interface with dashboards and graphics, as an outcome.

1.7.1 Objectives

The main objective of the proposed study is to develop and design an ALS with the help of EDM and LA for blended learning environments. To perform this task, the following objectives are proposed to be carried out.

1. To analyze existing Educational Data Mining, Learning Analytics and adaptive learning techniques.

2. To perform Educational Data Mining and Learning Analytics for identification and tracking of student learning behaviour.

3. To design and implement the adaptive learning system for blended learning environments.

4. To test and validate the proposed adaptive learning system for improving the quality of education.

1.7.2 Mapping of Objectives with Research Gaps

Table 1.3 represents the mapping of the above-proposed objectives with the research gaps identified in the field of EDM, LA, and ALS.

Table 1.3: Mapping of proposed objectives with research gaps

S. No.	Objectives	Research Gaps Mapped
1.	To analyze existing Educational Data Mining, Learning Analytics and adaptive learning techniques.	Since no strong evidence of machine learning techniques like classification and clustering techniques, sequential pattern mining, context-awareness, student's behavioural analysis applicable for Indian educational environments are found. Here efforts will be put to bridge the gap by analyzing the present state of EDM, LA, and ALS in India with respect to the world-class universities.
2.	To perform Educational Data Mining and Learning Analytics for identification and tracking of student learning behaviour.	With the increase in the cohort of students in the classrooms, lack of special focus on outstanding, weak, and outlier students, their learning progression tracking, timely feedback, and remediation is seen. Individualized proper guidance for students regarding the educational carrier pathways to choose aligned with industry and market needs, area of research *etc.* based on their performance, behaviour, and skill-set attainment is lagging far behind in present Indian educational scenarios.
3.	To design and implement the adaptive learning system for blended learning environments.	The adaptive system will act as a teaching assistant system for students in blended learning environments like India, which will support personalized learning for the students and adapt itself according to the learning style and pace of the student. The system will try to automatically detect the weak points of the students by tracking the student's learning history timely and display appropriate content and assessments. It also identifies the extra-ordinary as well as bottom-line students timely for better insight, direction, and skill-building.
4.	To test and validate the proposed adaptive learning system for improving the quality of education.	For Indian learning environments, models like flipped classrooms exist, but concrete proofs concerning the experimentation and implementation of educational data mining and learning analytics system, adaptive learning models for Indian educational learning environments is still lacking.

1.8 Research Methodology

The following methodology has been adopted for achieving the above-mentioned objectives.

- **Gaining an insight into Educational Data Mining and Learning Analytics:** A literature survey was done for gaining an insight regarding the various educational practices followed at international and national level in the field of EDM, LA and ALS. The various EDM and LA strategies like sequential pattern mining, association rule mining, correlation mining, clustering, social network analysis, domain structure discovery *etc.* were studied. These were found to form the basis behind the identification of the weak and outlier students, their learning progression tracking, timely feedback and guidance for students, educational carrier pathways based recommendations, area of research *etc.* based on their performance, behavioural traits, and skill-set attainment. Focussed studies regarding the behavioural analysis of students, pattern tracking for early-identification of at-risk students, model and domain based studies, datasets, tools, and evaluation parameters *etc.* were explored and analyzed. These focussed research studies are used for comparatively analysis of proposed models.

- **Behavioural Analysis:** The next phase involved behavioural analysis of the students of blended learning environments for efficient system designing. For distinguishing between the knowledge level of the students involving at-risk of failure or dropout students and provide personalized educational content, further research to identify the viewpoints of at-risk students, was conducted. A course-specific study was conducted in which the students having weak in-class performance were selected. Their characteristics, feedback, motivation parameters, and future viewpoints were analyzed. Further, second study was conducted for checking the reliability of the obtained behavioural feedback. The analysis was done for checking the existence of any gender based or socio-economic biases within the feedback. For this, direct data obtained from a large cohort of blended learning environment students as feedback, was selected. EDM and Statistical Analysis (SA) was performed for extraction of generalized relevant conclusions from the acquired educational datasets. After the complete analysis of generalized and student-specific feedback based studies, probable parameters that may work for efficient proposed system designing were collected and jotted down as an output for this phase.

- **At-Risk Model Generation with Online Educational Dataset:** This phase involved experimentation with various parameters on online educational data from online environments. The objective was to identify the workable parameters for online environments. As per the availability of the datasets involving different parameters and creation of the at-risk model, two different public datasets from online environments were selected. Two different experiments were done with differentiated parameters (activity and performance logs), to identify the importance of the parameter. The experiment involved feature selection, pre-processing involving relative and sequential data consideration, sequential model selection, model building, and predictions for identification of at-risk of failure or dropout students. Considering the online environments experiments, this phase helped to identify the parameters that work effectively for online environments. Effective parameters along with efficient at-risk models were the output for this phase.

- **At-Risk Model Generation for Blended Learning Environments with Pedagogy:** By this phase, there were two results regarding workable parameters for efficient system designing. One from behavioural analysis phase, as probable parameters and the other from at-risk model generation phase as effective parameters online environments. After the analysis of both the parameters, performance parameters were identified as effective and explored further for experimentation in blended learning environments. For this, firstly, an efficient and generalized pedagogy was designed to embed these performance parameters within the different course runs. After embedding these performance parameters into the pedagogical space, these were utilized for the identification of at-risk students for blended learning environments.

  The machine learning models were built in, and at-risk student model for blended learning environment, was created. As an output of this phase, a validated at-risk model and a newer pedagogy was proposed for the embedding of effective performance parameters within the blended learning environment scenarios. These were later utilized for the effective identification of at-risk students.

- **Developing Adaptive Learning System with Educational Data Mining and Learning Analytics:** Once the validated at-risk model was created, the designing and development of the basic LMS was done. It was further integrated with the relevant model for the creation of ALS. For differentiating between the different knowledge levels (low, medium, and high) of the students and providing them personalized educational content accordingly, a weighted adaptive learning rule based model was implemented. As an output of this phase, a topic based LMS was designed for students and instructors with all the basic functionalities, for blended learning environments. From students' perspective, it is having the capability of providing topic based personalized content according to their knowledge level. It utilizes non-weighted assessments as its input parameters.

  From instructor's perspective, it helps them in the early identification of at-risk students of their respective courses with light-weight assessments as input parameters. For better visualization of the learning progression and at-risk state of the class learners, an effective LA interface is also in place.

Table 1.4: Mapping of proposed objectives with thesis chapters

S. No.	Objectives	Associated Thesis Chapters
1.	To analyze existing Educational Data Mining, Learning Analytics and adaptive learning techniques.	Chapter 2: Literature Survey
2.	To perform Educational Data Mining and Learning Analytics for identification and tracking of student learning behaviour.	Chapter 3: Behavioural Analysis Chapter 4: At-Risk Model Generation
3.	To design and implement the adaptive learning system for blended learning environments.	Chapter 4: At-Risk Model Generation Chapter 5: Blended Pedagogy with At-Risk Model Chapter 6: Adaptive Learning System
4.	To test and validate the proposed adaptive learning system for improving the quality of education.	Chapter 4: At-Risk Model Generation Chapter 5: Blended Pedagogy with At-Risk Model

This LA visualization interface provides insights to the students regarding their learning progression. For the instructors, it provides insights regarding the student's learning behaviour or state, for their respective classes.

The complete generalized proposed research workflow for the system is shown in Figure 1.5. The mapping of research objectives with the proposed thesis chapters is shown in Table 1.4.

1.9 Research Contributions

As an outcome of this research, the proposed system contributes to the literature in following ways.

- Explores the basic characteristics, objectives, and reasons for at-risk behaviour of low performer students. Identifies whether the 21^{st} century learners are real strugglers or are willing to "risk" their academic performance for their priorities. Further explores the trustable parameters that these students are willing to work upon and act as catalysts for them.
- Behavioural analysis of students feedback for trustable feature analysis. It confirms the existence of biases in gender and socio-economic diversified blended learning educational environments. It further analyzes the after-effect of such policies and frameworks.
- Proposes a generalized deep learning architecture for at-risk student prediction using independent clickstream data. This model utilizes three-dimensional sequential data modelling across different time windows for data modelling. The model is validated across two public BED from diversified institutions. The proposed model resulted in an accuracy score of 0.876, precison as 0.893, recall value as 0.959, F1-score of 0.925 and AUC value of 0.881, for KDDCUP15 dataset. For OULAD, it resulted in accuracy score of 0.920, precision as 0.952, recall value as 0.868, F1-score of 0.908 and AUC value of 0.961. The proposed model produced comparable results when compared with the existing deep learning models on direct evaluation metrics values. However, it scored over others when compared on generalizability testing and real-world adaptiveness. As the model is more robust for handling the real-world unseen course instances, so

the results obtained for the proposed model are found to be more realistic and effective for educational learning environments.

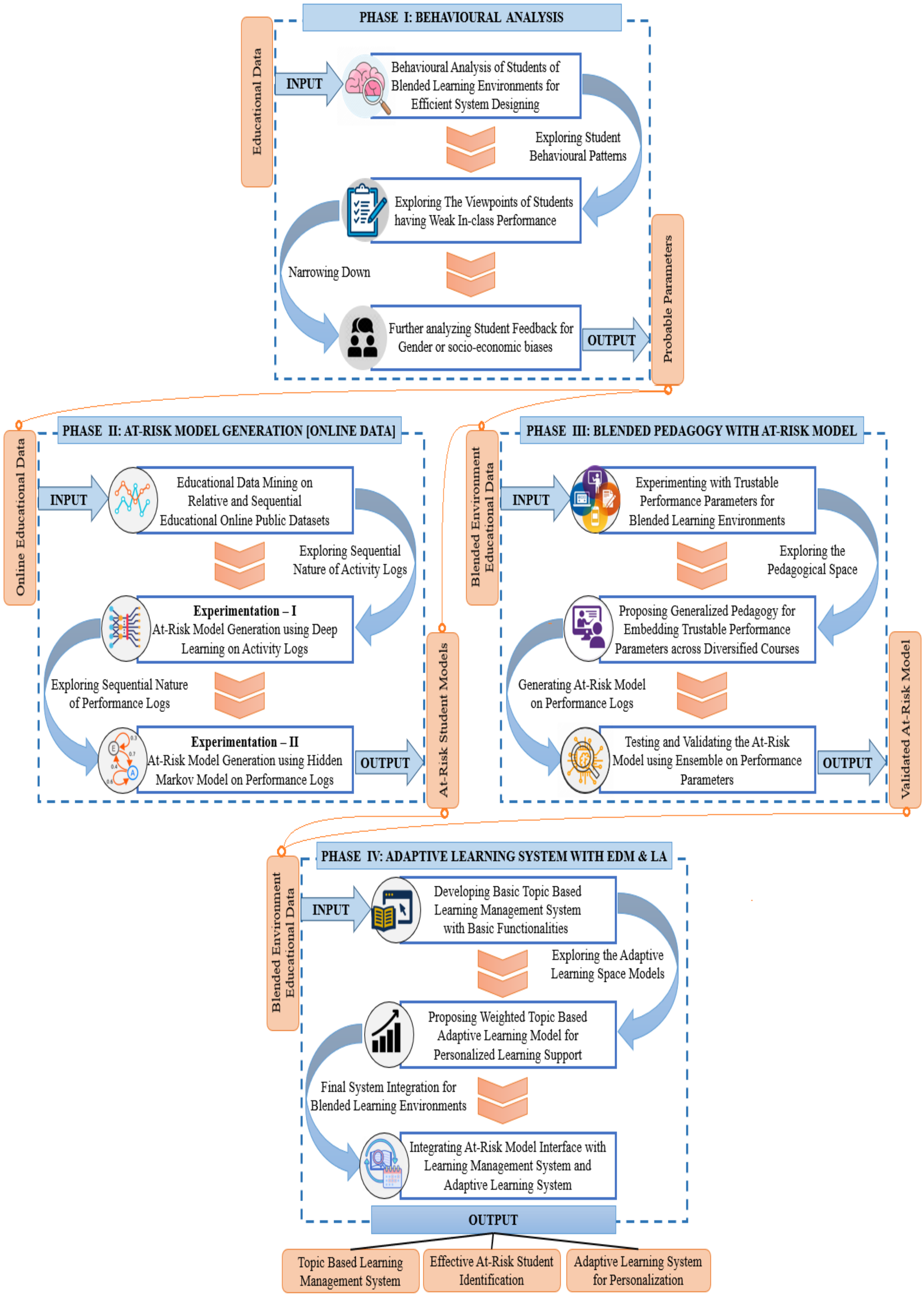


Figure 1.5: Adopted research workflow

- Proposes a generalized framework for at-risk student prediction using light-weight performance data. It utilizes a simple, transparent, and interpretable Hidden Markov Model (HMM) for student sequential learning trajectory recognition on performance logs. It also analyzes the periodic course data for the identification of an appropriate time period for its implementation. Post-model analysis of the obtained results on the public dataset for measuring the efficiency of the outcomes and associated inferences, is also provided.

  For OULAD dataset, most of the courses obtained an accuracy greater than 90%. Course CCC reported the highest accuracy of 94.83% and F1 score of 0.926. Correspondingly, kappa statistic also binned into the 0.81-1 slot, representing almost perfect reliability results. The AUC values ranged from 0.927 for course AAA to 0.989 for course CCC. The thorough analysis of the evaluation metrics suggests that light-weight performance parameters with sequential learning trajectory mining can assist the instructors in timely identification of at-risk students. The obtained results and analysis are inline and comparatively better as per the existing research studies. With the help of HMMs, sequential learning trajectories can easily and effectively identify the at-risk students of the course. The very high AUC values show that the model is capable enough of efficiently distinguishing between the at-risk and safe student states. With the help of the proposed process, the lower accuracies specifically for at-risk classes can also be mitigated.

- Proposes an ensemble machine learning model for blended learning environments. It helps the instructors in tracing the learning behaviour of the students and early identification of at-risk students. This assists the instructors to provide necessary and timely feedback to mitigate the risk of failure or dropout of the students in blended learning environments.

  The model is tested and validated for three different courses of computer science and engineering domain, namely: data structures, advanced data structures and database management systems. During the third week of the courses, the AUC values for the three courses ranged between 0.700 to 0.815. For sixth week of the courses, this range lied between 0.739 and 0.923. The final range, by the end of the courses, was between 0.957 and 0.988. This represented highly accurate predictions. On generalized terms, the results obtained in the proposed study are comparable to other existing research studies on peer instructions. This supports the proposed pedagogical architecture to be capable and efficient, for early identification of at-risk students, for blended learning environments.

- From the pedagogical perspective, this research proposes a generalized effective and tested pedagogy for blended learning environments that can be accompanied across the different courses for effective teaching. The pedagogy at the backend also helps the instructors in embedding effectively identified performance parameters within the proposed system. These further help the instructors in the early identification of course based at-risk students for blended learning environments.

- For blended learning environment courses, this research work proposes a generalized topic based LMS, as an outcome. The proposed LMS is available at the following link: `http://adaptivelms.in`. Considering the blended learning environments, the proposed system provides three basic interfaces: for students, instructors and machine learning interface.

  For students, the proposed system helps to provide topic-wise individualized learning guidance through its LA dashboards. The system adapts itself according to the knowledge level of the students and assists them in providing helpful topic based content and accompanying problems or assignments for solving. For instructors, the proposed system assists in managing and complementing the topic based LMS necessary activities with basic LA interfaces.

- The proposed system's machine interface, for instructors, contributes via its effective predictions of at-risk student students. Through its EDM, embedded machine learning models training and testing interface, and visual analytics, it helps the instructors in course based LA. The instructors are free to choose the expert trained models or create their own effective models for effective at-risk students' identification, varying across the courses.

Overall, the system acts as a teaching assistant for instructors and students of blended learning environments. It supports personalized learning for the students that adapt itself according to the learning style and pace of the student. The system automatically detects the student's weak points by tracing the student's learning history through practice assessments and display appropriate content and assignments. It also identifies the extra-ordinary as well as bottom-line students timely for better insight, direction, and skill-building.

In parallel, this system assists the instructors in the timely identification of at-risk students through its machine learning interface. Through this early-identification, the instructors can do the timely intervention and thus increase the student retention rates and decrease failure/ dropout rates, for blended learning environments.

1.10 Thesis Organization

The thesis has been structured into seven chapters. A brief overview of these chapters is given as follows.

- **Chapter 1:** presents the basic overview and latest trends of the educational field. It introduces the fields of educational data mining, learning analytics, adaptive learning systems, and blended learning environments. It also discusses the need for adaptive learning systems. The motivation, applications, and relevance of educational data mining, learning analytics, and adaptive learning systems in the present world. Further open challenges relating to these fields are discussed. The associated research gaps, research objectives, and mapping of research objectives with research gaps are discussed. The chapter concludes with the adopted research methodology and thesis contributions.

- **Chapter 2:** elaborates the major research objectives with the generalized standard approaches used for educational data mining, learning analytics and adaptive learning systems. It gives insights regarding the existing tools, technologies, and datasets that can be used for carrying out the required research in the educational field. Various existing International and National level existing systems that are being used for educational research purposes are represented further. Also, the focussed research on the context-specific studies comprising of the behavioural analysis based studies for studying the behavioural characteristics of the students and at-risk student models, existing domain based approaches *etc.*

are described. It concludes by providing insights regarding the existing research gaps and discussion.

- **Chapter 3:** explains the two case studies performed for behavioural analysis of blended learning environment students for efficient system designing. In the first study, the research was focused on at-risk students' behavioural analysis. As the final system ought to target the at-risk predictions through educational data mining and learning analytics, the search of probable parameters was conducted through this study. As an outcome, active learning based environments with short measurable assessments are found to motivate the students. For the second study, further analysis of the feedback of students for behaviour analysis and reliability, was performed. The objective was to check the existance of gender and socio-economic biases within the educational systems. The various aspects of the ratings given by the students to their instructors, were evaluated. The influence of environment and other factors on these ratings, in the form of biases, were analyzed. As an outcome of the two studies, various design reflections and suggestions are proposed.

- **Chapter 4:** explains building efficient generalized at-risk model through clickstream and performance data, separately, utilizing public datasets for online environments. Further, two studies were conducted to meet these objectives. In both the studies, the common point is the sequential nature of the educational data. For the first study, the activity logs were taken as input parameters. So, the sequential nature of activity logs was explored using the sequential deep learning models. For the second experiment, the sequential nature of performance logs was explored, and the at-risk model was generated using the sequential Hidden Markov Model. As an outcome of these two research studies, two generalized efficient models are proposed using activity logs and performance logs, respectively. Both are efficient, as they utilize sequential and relative nature of educational data. However, study utilizing performance parameters seem to be more feasible, with respect to blended learning environments.

- **Chapter 5:** explains the implementation of efficient ensemble learning model for at-risk analysis using blended learning environments. As for blended learning environments, activity data is found to be sparse due to the blended usage of face-to-face and digital tools, collectively. So, performance parameters are more reliable as also suggested by the behavioural analysis studies, performed earlier. Hence, the input parameters utilized were light-weight assessments. These are defined and experimented with as trustable parameters for blended learning environments. Further, pedagogical space was explored for embedding these assessments within the learning environments. New generalized pedagogy for embedding these light-weight assessments within the courses was proposed. A new ensemble model is built upon these performance parameters. The model was validated for three different courses of computer science and engineering domain. As an outcome, a generalized pedagogical architecture with reliable parameters embedded within it, is proposed.

- **Chapter 6:** describes the in-detail view of the proposed adaptive learning system with educational data mining and learning analytics. The research based system is available at the following link: `http://adaptivelms.in`. It explains the basic functionalities of the proposed topic based learning management system for posting the required educational content with proper interfacing. It then extends the support through a weighted topic based adaptive learning system for personalized learning support. Then it integrates the at-risk module in the above adaptive learning system for effective teaching of the blended learning environments.

- **Chapter 7:** concludes the research work presented in this thesis and presents the future scope of the work. It has been given the proposed ALS with EDM and LA seems to be very promising and can help the instructors of the blended learning environments. Also, various limitations and discussion are covered in this chapter. In the future, the proposed system can be further extended for including more functionalities, and further efficiency of the proposed models can be improved for at-risk predictions. Unexplored contextual data and other parameters can be further integrated within the system for better results. The adaptive learning module can also be extended for more input parameters and accurate adaptive algorithms for efficient predictions and enhanced self-learning of the students.

Chapter 2

LITERATURE REVIEW

2.1 Overview

This chapter describes the detailed literature review for various existing tools, technologies and methodologies in the fields of EDM, LA and ALS. The complete chapter workflow is shown in Figure 2.1. Section 2.1 describes the basic flow. Section 2.2 discusses the major research objectives of EDM and LA. Section 2.3 and 2.4 mentions the generalized standard approaches used for EDM, LA and ALS. Section 2.5 gives insights regarding the existing tools, technologies and datasets that can be used for carrying out the required research in the educational field. Various existing International and National level existing systems that are using or can be used for educational research purposes are represented in Section 2.6.

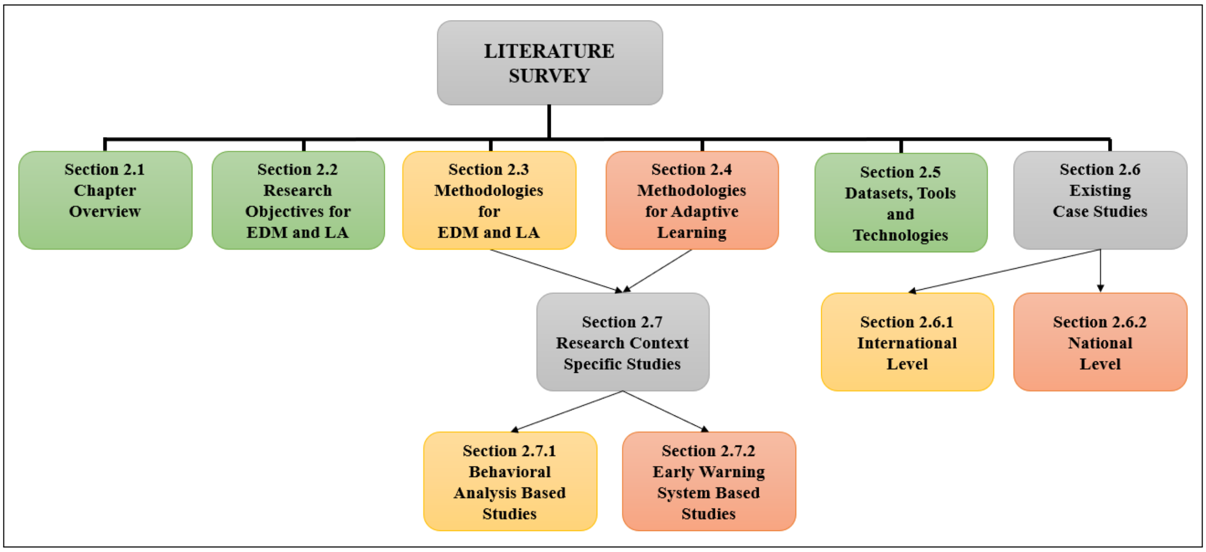


Figure 2.1: Literature survey chapter overview

Section 2.7 narrows down the research and focuses on the context-specific studies as required for building up the proposed ALS. It further comprises of behavioural analysis based studies utilized for studying the behavioural characteristics of the students. The second part consists of Early Warning System (EWS) based studies. EWS are the systems that help in early identification of at-risk students. They play a very important role in early identification of at-risk students through EDM and LA. This may further help in deciding the skill level of the students of blended learning environments. Based on the skill level these may assist in providing the adaptive content to the students. This may further help the instructors of blended learning environments for timely intervention. Section 2.8 provides the insights regarding the existing research gaps and discussion.

2.2 Research Objectives for EDM and LA

The main objectives of EDM and Learning Analytics are to improve the learning process, guiding student learning as well as side by side developing a deeper understanding of the educational phenomenon. These objectives, when quantified can be divided into several categories, each of which is discussed below [127].

- **Analysis and Visualization of Data (AVD):** In this field, the useful information is highlighted for making it noticeable and support decision making [118, 123].
- **Providing Feedback for Supporting Instructors (FSI):** Its objective is to support the instructors/administrators by providing them timely information (regarding organization of learning material resources, improve student's learning *etc.*) for taking proactive and appropriate measures and thus help in better decision making [62].
- **Recommendation for Students (RS):** Provide students with direct personalized recommendations for links to visit, next assignment or problem to attempt *etc.*, with respect to their personal activities [103].
- **Predicting Student's Performance (SP):** It helps in estimating the unknown value of learning variables for students like performance, knowledge, marks or score, success rate *etc.* [98, 99].
- **Student Modelling (SM):** Development of cognitive models is done, based on learner's characteristics like motivation, satisfaction, learning style *etc.* for the learners, which includes modelling of their skills as well as declarative knowledge [86].
- **Detecting Undesirable Student Behaviour (USB):** It helps to identify the unusual behaviour of the learners like misuse, erroneous activities, playing games, lower motivation levels, dropping out and failures *etc.* [39].

- **Grouping Students (GrS):** Identification of the common traits, features, characteristics amongst the learners for clustering them appropriately, so that further successful personalized and adaptive systems that promote effective group learning can be made and implemented [105].

- **Social Network Analysis (SNA):** Structural Analysis of the learner's network, targets to study relationships amongst the learners rather than as a learner's individual properties. Collaborative filtering and context-aware algorithms form the common approaches of this type of analysis [57].

- **Developing Concept Maps (CM):** Concept map is a conceptual hierarchical structure of knowledge graph that represents the relationships between concepts. So, the objective is to construct concept maps that help to automate the educational process. Text mining is also used, in educational domain, for automatically constructing academic articles [90].

- **Constructing Courseware (CCw):** Focus area of this field is to exchange, reuse and organize learning contents or resources automatically and develop the courseware [78].

- **Planning and Scheduling (PSc):** The target is to improve the traditional educational process by planning for the future courses and their scheduling, developing curriculum *etc.* [91].

  An extensive literature survey was carried out for studying the already existing systems in the learning analytics and adaptive systems research field. Table 2.1 contains the research studies with considerable contributions to the mentioned research objectives.

2.3 Methodologies for EDM and LA

For EDM and LA, there exist a number of methodologies that help to extract out the learner's statistics, behavioural patterns, performance prediction, create visualizations and dashboards, perform data mining *etc.* The most common ones are discussed below [165]. They are: *Prediction Methods, Structure Discovery, Relationship Mining, Distillation of data for human judgement* and *Discovery with Models.*

Table 2.1: Mapping of research studies with research objectives

Ref. No.	Contributors	AVD	FSI	RS	SP	SM	USB	Gr S	SNA	CM	CC w	PS c
[33]	Furugori *et al.* (2002)			✓				✓				
[41]	Machado *et al.* (2003)	✓	✓									
[49]	Talavera *et al.* (2004)	✓						✓				
[43]	Brusilovsky (2004)									✓	✓	✓
[58]	Mazza *et al.* (2004)	✓										
[42]	Alotaiby *et al.* (2004)			✓								
[46]	Lu (2004)			✓								
[45]	Hwang *et al.* (2004)							✓				
[48]	Romero *et al.* (2004)							✓				
[59]	Monk (2005)		✓									
[55]	Kelly *et al.* (2005)					✓						
[61]	Muehlenbrok (2005)		✓					✓				
[56]	Kristofic (2005)			✓				✓				
[53]	Healthcote (2005)		✓									
[54]	Karampiperis (2005)									✓	✓	
[63]	Calvo-Flores *et al.* (2006)				✓							
[66]	Retalis *et al.* (2006)								✓			
[65]	Etchells *et al.* (2006)				✓							
[64]	Desmarais *et al.* (2006)					✓						
[68]	Zinn *et al.* (2006)		✓									
[67]	Su *et al.* (2006)			✓							✓	
[74]	Healthcote *et al.* (2007)			✓								
[76]	Jong *et al.* (2007)					✓	✓					
[80]	Lu *et al.* (2007)			✓								
[77]	Jovanovic *et al.* (2007)		✓									
[72]	Castro *et al.* (2007)				✓		✓					
[75]	Hubscher *et al.* (2007)								✓			
[82]	Ba-Omar *et al.* (2007)					✓						
[79]	Liu *et al.* (2007)		✓									
[81]	Matsuda *et al.* (2007)					✓						

Ref. No.	Contributors	AVD	FSI	RS	SP	SM	USB	Gr S	SNA	CM	CC w	PS c
[70]	Baruque *et al.* (2007)		✓									✓
[101]	Ventura *et al.* (2008)	✓										
[88]	Ben-Naim *et al.* (2008)	✓										
[102]	Wang (2008)			✓		✓						
[89]	Chanchary *et al.* (2008)				✓							
[95]	Merceron *et al.* (2008)	✓										
[98]	Romero *et al.* (2008)	✓	✓					✓	✓			
[96]	Myszkowski *et al.* (2008)	✓	✓									
[109]	Garcia *et al.* (2009)			✓								
[107]	Chang *et al.* (2009)							✓				
[112]	Hamam *et al.* (2009)									✓		✓
[116]	Wang *et al.* (2009)					✓						
[110]	Garcia *et al.* (2009)							✓				
[104]	Amershi *et al.* (2009)					✓						
[117]	Zafra *et al.* (2009)				✓		✓					
[135]	Psaromiligkos *et al.* (2009)		✓							✓		
[111]	Guo *et al.* (2009)					✓						
[114]	Romero *et al.* (2009)									✓	✓	✓
[115]	Simko *et al.* (2009)				✓							
[119]	Budhiraja *et al.* (2010)										✓	
[120]	Chen *et al.* (2010)									✓	✓	✓
[121]	Essalmi *et al.* (2010)			✓								
[133]	Mampadi *et al.* (2011)	✓		✓		✓						
[147]	Romero-Zaldivar *et al.* (2011)		✓		✓							
[149]	Siemens (2012)	✓	✓									
[162]	Vesin *et al.* (2013)			✓								
[158]	Maguire & Maguire (2013)			✓			✓	✓				
[164]	Armendariz *et al.* (2014)			✓						✓		

Ref. No.	Contributors	AVD	FSI	RS	SP	SM	USB	Gr S	SNA	CM	CC w	PS c
[171]	Singh *et al.* (2014)		✓									
[180]	Ihantola *et al.* (2015)		✓									
[195]	Suchitra *et al.* (2015)		✓									
[192]	Sein-Echaluce *et al.* (2015)			✓	✓	✓						
[200]	Andersen *et al.* (2016)					✓						
[204]	Chaplot *et al.* (2016)					✓						
[201]	Avella *et al.* (2016)		✓									
[210]	Marbouti *et al.* (2016)				✓		✓					
[202]	Bhartiya *et al.* (2016)									✓		
[217]	Tarimo, Deeb & Hickey (2016)				✓							
[245]	Mishra *et al.* (2017)					✓						
[259]	Whitehill *et al.* (2017)						✓					
[257]	Wang *et al.* (2017)						✓					
[225]	Cascavilla *et al.* (2017)	✓				✓						
[268]	Kuzilek *et al.* (2018)					✓	✓					
[265]	Haiyang *et al.* (2018)						✓					
[287]	Olivé *et al.* (2019)						✓					
[288]	Qiu *et al.* (2019)						✓					
[274]	Chen *et al.* (2019)						✓					
[276]	Feng *et al.* (2019)						✓					
[272]	Aljohani *et al.* (2019)						✓					
[281]	Jha *et al.* (2019)						✓					
[284]	Liao *et al.* (2019)				✓		✓					
[289]	Al-Shabandar *et al.* (2019)						✓					
[294]	He *et al.* (2020)						✓					
[304]	Zheng *et al.* (2020)						✓					
[303]	Waheed *et al.* (2020)				✓		✓					
[302]	Veerasamy *et al.* (2020)				✓		✓					
[305]	Adnan *et al.* (2021)						✓					

- **Prediction Methods:** This comprise of prediction models, that are developed to conclude a single aspect of the data from combination of other aspects of the data. For example, one may capture data of 1000 students to find out the drop-out rate of the students, develop a prediction model and test and apply this model on new set of students for predicting the drop-out rate. Three types of prediction models most commonly used in EDM/LA are classifiers, regression, and latent knowledge estimation [21, 113, 146, 288, 296, 290, 303, 304, 305]. Table 2.2 discusses examples of how these techniques have been incorporated in educational environments.

Table 2.2: Examples of various prediction methodologies

Ref. No.	**Contributors**	**Prediction Methodologies**	**Explanation**
[108]	Dekker *et al.* (2009)	Classifier	Used decision trees as classifiers for predicting the students drop-out.
[146]	Rau *et al.* (2012)	Regression	Used step-wise linear regression for searching mediator variables that monotonically related to learning outcomes.
[21]	Corbett *et al.* (1995)	Bayesian Knowledge Tracing	Proposed one of the earliest knowledge tracing approaches, commonly used today, for judging the level of mastery attained by the learner based on probability estimates.
[113]	Pavlik *et al.* (2009)	Performance Factors Analysis	Proposed an alternative and comparative approach as compared to learning factor analysis and model based approaches, commonly for knowledge tracing. Predicts student performance based on the item difficulty and student historical performances.

- **Structure Discovery:** Structure discovery algorithms rely on finding structures within the datasets, without prior idea of knowing what should be found. Here, efforts are put to determine what structure evolves naturally from the given data. Common approaches to structure discovery in EDM/LA include clustering, factor analysis, social network analysis, and domain structure discovery [69, 106, 137]. Table 2.3 discusses examples of how these techniques have been incorporated in educational environments.

- **Relationship Mining:** In relationship mining, the basic goal is to discover relationships amongst the variables within a data set. Broadly, four types of relationship mining are there, namely association rule mining, correlation mining, sequential pattern mining, and causal data mining [97, 106, 144]. Table 2.4 discusses examples of how these techniques have been incorporated in educational environments.

Table 2.3: Examples of various structure discovery methodologies

Ref. No.	**Contributors**	**Structure Discovery Methodologies**	**Explanation**
[69]	Amershi *et al.* (2009)	Clustering	Used clusters to group students and student actions.
[106]	Baker *et al.* (2009)	Factor Analysis	Using factor analysis, determined which design choices are common during the design on Intelligent Tutoring Systems.
[137]	Suthers *et al.* (2011)	Social Network Analysis	Studied student's position in a social network as well as identified interaction and connectivity behaviour for sensing learner's success and engagement in the course.
[165]	Baker *et al.* (2014)	Domain Structure Discovery	Used for mapping problems top specific knowledge components or test items to skills.

Table 2.4: Examples of various relationship mining methodologies

Ref. No.	**Contributors**	**Structure Discovery Methodologies**	**Explanation**
[165]	Baker *et al.* (2014)	Association Rule Mining	Detected patterns of performance of successful students, using association rule mining, for giving suggestions to weak students for improving their performance.
[106]	Baker *et al.* (2009)	Correlation Mining	Computed correlations between features of Intelligent Tutoring Systems and student's prevalence of gaming the system.
[97]	Perera *et al.* (2009)	Sequential Pattern Mining	Determined the path of student group behaviours which led to a successful group project.
[144]	Fancsali (2012)	Causal Data Mining	Determined the causal factors that lead to poor performance of the student in the class.

- **Distillation of data for human judgment:** When the time factor is added with the data, the educational data in actually can become useful for the educators. With the immediate access to the visualizations of learner interactions/misconceptions the data becomes actionable and changes can be easily incorporated into the pedagogical activity of the instructor. This forms the basis of the distillation of data for human judgment. Some visualization methods used in education include heat maps, learning curves, and learnograms [93, 168, 165]. Table 2.5 discusses examples of how these visualization techniques have been incorporated in educational environments.

Table 2.5: Examples of various visualization techniques

Ref. No.	**Contributors**	**Structure Discovery Methodologies**	**Explanation**
[118]	Bowers (2010)	Heat Maps	Used heat maps for visualization of Hierarchical cluster analysis for drop-out identification.
[123]	Koedinger *et al.* (2010)	Learning Curves	Used learning curve for visualization of student learning trajectory over time for depicting the error rate, *i.e.*, the percentage of students who asked for hints/made incorrect attempts on various steps associated with a specific knowledge component.
[93]	Hershkovitz *et al.* (2008)	Learnograms	Used Learnograms for identification of the variables over time, clustering and classification of these variables within the framework, from the collected log files.

- **Discovery with Models:** In discovery with models, the results of one data mining analysis task are utilized within another data mining analysis task. Model desired to have some particular functionality is obtained via prediction methods, relationship mining analysis, cluster analysis or knowledge engineering. Then, model is applied to data for assessing of the functionality which the model has identified [87, 165]. Table 2.6 discusses examples of how these have been incorporated in educational environments.

Table 2.6: Examples of discovery with models

Ref. No.	**Contributors**	**Explanation**
[87]	Beal *et al.* (2008)	Developed a prediction model for identifying the gaming nature of the student which in turn correlated to student individual differences.
[165]	Baker *et al.* (2014)	Prediction models of robust learning of students depended on models of student meta-cognitive behaviour which further depended on assessments of latent student knowledge and domain structure.

2.4 Methodologies for Adaptive Learning

For ALS, the applicative branch of LA, there exist four different variants of algorithms namely machine learning based adaptive systems; advanced algorithm adaptive systems; rule based adaptive systems; and decision-tree adaptive systems [215, 194]. The details for each of these approaches are discussed below.

- **Machine Learning Based Adaptive Systems:** Machine Learning (ML) based systems try to find out real time predictions of the student's concept mastery through the use of programmed algorithms that form the core of this adaptive science. These systems use the learning algorithms, that further help in creating other algorithms which form adaptive sequences. On the basis of these adaptive sequences, predictive analytics is used for guiding the student through a specific learning path.

- **Advanced Algorithm Adaptive Systems:** Advanced Algorithm (AA) adaptive systems provide one to one direct intercation between computer and student. Based on the mastery level of the student with applied knowledge activity, specific and individualized contents are prescribed to the student. In AA systems, the real time data for individual learner is analyzed and compared with other students exposed to similar content. Then appropriate and personalized learning pathways, automated feedback, and educational content are displayed to the learners.

- **Rule Based Adaptive Systems:** Rule Based (RB) adaptive systems focus on the predetermined set of rules as defined by the experts. Students follow a fixed sequence of content and assessments set by the instructor instead of focussing on individual learner profile. However, depending on persistent diagnostic assessments, the learner can either advance or regress accordingly. According to the learner's activity, feedback is provided based on the predetermined set of rules.

- **Decision Tree Adaptive Systems:** Decision Tree (DT) adaptive systems use classification tree for hierarchically arranged limited resources of educational content and assessment, and usually use binary type based assessments. As per the comparative analysis of RB and DT systems, in DT systems the set of rules and the educational content are relatively static. DT systems use their static branching sequences, stored in the form of "if this, then that", and don't consider specific student profile. Depending upon the requirements, analysis tasks, usage statistics and implementation environments these LA and adaptive systems approaches/methodologies can be leveraged upon and adopted accordingly.

2.5 Datasets, Tools and Technologies

The field of EDM, LA and ALS use a wide variety of tools and technologies. However, the educational field has limited number of public LA datasets that are targeted for making predictions regarding students learning behaviour, skill mastery, dropouts *etc.*

Table 2.7 and describes some of the open public datasets that are available for the educational researchers for carrying over the tasks of EDM, LA and ALS.

Table 2.7 Public educational datasets

S. No.	Datasets	Description	Link
1	PSLC DataShop	Data Repository and analysis service for learning community	`https://pslcdatashop.web.cmu.edu/`
2	MITx and HarvardX Dataverse	De-identified data from HarvardX and MITx courses on the edX platform	`https://dataverse.harvard.edu/dataverse/mxhx`
3	KDDCUP15	MOOC Dropout Prediction Dataset	`https://data-mining.philippe-fournier-viger.com/the-kddcup-2015-dataset-download-link/`
4	OULAD	Open University Learning Analytics Dataset	`https://analyse.kmi.open.ac.uk/open_dataset`
5	NeurIPS Education Dataset	NeurIPS 2020 Education Challenge Dataset	`https://eedi.com/projects/neurips-education-challenge`

Slater *et al.* (2017), discussed about the availability of the various sources of data, tools and technologies involved in the process of EDM and LA [252]. The extensive list of available tools and technologies alongwith their available urls for EDM and LA are summarized in Table 2.8. The evolving tools and technologies provide ample opportunities for the educational researchers, to analyze and contribute effectively to this evolving educational data science research field.

Table 2.8: Various EDM and LA tools and technologies

S. No.	Application Area	Tool	Link
1	Data Manipulation & Feature Engineering	Microsoft Excel	https://products.office.com/en-in/excel
2		EDM Workbench	http://penoy.admu.edu.ph/~alls/downloads-2
3		Jupyter notebook	http://jupyter.org/
4		SQL	https://www.mysql.com/
5	Algorithmic Analysis	Rapidminer	http://rapid-i.com/content/view/181/190/
6		WEKA	http://www.cs.waikato.ac.nz/ml/weka/
7		SPSS	http://www.ibm.com/analytics/us/en/technology/spss/
8		KNIME	https://www.knime.com/
9		Orange	https://orangedatamining.com/
10		KEEL	http://sci2s.ugr.es/keel/
11		Spark MLLib	http://spark.apache.org/mllib/
12	Visualizations	Tableau	https://www.tableau.com
13		D3js	https://d3js.org/
14	Bayesian Knowledge Tracing	BKT-BF	http://www.columbia.edu/~rsb2162/BKT-BruteForce.zip
15		BNT-SF	http://www.cs.cmu.edu/~listen/BNT-SM
16		Hmmsclbl	http://yudelson.info/hmmsclbl.html
17	Text Mining	WMatrix	http://ucrel.lancs.ac.uk/wmatrix/
18		Latent Semantic Analysis	http://tml-java.sourceforge.net/
19		NLP toolkit	www.nltk.org
20		ConceptNet	www.conceptnet.io/
21		TAGME	https://tagme.d4science.org/tagme/
22		Apache Stanbol	https://stanbol.apache.org/docs/trunk/scenarios.html
23	Social Network Analysis	Gephi	https://gephi.org/
24		EgoNet	http://egonet.sf.net
25		NodeXL	http://nodexl.codeplex.com
26		Pajek	http://mrvar.fdv.uni-lj.si/pajek
27		NetMiner	http://www.netminer.com
28		SocNetV	http://socnetv.sourceforge.net
29		NetworkX	http://networkx.github.io
30		SNAPP	https://github.com/aneesha/SNAPPVis
31		R Packages	https://www.r-project.org/
32	Process & Sequence Mining	ProM	https://www.promtools.org/doku.php
33		TraMineR	http://traminer.unige.ch

2.6 Existing Case Studies

This section describes the present scenario of the various existing LA and ALS systems, being used at different places, at international and national level. First section discusses about the various international level studies. Next section elaborates the online systems present at national level.

2.6.1 International Level

- **Jpoll:** Implemented in Griffith University and originally developed as a replacement for clicker-type technologies this ubiquitous classroom polling and student-response system engages students using a range of interactive teaching situations and produces data based on student opinions of teaching events. Snapshot of the system is shown in Figure 2.2.

Figure 2.2: Jpoll system snapshot [239]

- **Moodog:** Course management system of University of California, Santa Barbara provides a log analysis tool to track student's online learning activities. It provides instructors with an insight about how students interact with online course materials. It also allows students to compare their own progress with other students in the class. Moodog also has the facility to provide automatic email reminders to students and thus encouraging them to view already available materials that they have not seen or accessed yet. Figure 2.3 shows the all student's activity report snapshot.

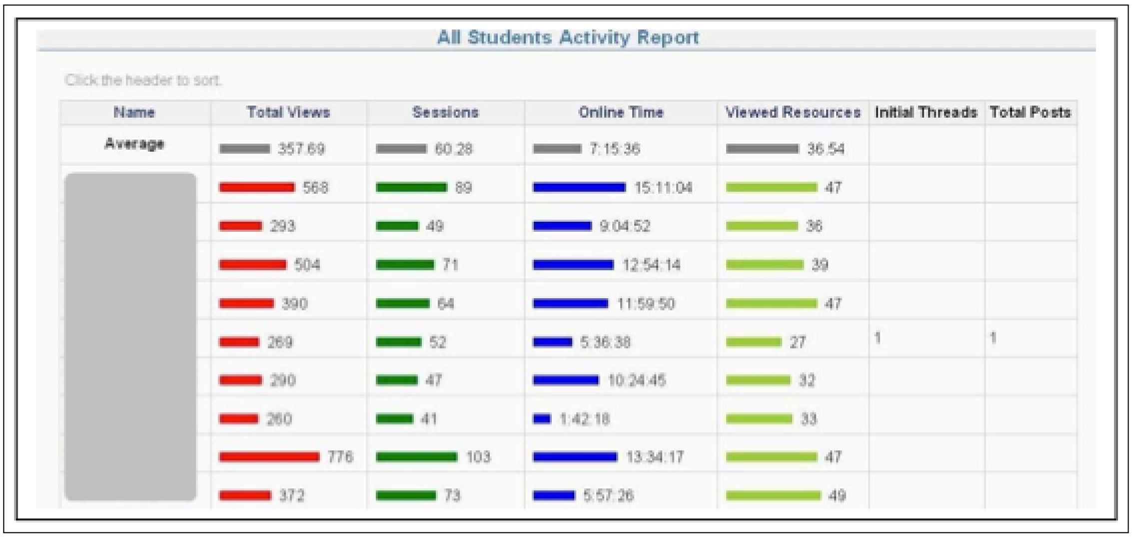


Figure 2.3: Moodog snapshot [85]

- **Equella:** In University of Wollongong, Equella provides evidence of appropriate curriculum coverage, student engagement, and equity while students are on clinical placement, which provides a clinical education as an external facility. Figure 2.4 shows the main home page of the Equella.

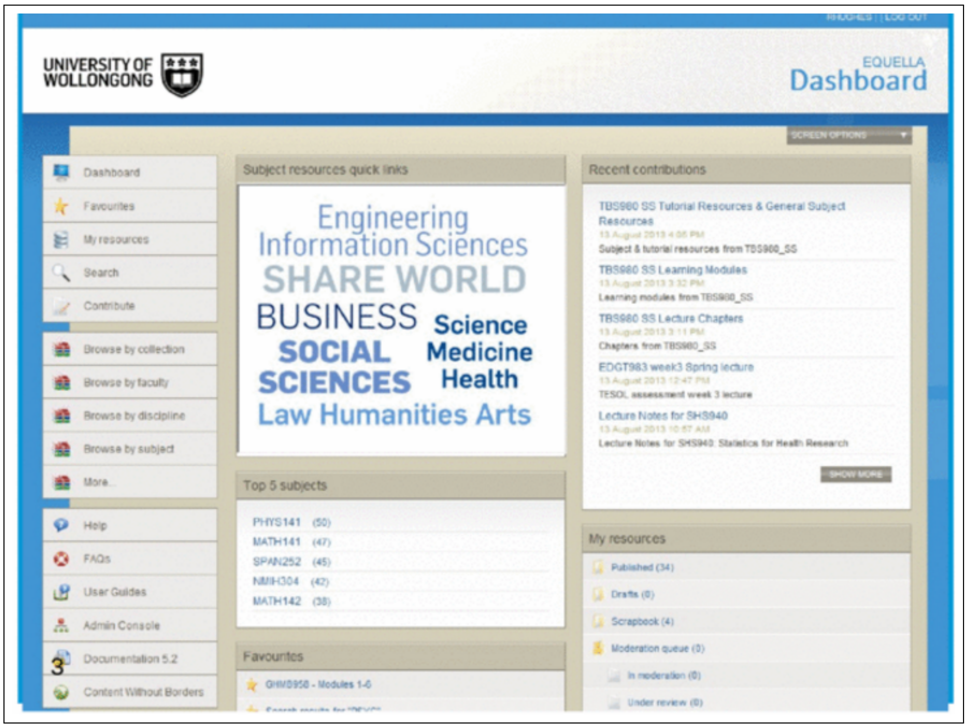


Figure 2.4: Equella snapshot [254]

- E^2 **Coach:** In University of Michigan, this computer based coaching system provides a model for an intervention engine which is capable of dealing with actionable information generated for large number of students. The system is capable of sending personalized messages to the students on the basis of its analysis. The basic working of the E^2 Coach is shown in Figure 2.5.

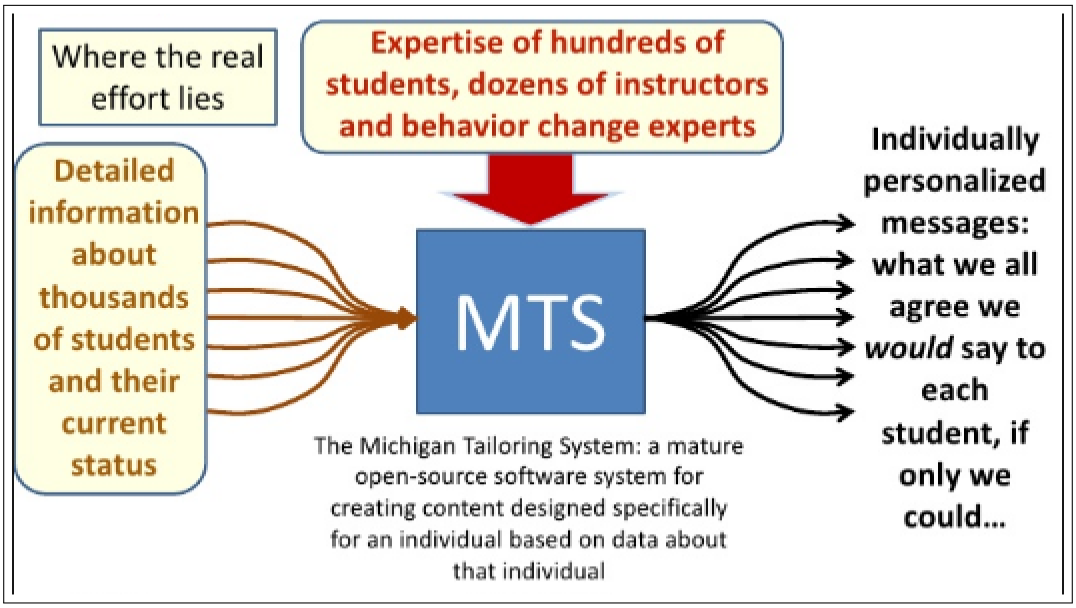


Figure 2.5: E^2 Coach system working [228]

Figure 2.6: Signals snapshot [250]

- **Signals:** Implemented in Purdue University, this system makes predictions regarding the success and failure of a student in a given course with the help of colors. It takes course management system data into account at the back end. Dashboard for the system is shown in Figure 2.6.

- **Sherpa:** In South Orange County Community College, this course recommender system uses a service-oriented architecture for guiding students during registration in phase one, to pick a substitute class if their first preference choice is full. During second phase, it provides administrator tools to send "nudges" to students via portal messages, emails, SMS messages, and text-to-speech phone calls as shown in Figure 2.7. The third phase revamps the student portal with a to-do list, news feed, and calendar, pre-populated with enrollments and important dates.

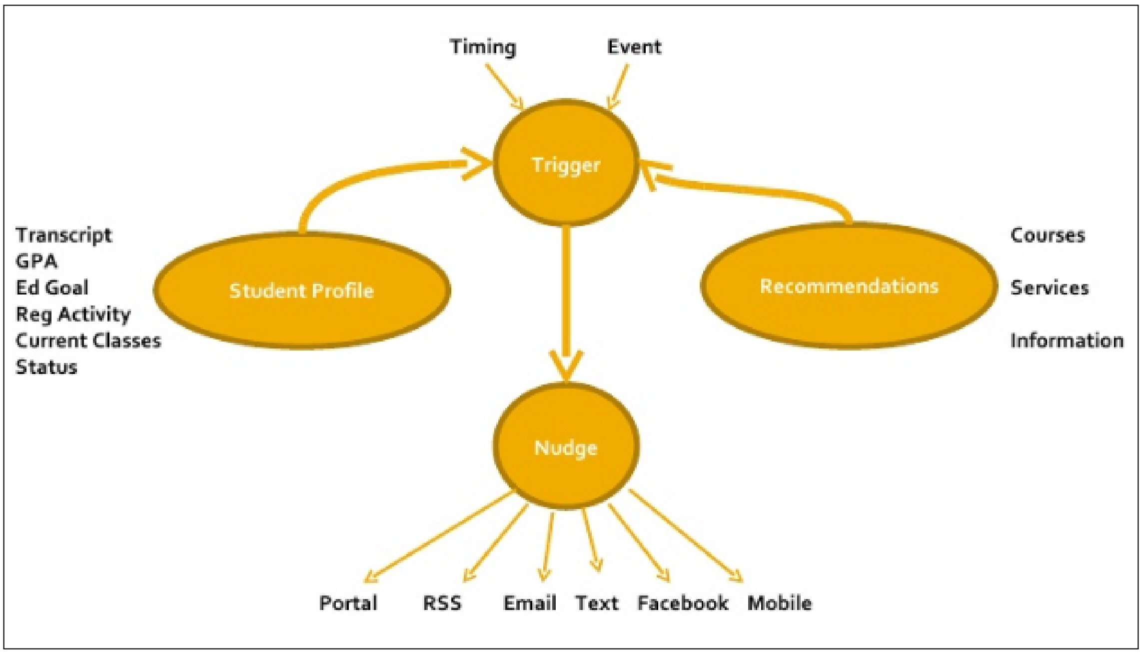


Figure 2.7: Sherpa snapshot [253]

- **Rio Salado College:** Rio Salado College via its LA, predicative analysis and dashboards has developed its own in-house Course Management System that gives the following leverages, as shown in Figure 2.8. Students can join a course anytime in the academic year. Student's risk behaviour can be easily traced in by the instructor via the software which keeps track on student's course engagement. Student can track its progress in the course towards the degree completion with the help of the dashboards. Instructor can also track the student's behaviour and even can act timely and according to the student need so that a better completion and retention rate is attained at the university level.

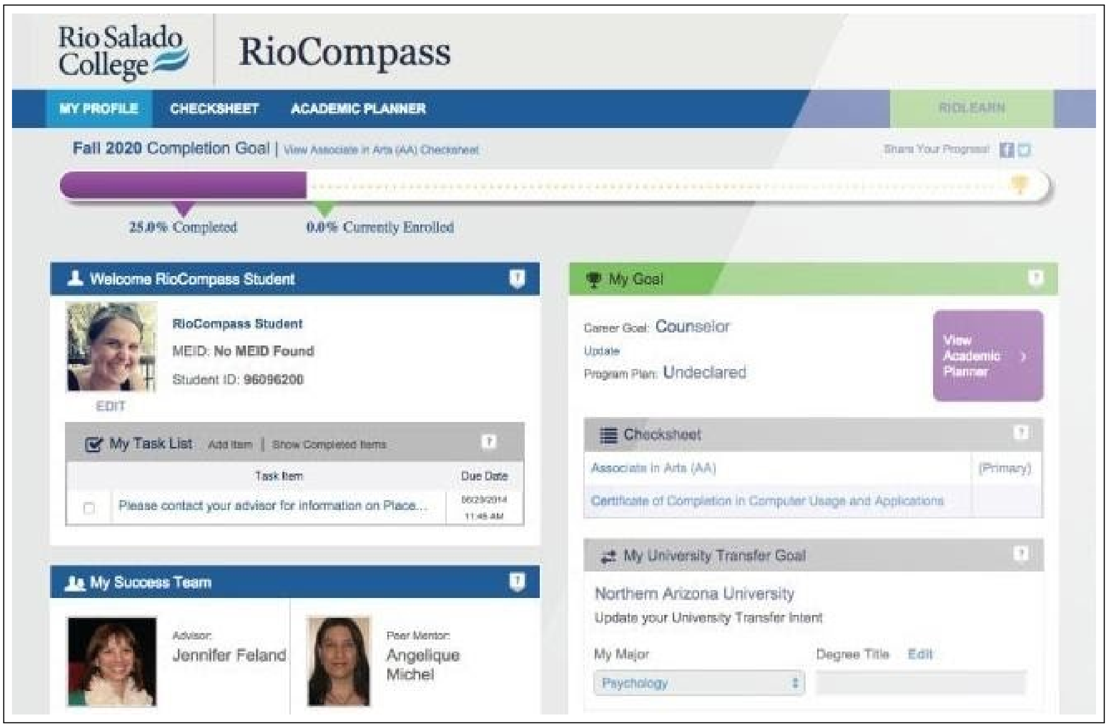


Figure 2.8: Riocompass snapshot [249]

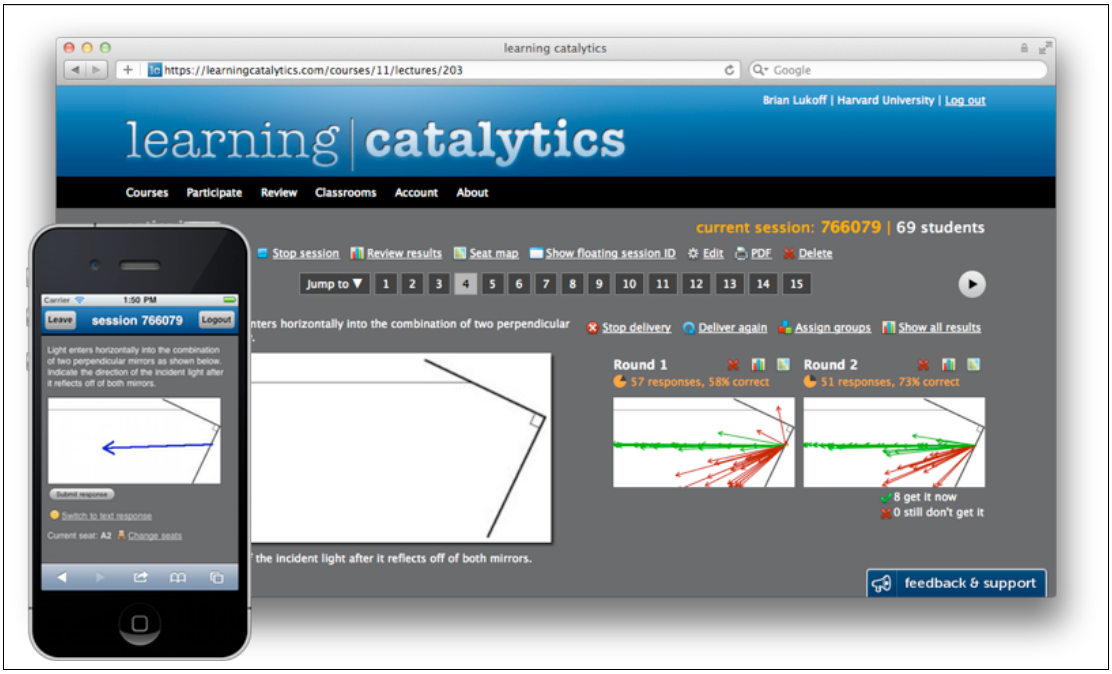


Figure 2.9: Learning Catalytics snapshot [243]

- **Harvard University:** With the help of its Learning Catalytics system as in Figure 2.9, Harvard University provides better help and assistance to the students. Learning Catalytics is a classroom based system which is developed to help the instructor in finding like-minded students in the class and helps in their grouping for classroom activities. It also helps the instructor by providing suggestions on which group to assist for providing direct learning support to the students.

- **Austin Peay State University (APSU):** APSU has implemented dashboards and predictive analysis systems for better and timely decision making. It has automated workflows regarding the prediction of grades, courses and major changes which help in creating dashboards showing the predictive analysis on different aspects like class enrollments, future class sizes, major shifts *etc.* as in Figure 2.10.

Figure 2.10: APSU dashboard and predictive analytics system [140]

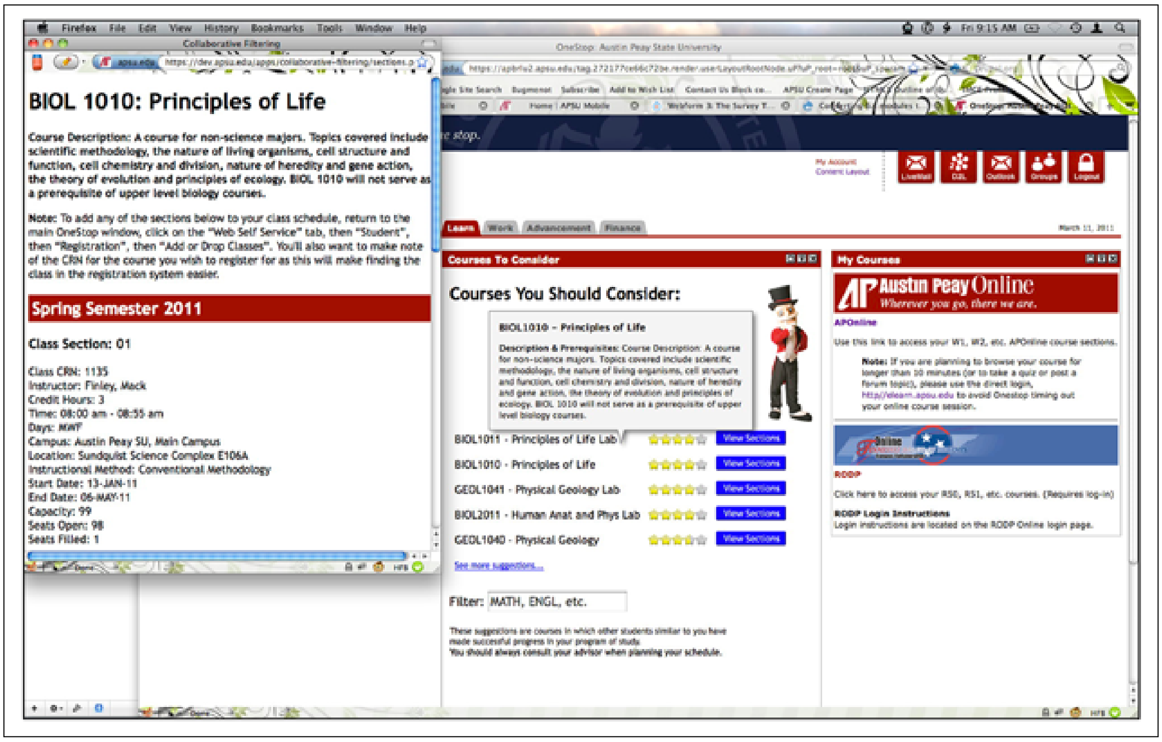


Figure 2.11: APSU Degree Compass snapshot [140]

Degree Compass is APSU's course recommender system built on the data derived from the student's past track record, grade cards and with the help of predictive analysis it recommends to the students with whom to pair with and even which course to select that he or she may be more interested in as shown in Figure 2.11.

- **Colorado Technical University:** Intellipath is a personalized learning system. With the help of questionnaires it keeps track of what a student already knows and predicts what can be beneficial for the learner in near future and helps to take and the courses and designing a student's own carrier path. As whole of the student's information is kept online, this platform is completely independent of the mode of taking the class by a student as shown in Figure 2.12.

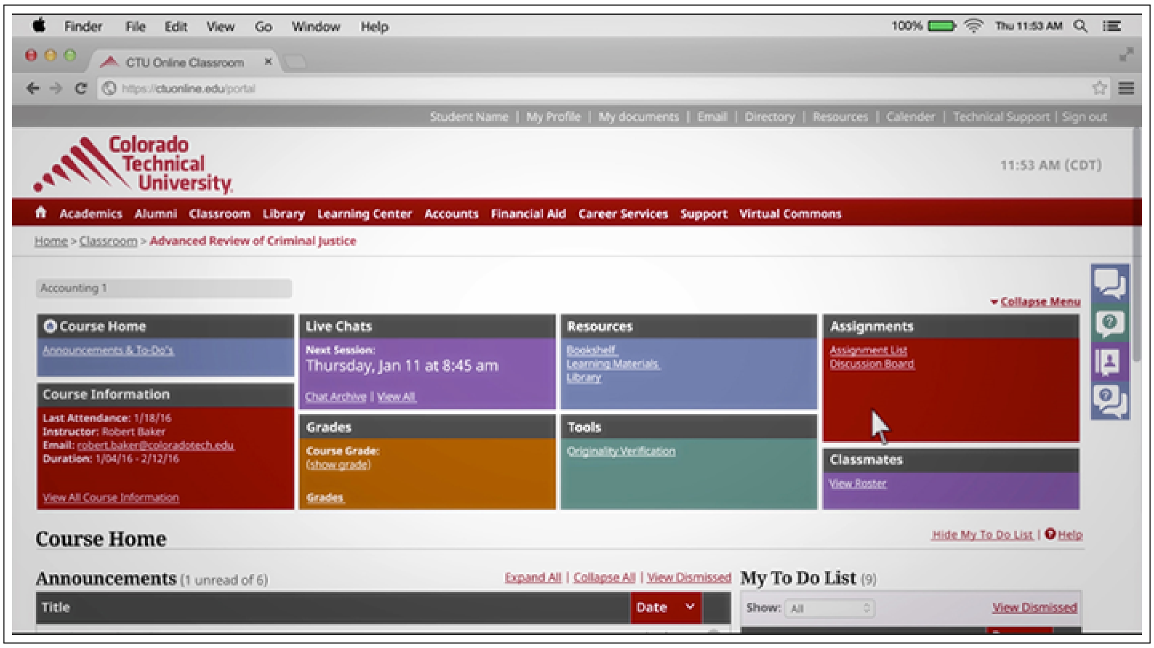


Figure 2.12: Intellipath student dashboard snapshot [237]

- **Learning Analytics Community Exchange (LACE):** Key European players with the help of LACE project (Figure 2.13) are trying to leverage the benefits of LA in the future, by performing a range of activities and integrating different communities in order to support the knowledge creation process and exchange of the information so that an evidence base can be formed. And afterwards that can be used to solve the future learning objectives as well as proper policies which are to be identified, needs to be in place for better interoperability and data sharing.

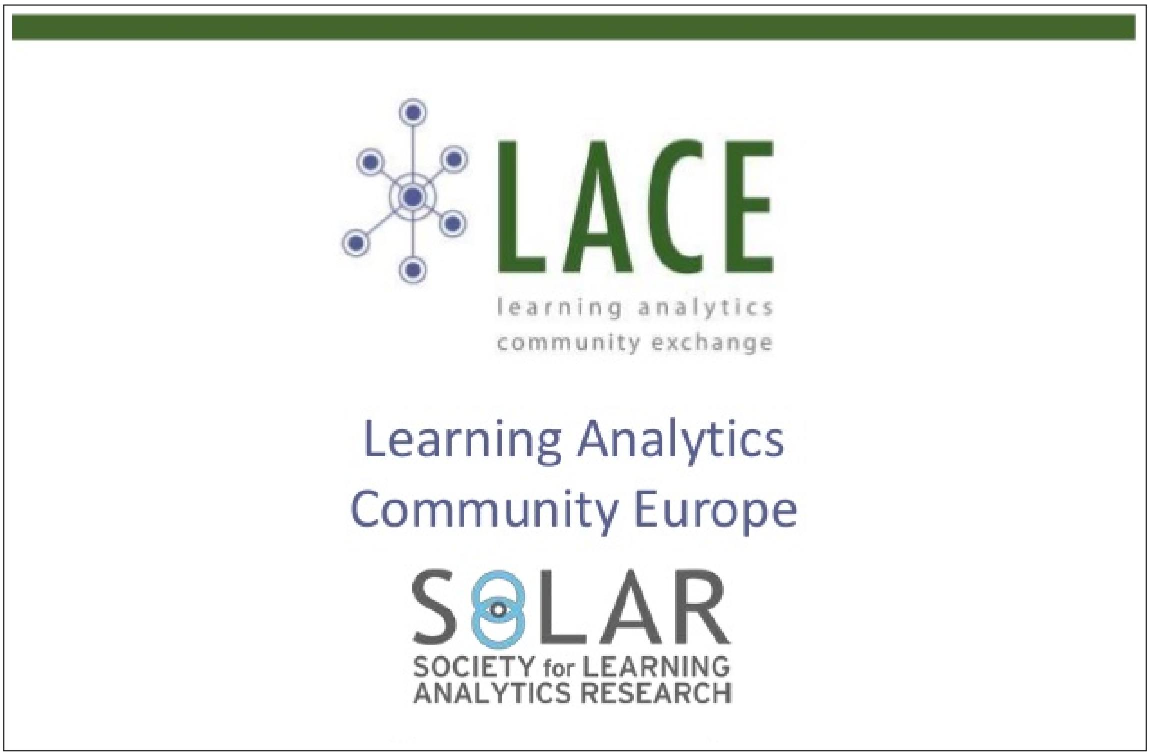


Figure 2.13: Learning Analytics Community Exchange [233]

- **Learning Interaction Mentoring Evaluation (iLIME):** An initiative by Universidad International De La Rioja (UNIR) Research, this project is developed in order to bridge the gap between the LMS and Social Network Interaction as shown in Figure 2.14. The project is designed to give automatized itinerary recommendations to the students on the behalf of teachers. It leverages on the formal interaction via LMS and informal interaction via social networks, giving a complete personalized learning environment to the students.

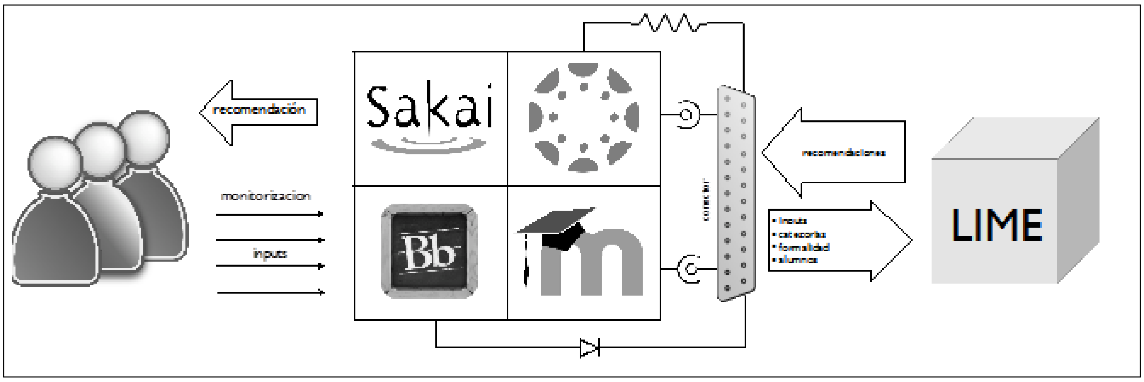


Figure 2.14: iLIME architecture [231]

- **QuizGuide:** QuizGuide is a web based educational system for ALS. It uses topic based personalization approach for adaptive educational systems. Its coarse grained knowledge units are known as topics. Complete course structure are built using topics. This topic based course structure is further used for student modelling, domain modelling and personalization. Fig 2.15 represents the system snapshot for QuizGuide.

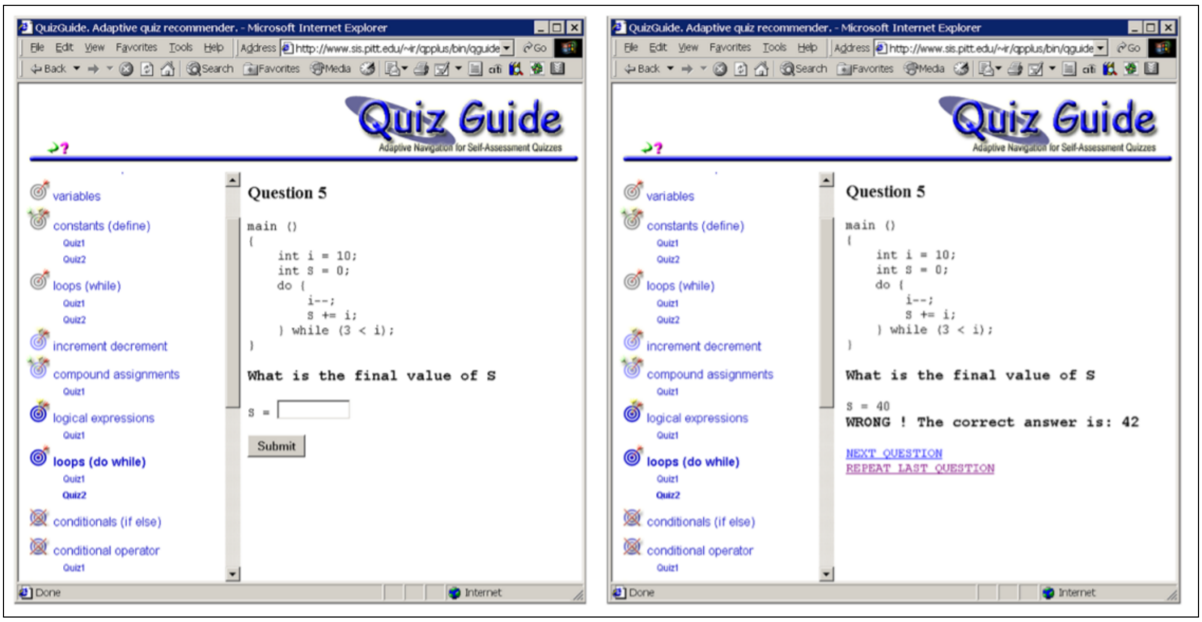


Figure 2.15: QuizGuide [194]

The systems discussed above are just some of the variant examples of the implementation of LA and ALS. These case studies reveal how LA and adaptive systems can be efficiently implemented in different learning environments according to the learning environments requirements and usage.

2.6.2 National Level

With the onset of online education, massive open online courses, the educational scenario is also on the verge of a big change in India. The government, higher level educational institutes are highly aware as well as active in this perspective and are trying to implement and append these changing educational environments in the present Indian educational environments. Some of the major considerable steps taken by the government of India and Higher Educational Institutes are discussed below.

- **National Programme on Technology Enhanced Learning (NPTEL):** NPTEL is a project funded by the Ministry of Human Resource Development

(MHRD) and an initiative by IITs and IISc Bangalore. It encourages e-learning through online courses in Engineering, Sciences, Technology, Management and Humanities. It targets students and faculty of the Under Graduate engineering programs. Snapshot for NPTEL is shown in Figure 2.16.

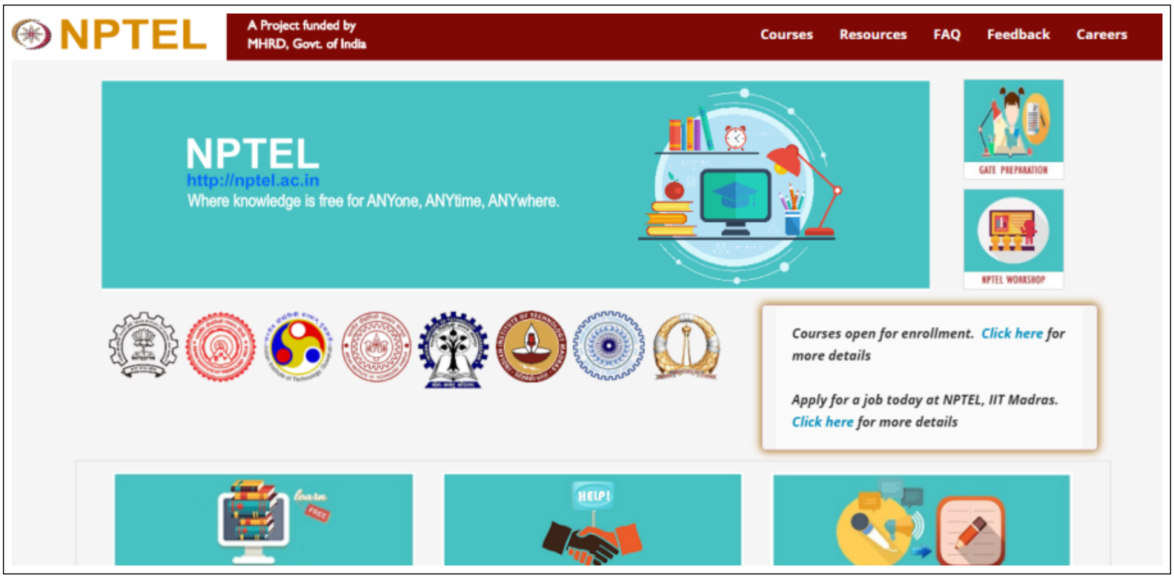


Figure 2.16: NPTEL snapshot [247]

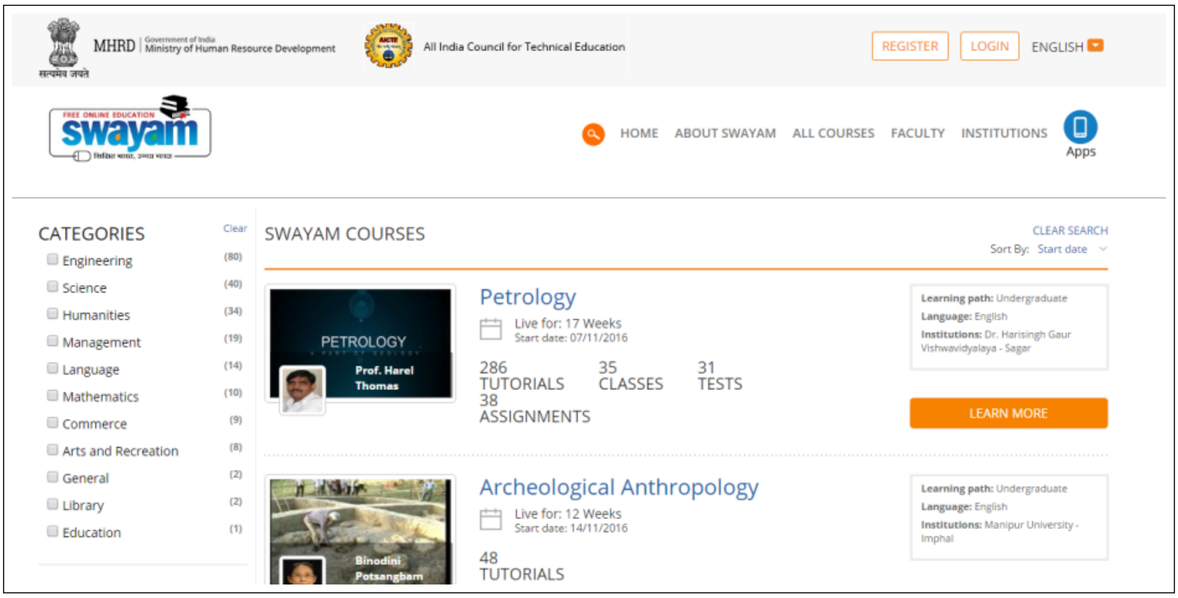


Figure 2.17: SWAYAM snapshot [229]

- **Study Webs of Active – Learning for Young Aspiring Minds (SWAYAM):** In MHRD program of SWAYAM, professors of centrally funded institutions like IITs, IIMs and Central Universities offer free online courses to people of India.

As shown in Figure 2.17, it acts as an instrument for gaining life-long learning experience. It has also the facility of transferring credits earned by the student, while taking these courses into their academic record.

- **Indian School of Business (ISB):** In November 2014, ISB signed the partnership agreement with Coursera, the US based online education provider and became Coursera's first Indian Partner to produce and own content which is delivered by its online portal to learners worldwide. Figure 2.18 represents its snapshot.

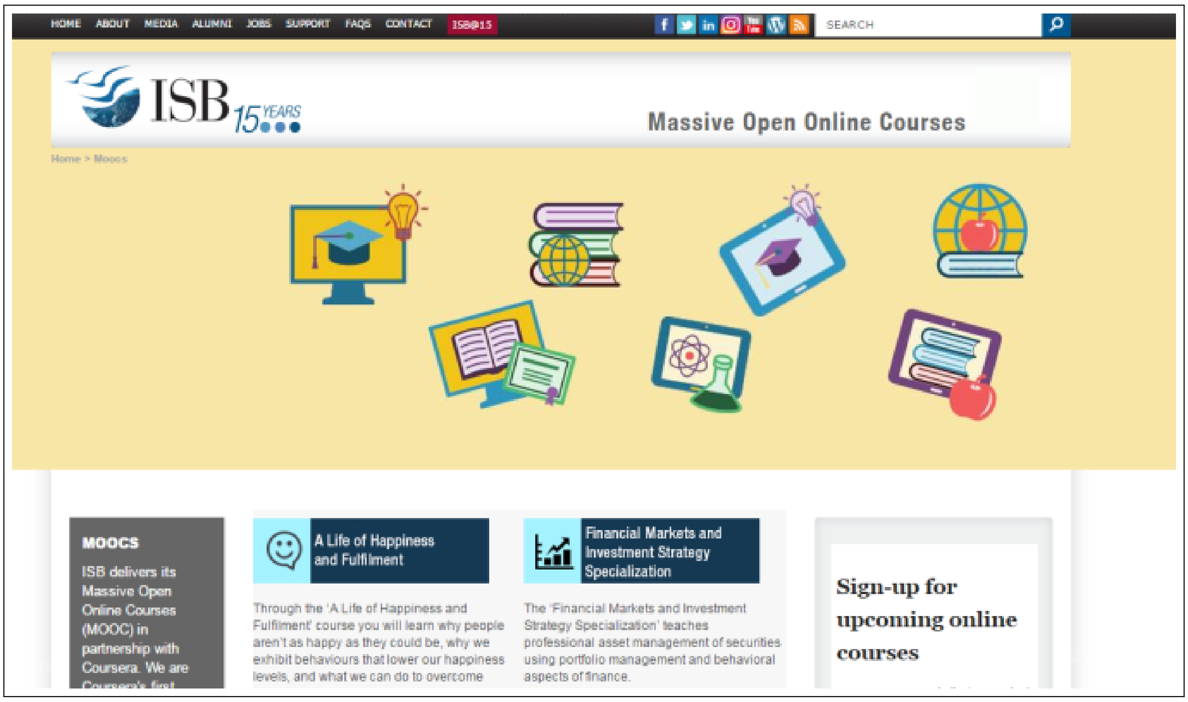


Figure 2.18: ISB MOOC snapshot [236]

- **IIM Bangalore (IIMBx):** IIM Bangalore through its IIMBx MOOC platform offers free online courses. IIMBx is a member in edX program. Since its start, it has now expanded and is offering MOOCs on topics like Marketing, Strategy, Accounting, Operations Management, Information Systems, Human Relations, Finance and Statistics and other management topics such as Analytics, Banking and Financial Markets, Information Technology Management, International Business Management and Sustainability. It also runs Faculty Development Programme (FDP) that equips the faculty with the required skills to conduct and embed MOOC courses into their classrooms. IIMBx snapshot is shown in Figure 2.19.

Figure 2.19: IIMBx snapshot [234]

- **IIT Bombay (IITBx):** With the tagline "We're empowering learning in the classroom and around the world" IITBx believes in the highest quality education for online and classroom environments. Along with the basic goal of offering courses and free content to the learners, IITBx is committed to research that helps to understand how learners get trained, how technology can transform learning, and also side by side promotes success in Indian massive open online learning. Figure 2.20 shows the snapshot of IIT Bombay MOOCs offered via edX platform.

Figure 2.20: IITBx snapshot [235]

- **IIT Kanpur:** Indian Institute of Technology Kanpur started offering MOOCs since 2012. mooKIT, a MOOC Management System was built from scratch at the CSE department of IIT Kanpur with best-of-breed features and state-of-art technology. It has the potential of scalability and offer online courses from micro to massive level. Figure 2.21 represents the mooKIT site snapshot.

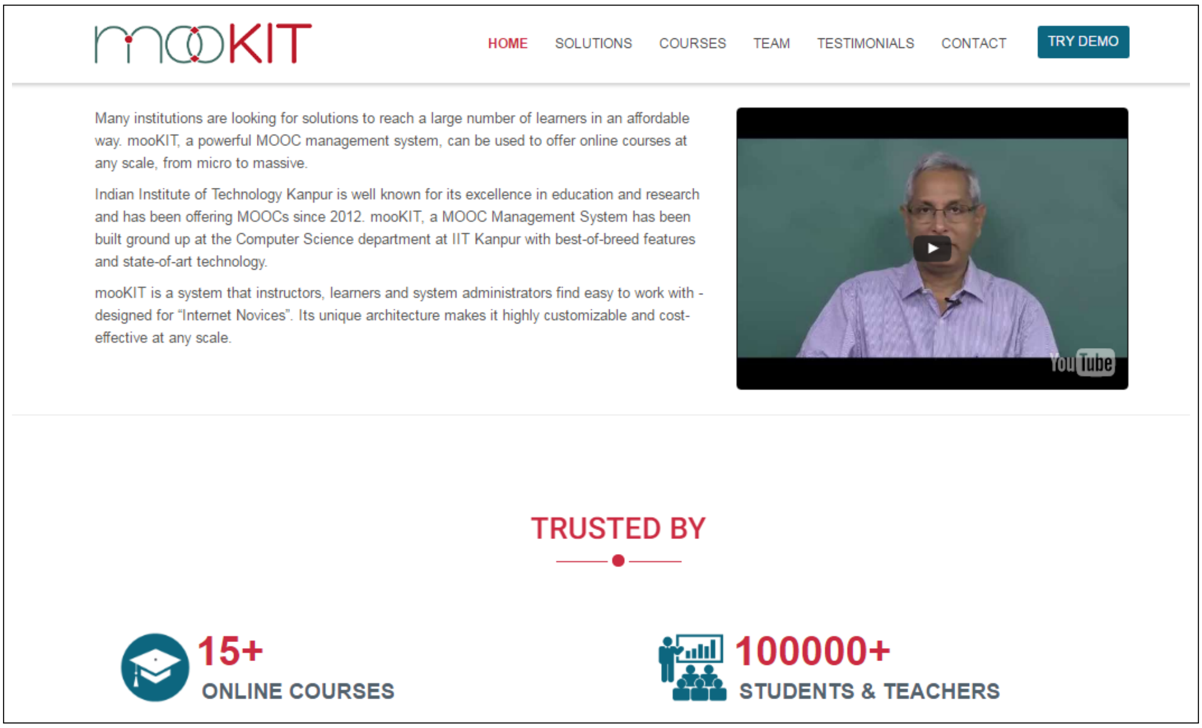


Figure 2.21: mooKIT snapshot [246]

These are some of the case studies/efforts of Indians towards improving the quality of higher education as side by side leveraging upon the changing educational wave through technological advancements inculcation and pedagogical changes in blended learning environments of India.

2.7 Research Context Specific Studies

This section discusses about the in-detail research studies that have been studied for carrying out the present research. After the analysis of EDM, LA and ALS methodologies, the pathway for designing of the blended learning environments based ALS was laid. As per the requirement of blended learning environments based ALS, there was need to trace the learning behaviour of the students, that will be forming the part of the study at later stages for system validation purposes. After analyzing the learning behaviour, useful inputs regarding the input parameters can be derived. Just like other existing studies that help in prediction of student performance parameters or their safe / failure / at-risk status, these relevant input parameters can be put in place. As per the requirements and characteristics of the involved input parameters, relevant models can be designed, tested and validated for blended learning environments. Once validated, these can be embedded within the blended learning environment based ALS.

In lieu of the above requirements, the in-detail analysis was performed for two major categories. One consisted of the studies comprising of the behavioural analysis of the students and the other one was based on studies related to EWS. These help in early identification by predicting the current status of the students that may prove to be very helpful for ALS.

2.7.1 Behavioural Analysis Based Studies

This section comprises of studies that are based upon the behavioural analysis of the student's at-risk behaviour alongwith its detailed analysis regarding existence of biases. The data for behavioural analysis can be obtained via various parameters like teaching feedback given by the students, survey scores, face-to-face interactions like interviews *etc.* Based on the requiremnets of the behavioural analysis of blended learning environment students, this section is divided into two parts: studies based on behavioural analysis regarding gender and socio-economic biases and studies related to behavioural analysis of at-risk students, as shown in Figure 2.22.

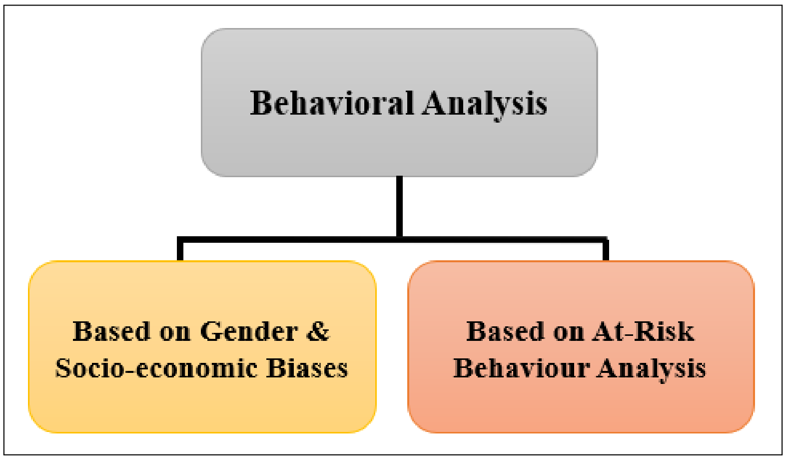


Figure 2.22: Behavioural analysis based categorization

2.7.1.1 Based on Gender and Socio-economic Biases: An extensive literature exists on the role of gender in teaching examined through student feedback. Centra and

Gautbatz (2000) examined gender differences via two analyses, one focused on student gender effect and one on teacher gender effect, across eight disciplines: health sciences, business, education, social sciences, fine art, natural sciences, technology and humanities [29]. Some same-gender preference was detected, but was not considered significant, due to small variations; they argued that reaction to higher education by a female teacher reflected differences in teaching styles, instead of gender bias.

Bettinger and Long (2005) examined a comprehensive data-set of 54,000 students across two main disciplines (sciences, and humanities and social sciences), to explore whether student interest in a subject is affected by the presence of same gender faculty [50]. This study revealed a role model effect; the presence of a female instructor positively influenced course selection and major choices for some disciplines.

Basow and Silberg (1987) evaluated over 1000 male and female students of 16 male and female professors, across social sciences, natural sciences, engineering, humanities discipline examining teaching effectiveness and sex-type characteristics [9]. Female professors were less supported and rated lower than male professors by students of both genders. Feldman conducted two reviews on the role of gender in teaching.

Feldman's first study (1992), provides evidence from the social laboratory and experiments [17]. It reveals that in most cases no differences were found to exist between the two genders, and also states that in some minor cases, no systematic trend exists for teacher ratings. In some studies, teachers' ratings were improved by gender-typical attributes and behaviour, whereas in some studies, the ratings were influenced by gender-atypical attributes and behaviour.

Feldman's second study (1993) provides evidence from the classroom [19]. The majority of studies confirmed earlier observation of there being no difference between the genders' evaluations. Some trace was found of a preference for female teachers over male teachers, same-gendered teachers over opposite-gendered teachers, and gender-typical and gender-atypical behaviour of students in terms of attributes, behaviours and positions, but Feldman felt their inconsistency across studies, and small statistical significance, meant they were insignificant in practical terms.

Another major study in the field of gender biases by Boring (2015, 2017), uses over five successive years of data in the field of social sciences from a large French university to analyze the gender biases in student evaluations of teaching [175, 222]. This study revealed the existence of gender bias, with male professors being preferred to female professors. Across the teaching dimensions valued by students, professors tended to match their gender stereotypes. Male teachers were rated higher in aspects like class leadership and being well-informed on current issues, while female teachers scored well in time-consuming aspects such as course preparation and organization.

Price *et al.* (2017) analyzed 8,888 sets of student ratings from a large Swedish university for differences between computer science and engineering, and environmental engineering [248]. They found that teachers tended to receive higher ratings in subjects more typical for their gender, rather than subjects less typical for their gender, but the authors termed these findings of little theoretical or practical importance, because the statistically effect magnitude was statistically small and insignificant. Other studies measured the effect on student ratings of teacher gender, and of factors such as physical attractiveness, teaching philosophy, or age, and found differences in ratings across educational scenarios [12, 196, 134, 214].

Next, studies of socio-economic diversity in education are discussed [154, 51, 7]. Delvin analyzed the key literature from Australia, New Zealand, the United Kingdom, and North America for conceptual frames to consider the success and achievements of students of low socio-economic status in Australian higher education. He suggested a 'joint venture' concept for bridging the existing gap of socio-cultural incongruity [154]. Dee (2005) analyzed eighth-grade students through NELS:88 survey data to evaluate whether 'assignment to a demographically similar teacher influences the teacher's subjective evaluations of student behaviour' [51]. Race and ethnicity had consistently large effects, but this was concentrated among students of low socio-economic status. The study discusses how to remove these effects by recruiting underrepresented teachers.

There is a need to extend this research further, by exploring the student ratings for the existence of gender or socio-economic biases, for teaching quality of higher education.

2.7.1.2 Based on At-Risk Behaviour Analysis: Studies directly relating to the at-risk students with their behaviour, are found limited within the literature. However, some studies related to the class absenteeism and its effect on student performance have been traced in the literature and are discussed below.

Paisey and Paisey (2004) discussed in their study the reason for non-attendance of classes by the students and their positively correlated course performance in accounting context, of higher education [47]. The main reasons for the non-attendance in lectures and seminars included part-time employment, working on coursework, group work, medical reasons, personal reasons, timetable issues, lack of motivation, did not find classes useful *etc.* Schmuliana and Coetzeea (2011) supported the above mentioned reasons for class absenteeism, however generalizability of positive correlation between course performance and attendance was questioned [136].

López-Bonilla and López-Bonilla (2015), focussed their research study on identifying common reasons for absenteeism in university students [188]. They identified seven factors for student absenteeism namely teaching style, efficiency, academic interest, teaching contents and format, classmates influence and fears, imponderables and convenience. Mestan (2016) in the research study discusses the reasons for the students leaving Bachelor of Arts in the humanities and social sciences, which are course related and personal reasons [212]. Yan and He (2019) in their research study discussed the main reasons for non-attendance of classes by final year students [291]. The main factors that contributed towards the skipping of classes included "students' obsession with employment, a series of curricular and pedagogical shortcomings and students' limited self-discipline and management".

Some studies that analysed the reasons for student dropout are discussed ahead. Xenos et. al. (2002) aimed to investigate the main reasons for student dropout in distance education in computers field [37]. The main reasons included inability of the students in estimating the time required for professional university-level study, the higher level of difficulty of the computer courses along with other personal reasons. Varre et. al. (2014) in their research study identified five basic factors namely time constraints, academic motivation, technological and platform issues and lack of immediate availability of the teacher, for online student dropout [166].

Helal et. al. (2019) in their study tried to identify the key factors behind the low academic performance of the students [278]. The study revealed that students who have lower level of interaction with the online educational environments as well as lower level of contribution to the course activities, are more likely to be the low-performing students. Bahadır (2020) in the research study suggested that success is a relative concept, as per today's students' perception [292]. Some students having high Cumulative Grade Point Averages (CGPA) considered themselves unsuccessful whereas some students having low CGPA, considered themselves as successful, depending on their own perceptions of success.

So, there seems to be a need to identify the changing needs and perceptions of 21^{st} century students. Studies that can relate to the at-risk behaviour of students along with their changing long-term aspirations and needs, especially in blended learning environments are found missing within the literature. The reason behind this can be that it is assumed that low performer students are either the strugglers who are unable to grasp the concepts taught in the classrooms or match the learning pace of their peers, or either are completely not interested in the courses they are enrolled in.

There is a need to fill in this gap. This research direction must be explored further for finding out the basic characteristics, objectives and reasons for at-risk behaviour of low performer students. The study that tries to identify that whether the 21^{st} century learners are real strugglers or are willing to "risk" their academic performance in order to enhance their newly evolved 21^{st} century skill-set and achieve their long-term goals. There is need for a study that contributes to the literature through the behavioural analysis of the students and help the researchers to identify relevant input parameters that may help in effectively identification of the at-risk students. There is need for identification of the factors or input parameters that may even in turn motivate these at-risk students through timely interventions by the instructors.

2.7.2 Early Warning Systems Based Studies

EWS help the educational researchers in getting a better insight into their online or blended learning classrooms and timely intervene the student with appropriate assistance [197]. These assist in early identification of at-risk students. The objective is to increase the quality of education and retention rates. EWS can be distinguished further with respect to the following paaremters: Based on Objectives, Input Features, Datasets, Machine Learning, Sequential and Deep Learning Models as shown in Figure 2.23. These EWS along with existing CSE domain based studies and common evaluation parameters used are discussed below.

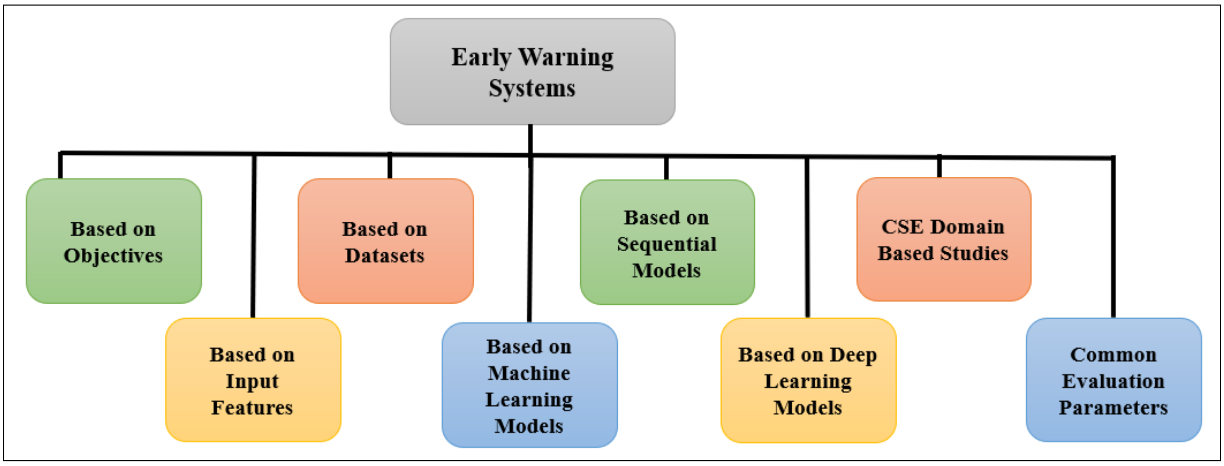


Figure 2.23: Early warning systems based categorization

2.7.2.1 Based on Objectives: The objective of EWS is to timely or early identify the at-risk students. Their domain may range from course level to institutional level [139, 184, 186]. However, the target variables are different. Some researchers try to predict the continuous performance parameters like final scores or grades for their courses [183, 238]. Others convert the prediction problem into the binary-classes: Pass- At-Risk, Pass-Fail, Pass-Withdrawn *etc.* for dropout or at-risk student's early identification. Research studies involving multiple classes also exist within the literature, that focus on identifying different classes and their combinations like: Distinction, Pass, Fail, Withdrawn [303].

2.7.2.2 Based on Input Features: The input parameters feeded into the EWS, belong to various categories. These can be divided into the following major types: legacy data, demographic data, clickstream data or activity logs, assessment or performance data and other additional sources. Legacy data contains the information regarding past performance of the student and is helpful in predicting the current course grades [238]. Demographic data deals with the background or enrolment information of the student. It contains fields like student family background, the area to which the student belongs, the family status and level *etc.* Along with other variables, this data is also used frequently for determining basic psychological and behavioural understanding of the student [124].

Clickstream or activity logs capture all the student-interface interactions data. They contain the information about the login sessions, number of clicks, time of accessing, time spent on each resource, number of messages posted on discussion forums *etc.* This interaction data, independently as well as in combination with other variables, help in efficiently determining the at-risk students [125, 160, 181, 199, 220, 221]. Assessment or performance data contains the information about the ongoing performance of the student. According to the research studies, this is one of the most reliable and efficient parameter in predicting at-risk students [156, 206]. You (2016) in the study support the potential of using learning performance data for early identification [220]. Other additional input sources data include questionnaires [84].

- **Performance parameters:** According to the literature, performance parameters are considered as one of the most reliable parameters in early identification of at-risk students [206, 156, 210]. The performance parameters involve Secondary School Performance, Pre-Course Performance, Current Course Performance, Concept Assessment in the form of quizzes or questionnaires, Post-Course Performance, and so forth [266]. Further there are two types of assessments in current course performance: Formative and Summative Assessments. Summative assessments are usually composed of Mid Semester Examinations (MSE) and End Semester Examinations (ESE). They form a major part of the course weightage. But their timings are usually late as MSE occurs when half of the course is completed, and ESE is when complete course is finished. Reliability on these as only parameters for early-identification often result in delayed interventions, as these occur late during the courses. So, the researchers often experiment with formative assessments. They carry lower weightage, but their continuous usage may prove to be efficient in early identification of at-risk students. These are further discussed in detail in the following part.

- **Lightweight formative assessments:** Recent research trend focusses on checking the potential usage of active learning strategy like PIs with clickers for early identification of at-risk students in large, blended learning environments.

Clickers are found to be successful in early prediction of at-risk students. Porter *et al.* (2014) in their research study suggested to use clicker questions for early identification of at-risk students, as these are very helpful in predicting the final student outcomes [169]. Griff and Matter (2008) conducted a research study on usage of personal response system in early identification for Biology course. They identified that students who registered early for personal response systems had higher probability of succeeding later within the course [92].

Lee *et al.* (2015) in their research study explored the usage of two major parameters, namely, pre-course assessment scores and clicker data for robust predictions of at-risk students in EWS. They found these to be effective in early identification of at-risk students. However, for better generalizability, the study suggested to explore these parameters in other STEM courses and institutions as well [187].

Liao *et al.* (2016) research study proposed a lightweight modelling technique for PI classrooms with the help of clickers. The study also suggests that with appropriate planning and alignment of instructor's goals along with lightweight assessments, one can identify the poor performers early within the CS1 course. However, this study restricts itself to only specific domain courses, that is, CS1 course [209]. In another study, Liao *et al.* (2019) presented a modelling technique using Support Vector Machines (SVM) through which they were able to predict the scores within third week of the five twelve-week course(s), with competitive levels of area under curve (AUC) values [284]. The term lightweight assessment was used as the authors believed that automated clicker questions can be easily replaced by other formative assessments. These include online quizzes, assignments or even these can be used along with clickers for incremental improvement [285].

As per the Caldwell's research study (2007), clickers have been used in variety of ways in the classrooms for increasing the engagement levels, retention rates, student performance and for creating a positive and active atmosphere in the large classrooms [71]. However, according to the best practices like preparing good questions, generating large question bank, and then embedding clickers in daily classrooms does not seem to be a feasible solution. It adds up to the instructor's daily workload. Its success within the class also depends on the infrastructure availability, seriousness and perception of the students, regarding the clickers.

2.7.2.3 Based on Datasets: The KDD Cup 2015 (KDDCUP15) dataset is a MOOC dropout prediction public dataset and is part of XuetangX, one of the largest MOOC platforms in China [163, 182]. Since its launch as a competition dataset in 2015, it has been considered as a benchmark dataset for the identification of students who are at-risk of dropout. The researchers have explored its clickstream data, and other contextual information and learner's behavioural information for dropout predictions [257, 288, 274, 276, 304].

Open University Learning Analytics Dataset (OULAD) is another public educational dataset that contains logs about distance education courses [241]. It contains the clickstream data logs of virtual learning environments, assessment data logs as well as demographic data logs of the learners. The dataset comprises students' instances belonging to four different categories: 'pass', 'fail', 'distinction' and 'withdrawn'. The researchers have been combining and using different instances of the dataset according to the objectives of their research study. The researchers utilize the partial or complete course logs for at-risk category students prediction on this dataset [272, 281, 294, 303, 305].

Al-Shabandar *et al.* (2019) worked on dropout prediction for the Social Science course of the OULAD dataset and four courses of the HarvardX dataset. Clickstream with demographic and behavioural attributes was used as inputs. Machine learning models consisted of RF, Feed-forward Neural Network (NNET1), Multi-Layer Perceptron with two hidden layers (NNET2), GBM, and Generalized Linear Model (GLM). Two models for learning achievement and at-risk students' prediction were constructed. GBM outperformed with 0.894 and 0.952 accuracies for both models [289]. Feng *et al.* (2019), in their study, used clickstream as well as contextual information for the identification of users' learning behaviour. They clustered the data based on the learning behaviour and even identified strong correlation and influence amongst the learners and courses. The study proposed a Context-aware Feature Interaction Network (CFIN) and validated it on two datasets, namely KDDCUP15 and XuetangX, both from XeutangX, one of the largest Chinese MOOC platforms. An AUC score of 0.909 and 0.867 and F1-score of 0.928 and 0.909 were achieved for KDDCUP and XeutangX dataset, respectively [276].

2.7.2.4 Based on Machine Learning Models: A wide variety of models are included in early identification of at-risk students. Since the problem is simply a binary classification problem, that is, the model needs to identify whether the student under consideration is at- risk or not. So, various machine learning classification models and data mining techniques using the cross- sectional data properties, are used for the early predictions [128, 251]. These involve Logistic Regression (LR), Bayesian classifiers, Bayesian Additive Regression Trees, k-Nearest Neighbour (kNN), eXtreme Gradient Boosting (XGB), Adaptive Boosting, Random Forest (RF) with its variants and SVMs [60, 177, 189, 205, 226, 259, 267, 270]. Traces of semi-supervised learning are also found in early identification of at-risk students [185, 260]. Other designed algorithmic approaches include Interpretable Classification Rule Mining Algorithm [152, 211], genetic programming and evolutionary algorithms [159, 198], Multiview learning [273, 283], Multi-Objective Optimization [282], Ensemble models [210], and deep learning models [287, 290].

In case of unlabelled data, clustering based approaches are used where the students are grouped according to their "similar-ness" on the basis of online patterns or activities like number of resources accessed, quizzes attempted, marks obtained, average scores, taking part in discussion forums *etc.* This helps to identify different levels of student engagements or their learning strategies. For example, Lust et. al. (2011) identified three different patterns using k-means clustering in a blended learning course [132]. Carroll and White (2017) used Latent Class Analysis for identification of different level of engagements of the students using four different clusters in a large blended business course [224].

Huang and Fang (2013), in their study, predicted student performance for an Engineering Dynamics Course using various performance parameters. The study involved the implementation of Multiple Linear Regression (MLR), Multilayer Perceptron (MLP), Radial Basis Function (RBF), and Support Vector Machine (SVM). Percentage of accurate predictions was used as the evaluation parameter. For the prediction of individual student academic performance, the SVM model with six performance parameters as predictor variables was found to perform the highest [156].

Zacharis (2015) developed a predictive model for at-risk students' identification. The model was validated on a Moodle LMS based programming course with fourteen

LMS usage variables. Stepwise Multivariate Regression and Logistic Regression (LR) were used as predictive models and correlation analysis and accuracy as an evaluation criterion. A considerable overall accuracy (weighted average) of 81.3% was obtained using the above models [199].

Mueen *et al.* (2016), in their study, used performance parameters, attendance, and participation data for Programming Fundamental and Advanced Operating System courses, in order to predict student performance. The study employed Naïve Bayes (NB), MLP, and Decision Tree (DT) (C4.5 algorithm) as machine learning models and accuracy as an evaluation criterion. NB classifier was found to perform best with an overall accuracy of 86% [213].

Costa *et al.* (2017) utilized two datasets from programming courses, distance education and on-campus, for the identification of at-risk students. Input parameters included learning logs with feature selection via Information Gain Algorithm. Four machine learning models were employed, namely, SVM, DT (J48 algorithm), NN, and NB. F-measure was used as a measure for evaluation criterion. SVM performed best for both datasets with an F-measure value of 0.92 and 0.83 on different datasets [227]. Chung and Lee (2019), in their study, made student dropout predictions on high school students' data. Twelve features representing key risk indicators were used as input parameters for the study. Random Forest (RF) was used as the machine learning model, and accuracy, sensitivity, specificity, and AUC were the evaluation parameters. An excellent and considerable AUC score of 0.97 was obtained through the predicted model [275].

Cui *et al.* (2020) predicted student learning performance on three different courses from Western Canadian University with the data extracted from LMS. The machine learning models involved LR, NB, SVM, DT, RF, k Nearest Neighbor (kNN), Neural Network (NN), Gradient Boosting Machine (GBM), and Ensemble Model (EM). Sensitivity, Specificity, and Area Under the Curve (AUC) were used as evaluation criteria. NN, RF, GBM, and EM showed better performance as compared to other classifiers [293]. Table 2.9 provides glimpse of studies with considerable results for machine learning models.

Table 2.9: Studies with considerable results for machine learning models

Ref. No.	Year	Objective	Inputs	Dataset	Model	Results
[259]	2017	Obtaining reliable accuracy for MOOCs dropout prediction (training + testing regime)	Clickstream data	40 MOOCs data from HarvardX	Logistic Regression	AUC: 87.33% averaged over 8 weeks (Train using proxy labels)
[210]	2016	Early identification of at-risk students using standard based grading	Performance data	Secondary data collected at a large university	Ensemble Model	Accuracy: 85% and F1.5: 0.61
[287]	2019	Early Prediction of at-risk Students	Student's activity, course and assessment activity, peer activity	5 different datasets from Moodle Pvt. Ltd. and their partner institutions	Neural Network	Accuracy: 67.46-81.63% and F1 Score: 71.30-83.09%
[268]	2018	Predicting withdrawal amongst the active and passive students	Activity logs	OULA Dataset	Markov Chain Model	Withdrawal Probability: 0.25 for active students; 0.95 for passive students
[265]	2018	Considered day-wise sequences for early prediction of dropouts	Clickstream data	OULA Dataset	Decision Trees (10 fold cross validation)	Accuracy: 90% (approx.)

Although the different machine learning models have shown significant results for smaller, in-house datasets, these often lag behind in the case of big educational datasets with deep learning model implementations, as described in the following part. However, as per the wide variety of diversity in educational data, the solution to this problem has not converged over any one model. It is usually dependent on a wide variety of factors involved like data size, data type and pedagogy involved.

2.7.2.5 Based on Sequential Models: The models that rely on the sequential properties of the data for early prediction, also exist within the education based literature.

Kuzilek *et al.* (2018) used Markov modelling for predicting the student behaviour and also identifying its impact on student dropout [268]. Kuzilek *et al.* (2020) used markov models for unrevealing the exam strategies of first year students, in order to improve the retention rates [297]. Fei and Yeung (2015) categorize dropout as time series prediction problem and used the MOOCs sequential dataset properties for early identification of at-risk students, using activity based datasets [178]. Haiyang *et al.* (2018) proposed time series forest classification algorithm built upon independent student interaction data, for two courses of virtual learning environments [265]. The findings reveal that there exists a linear relationship between the data and accuracy. They also show that high prediction accuracy can also be possible with only small amount of data for some dataset.

Brooks *et al.* (2015) in their study used generated features from the interaction logs, for their usage as time-series data in predictive modelling [176]. The post hoc analysis of results revealed high reliability with kappa value greater than 0.9, but lacked explanatory power. Models were found to be moderately accurate on real-world datasets. The existing literature is found to benefit from the sequential nature of the markov decision process, HMM models and its deep variants. Markov decision processes have been used for modelling the MOOC user behaviour [280]. HMM have their applications in knowledge tracing of the students *i.e.*, identifying whether the student has mastered a skill or not [21].

Similarly, deep knowledge tracing utilizes Recurrent Neural Networks to model the student learning [191, 309]. HMMs have been used for binary classification between low scorers and high scorers, by analyzing the educational game features [301]. HMMs are found to be effective in identifying, determining, and interpreting the student's pattern of activities, automatically discovering the student behavioural patterns on clickstream data [94, 230]. Overall, sequential or temporal models like HMMs are found to be effective for activity interaction data. But studies related to their applicability on performance data for binary classification of at-risk behaviour, is found missing.

2.7.2.6 Based on Deep Learning Models: Fei and Yeung (2015) experimented with the sequential models for Massive Open Online Courses (MOOCs) student dropout prediction. They used temporal models like Input-output Hidden Markov Model (IOHMM), Recurrent Neural Network (RNN), and RNN with Long Short-Term Memory (LSTM) cells for dropout prediction. Two-course datasets were involved that included activity logs of a Gastronomy course from Coursera and a Programming course from edX. The results revealed that LSTM performed consistently better for both courses [178]. Whitehill *et al.* (2017) proposed a Net2Net feed-forward neural network with five hidden layers for dropout prediction on 40 courses from HarvardX MOOCs. The model was trained and tested on four different training paradigms in order to avoid overestimation of the accuracy. Demographics, as well as clickstream data with additional features, were used as input for the study. Net2Net achieved an accuracy of 97.55% over the baseline model of LR [258].

Tang *et al.* (2018) treated dropout prediction as a time series problem and extracted the learner's log information from the XeutangX dataset. Daily activities of learners were then fed into the time series model RNN with LSTM, and results were compared with other existing baseline models. Time Series model gave the best results with the highest AUC values over other baseline models [271]. Liu *et al.* (2018) proposed a dropout prediction model based on RNN-LSTMs. Six courses dataset from Chinese University MOOCs were considered. Clickstream data consisting of a quiz, discussion, access logs, *etc.*, were used as inputs. Average accuracy of 90% was achieved for each course [269]. Xing and Du (2018) used a deep learning algorithm for dropout prediction in a project management MOOC course. The input data consisted of clickstream, forum, and performance data. An average AUC score of 0.968 was achieved [290]. Imran *et al.* (2019) utilized feed-forward deep neural networks to address the problem of student dropout prediction. HarvardX and MITx person course dataset with twenty attributes was used for validation. The Deep Learning Model with seven hidden layers and 64 neurons gave the highest accuracy of 88.76% and dropout prediction accuracy of 99.80% [279].

Mubarak *et al.* (2021) predicted learner behaviour utilizing video clickstream data. The study employed deep neural network LSTM for making predictions. The overall accuracy of 82%-93% was achieved across the courses that outperformed the baseline models like ANNs, SVM, and LR [308].

Table 2.10: Studies with considerable results for deep learning models

Ref. No.	Year	Dataset	Features	Models	Metrics	Results
[257]	2017	KDDCUP15	Student activity data	CNN-RNN	Precision, Recall, AUC, F1-score	AUC: 0.874; Precision: 0.886; Recall: 0.965; F1-score: 0.924
[288]	2019	KDDCUP15	Student activities data	DP-CNN	Precision, Recall, AUC, F1-score	AUC: 0.86; Precision: 0.86; Recall: 0.87; F1-score: 0.863
[274]	2019	KDDCUP15	Learning behaviour records	DT-ELM	Accuracy, AUC, F1-score	AUC: 0.858; Accuracy: 89.28%; F1-score: 0.915
[276]	2019	KDDCUP15, XuetangX	Student Interaction data, contextual information	CFIN	AUC, F1-score	AUC: 0.909; F1-score: 0.928
[272]	2019	OULAD	VLE Interaction data	LSTM	Accuracy, Precision, Recall	Accuracy: 95.23%; Precision: 0.935; Recall: 0.758
[281]	2019	OULAD	Student's Interaction data	RF, GBM, GLM, Deep Learning	AUC	AUC: 0.91
[304]	2020	KDDCUP15	Clickstream data	FWTS-CNN	Accuracy, Precision, Recall, F1-score	Accuracy: 87.1%; Precision: 0.863; Recall: 0.865; F1-score: 0.864
[294]	2020	OULAD	VLE interaction Demographics, Assessment data	RNN-GRU Network	Accuracy, Recall	Accuracy: 90%; Recall: 85%
[303]	2020	OULAD	Demographics, Assessments, Clickstream data	Deep ANN	Accuracy, Precision, Recall	Pass-Fail Accuracy: 88.62%; Withdrawal-Pass Accuracy: 93.2%
[305]	2021	OULAD	Demographics, Assessment, Clickstream data	DFFNN, SVM, RF, AdaBoost, kNN, GBM	Accuracy, Precision, Recall, F1-score	Accuracy: 91%; Precision: 0.92; Recall: 0.91; F1-Score: 0.91

Table 2.10 provides glimpse of various deep learning models with significant results. As per the trend across the studies, sequential and deeper networks like LSTM with multiple layers have resulted in significant results. Educational data, when treated as time series analysis data along with these sequential and deeper networks, is expected to yield good results.

Table 2.11: Comparative analysis of existing literature in CSE domain

Ref. No.	**Year**	**Objective**	**Features**	**Courses with sample size**	**Model**	**Outcomes**
[158]	2013	Impact of clickers with group based learning	Clickers	Data Structures and Algorithms (120)	Statistical Comparison	Increased student retention, engagement and attendance but decreased performance.
[209]	2016	Determine the impact of clickers on early prediction of at-risk students in CS1 courses	In-class clicker questions	CS1 course: Python (Train: 171 - Test: 142)	Linear Regression	Early Prediction of at-risk students [70% correct classification in week 3 of 12 week course].
[217]	2016	Early detection of at-risk students	Formative assessments, feedback and in-class discussion	Programming in Java (284)	Correlation Analysis	Strong correlation between students interaction and their overall performance.
[284]	2019	Early prediction of final exam scores with the use of peer instruction pedagogy	Clickers data	(Train-Test) Python (192-142), CS1-Java (373–374), CS2-Java (169-176), ADS (197-191), Architecture (339-266)	Support Vector	Machine Lightweight source of student data have potential for early prediction of at-risk students across multiple CS courses as per the data validation.
[302]	2020	Early Prediction of student performance	Formative assessments	Introductory programming course (289)	Random Forest	60% overall accuracy and 77% at-risk class prediction accuracy in week 3 of a 12-week course.

2.7.2.7 CSE Domain Based Studies: Educators have experimented with wide variety of input parameters as well as models, for early identification of at-risk students, in CSE domain. Most of their focus points in this domain are the introductory programming courses [209, 284, 158, 217, 302].

Table 2.11 represents the comparative analysis of some of the relevant research studies in CSE domain. However, research study involving core subjects that follow different pedagogical aspects for CSE domain is found to be lacking within the literature. The studies that bridge these existing gaps across core courses of CSE domain with different pedagogical aspects like programming, problem based and project based learning, are required to be inplace.

2.7.2.8 Common Evaluation Parameters: The most common evaluation parameters that have been used for binary classification of at-risk students are discussed below. The rate of classification of an at-risk student to the safe category is a costlier operation than vice-versa. So, along with Accuracy, other parameters like Precision, Recall and ROC-AUC are also taken into consideration. The analysis is mostly performed using the following evaluation parameters: Accuracy, ROC-AUC, Precision, Recall, F1-Score and Cohen's kappa statistics. Each statistic is briefly described below:

- **Confusion Matrix:** It represents a table that describes the performance of the classifier model and provides a mapping of actual versus predicted classes, as an outcome. Confusion matrix for a binary classification is represented in Table 2.12.

Table 2.12: Confusion matrix for binary classification

		Actual	
		Class 1	**Class 2**
Predicted	**Class 1**	True Positive (TP)	False Positive (FP)
	Class 2	False Negative (FN)	True Negative (TN)

Here, True Positive (TP) are from class 1 and were correctly classified in class 1. True Negative (TN) are actually from class 2 and were correctly classified in class 2. False Positive (FP) belonged to class 2 and were misclassified to be in class 1, by the classifier. Similarly, False Negative (FN) belonged to class 1 and were misclassified in class 2.

- **Accuracy:** It determines the correct predictions made by classifier, out of the total number of predictions made. It can be calculated as follows:

$$Accuracy = \frac{TP + NP}{TP + FP + FN + TN}$$

- **Precision:** It determines how often the classifier model is correct. It is the ratio between true positives classified by the model versus total actual positives and can be calculated as:

$$Precision = \frac{TP}{TP + FP}$$

- **Recall:** It gives the true positive rate and is termed as sensitivity of the model. It can be calculated as:

$$Recall = \frac{TP}{TP + FN}$$

- **F1-Score:** A statistical measure that calculates weighted average of Precision and Recall. It can be calculated as:

$$F1Score = 2 * \frac{Precision * Recall}{Precision + Recall}$$

- **ROC-AUC Curve:** ROC stands for Receiver Operating Characteristics Curve. It is a graph and AUC represents the Area Under the ROC Curve for this graph. It is plotted between true positive rate (sensitivity) versus false positive rate (specificity). It shows how well the classifier model can distinguish between the classes. The ROC-AUC value of 1 represents exactly accurate predictions.

- **Cohen's Kappa:** Also known as kappa statistic, it is a measure of reliability for categorical data. It shows an agreement between the two raters and is calculated as:

$$Cohen'sKappa(k) = \frac{p_o - p_e}{1 - p_e}$$

  where p_o is the observed agreement and p_e is the expected agreement [6, 145]. Its value is ranges between 0 to 1. Its value interpretation is: value $<$ 0 represents no agreement, from 0-0.2 represents slight agreement, 0.21-0.40 shows fair agreement, 0.41-0.60 displays moderate agreement, 0.61-0.80 as considerable and 0.81-1 as near to perfect agreement.

2.8 Discussion

After the analysis of the work done in the field of EDM, LA and ALS systems for blended learning environments, the important part are the input parameters. The input parameters for ALS are the performance parameters. For EWS, the parameters can be clickstream or performance data. Out of ALS and EWS, EWS is given more attention for this research, as for blended learning environments like India, routine classrooms are emphasized and carry more weightage than mastery based learning. However, concrete results for the input parameters that work effectively for blended learning environments are found to be missing. For this, there is need to conduct studies regarding the behavioural analysis for finding the trustable parameters for EWS that work in blended learning environments. This may help the researchers to identify relevant input parameters that may help in effectively identification of the at-risk students. There is need for identification of the factors or input parameters that may even in turn motivate these at-risk students through timely interventions by the instructors. For at-risk models, context-specific systems lack applicability across the domains. As per the literature, they are usually trained and tested on same data. Real-world testing on unseen data is lacking. Interpretability of the predicted results is found missing. Studies leveraging upon the sequential nature of educational data along with sequential models are limited. Also, the timings for "*early*" in "*early-identification of at-risk*" students need to be defined for blended learning environments. These existing limitations studied so far provides a direction to be followed further for quantitative and qualitative research.

Chapter 3

BEHAVIOURAL ANALYSIS

3.1 Overview

For efficient system designing for blended learning environments, the search for reliable and efficient parameters formed the basic requirement. For obtaining the reliable parameters, the students' viewpoints, their dependencies, motivation, biases and an overall behavioural analysis was performed. There seems to be a need to identify the changing needs and perceptions of 21^{st} century students. Studies that can relate to the at-risk behaviour of students along with their changing long-term aspirations and needs, especially in blended learning environments are found missing within the literature. The reason behind this can be that it is assumed that low performer students are strugglers. They are unable to grasp the concepts taught in the classrooms or match the learning pace of their peers, or either are completely not interested in the courses they are enrolled in. So, a detailed analysis of all students' direct feedback based behaviour and a dedicated study for at-risk behaviour was performed.

For this, two research studies were conducted. First case study was performed in order to identify the beliefs and probable success factors for at-risk students. Course specific study was conducted in which the students having weak in-class performance were selected. The students were directy interviewed and the reflections were noted down. Their characteristics, feedback and future viewpoints were analyzed for identification of probable parameters. The further research was conducted to analyse the reliability of the student feedback. The second case study involved analyzing the student's feedback for checking the existence of gender and socio-economic biases. For this, the direct feedback data was obtained from large cohort of blended learning environment's students. EDM and SA was performed for extraction of generalized relevant conclusions from the acquired educational datasets. The study confirms the existence of biases. Once the complete analysis of generalized and student-specific feedback was obtained for blended learning environments, the probable parameters were identified. The parameters that may work for efficient proposed system designing, were collected as an output for this phase.

3.2 Chapter Flow

With the objective of behavioural analysis of blended learning environment students for efficient system designing, the research was carried in two phases. During the first phase, the research was focused on at-risk students. As the final system ought to target the at-risk predictions through EDM and LA, the search of probable parameters was conducted through this study. So, the viewpoints of at-risk students were analyzed across different parameters. The second phase involved the further evaluation of the student's feedback on teaching quality, for behavioural analysis. The ratings given by the students to their instructors in various aspects of their study, were evaluated. The influence of environment and other factors on these ratings, in the form of biases, were analyzed. This study was conducted to get a generalized idea on the student conduct in the blended learning environments. The outcomes and suggestions of this study acted as relevant inputs in designing of the generalized pedagogy at later stages of this complete research study.

As an outcome of these studies, various design reflections, suggestions and probable parameters that may be effective for blended learning environments, are proposed. Figure 3.1 represents the research workflow for student's behavioural analysis.

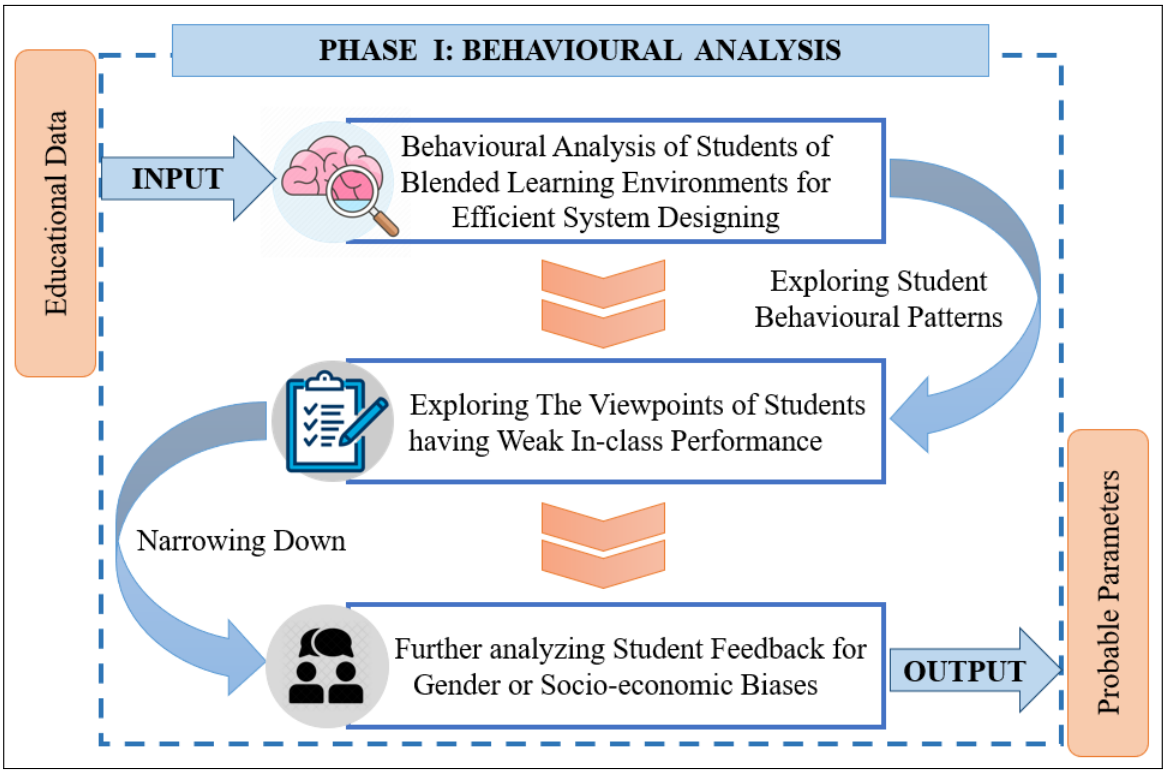


Figure 3.1: Adopted research workflow for behavioural analysis of students

3.3 At-Risk Behavioural Analysis

This research case study relates to the at-risk behavioural analysis of students via interviews, in normal classroom environments.

3.3.1 Overview

The 21^{st} century is characterized by the information explosion and ubiquitous presence of communication technologies which in turn has resulted into globalization in this seamless world. This has resulted into the establishment of knowledge based societies that have considerable impact on the functioning of the large world economies. In order to meet the pace of the changing technological needs of these knowledge based societies, education sector plays significant role as it helps in contributing knowledgeable and skilled taskforce. Unlike the previous academic skill-set used for judging these knowledgeable and skilled taskforce, new additional skill-set that support technological know-hows, innovation, critical thinking, collaboration, flexibility *etc.* and support lifelong learning are desired to be in-place. These are collectively known as 21^{st} century skill-set and are shown in Figure 3.2 [148, 173, 256, 242]. The 21^{st} century learners are expected to be well equipped with these skill-set for marching ahead on the path of creation of technology-enabled, efficient and skilled taskforce. However, in education sector, major hindrance to this are the at-risk students. At-risk students are those who are either at-risk of failure or at-risk of dropout from the course or program under consideration.

At-Risk of failure or low performer students have always drawn the attention of the educators. The researchers have dedicated themselves in taking appropriate measures for early identification of these students, so that timely intervention and assistance of the instructor can help them in better understanding of the concepts. This in turn saves them from failure in the courses and also help the instructors and institutions with increased retention rates and decreased drop-out rates. Early warning systems help to identify this group of population within the early weeks of the start of the courses. The human interventions taken by the instructors for these groups of students vary from student to student depending upon their respective reasons and requirements. These efforts are drawn towards eliminating or filling in the gaps that are hindering the students to march ahead towards the successful completion of the enrolled degree programs. This also have high direct impact on the quality, retention rates and drop-out rates at the course level as well as institution level.

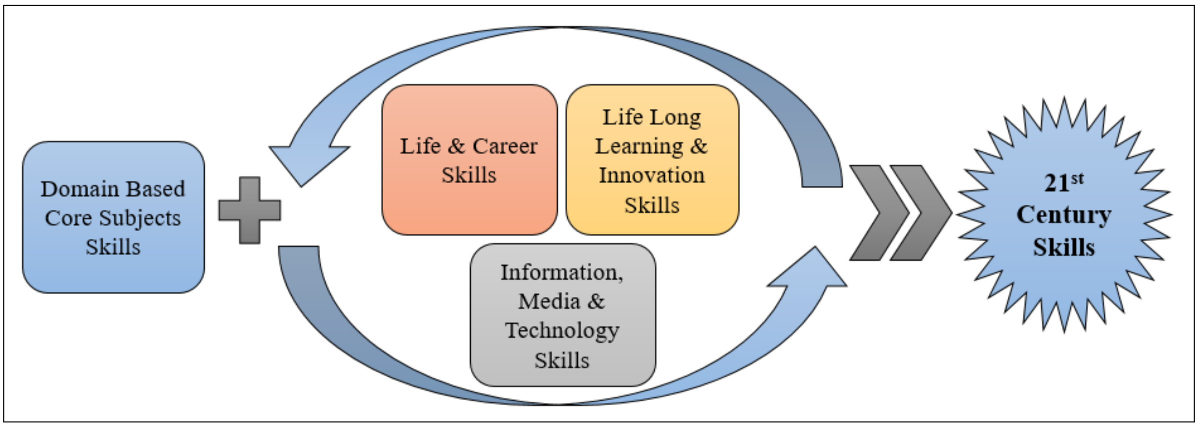


Figure 3.2: 21^{st} century skill-set

Blended Learning Environments: According to Bonk and Graham (2012), Blended Learning Environments can be defined as a learning environment that combines face-to-face instruction with technology-mediated instruction [141]. Boelens et. al. (2015) define blended learning as learning that happens in an instructional context which is characterized by a deliberate combination of online and classroom based interventions to instigate and support learning [174]. Blended learning environments have significant merits like strategic use of classroom time, one-to-one connection, increased access and convenience, improved course outcomes, greater cost effectiveness *etc.* [223, 172]. So, blended learning environments are more common in case of higher education.

Despite of the benefits of blended learning environments, the 21^{st} century students are finding it to be quiet restricting. Traditional classroom based attendance concept, instructor as the main source of course content *etc.* are soon losing their relevance. The 21^{st} century higher education students are highly influenced by the trending anywhere and anytime online education and are able to find easy replacements for these in the form of flexible online Open Learning Initiative course contents, self-paced and personalized MOOCs, simulations and virtual learning laboratories and environments *etc.* So, these blended learning environments seem to be a boundation to the students as its fixed schedule directly affects their working or learning hours as well as their learning pace and priorities.

In order to fill in this gap, this study tries to explore and analyze the learning perceptions, behaviour, reasons and objectives of the 21^{st} century at-risk, low performer students in blended learning educational environments. On the basis of its research analysis, it further tries to explore some flexible design reflections that can help to enhance the teaching quality for blended learning environments. This can in parallel, meet the study needs of the present day scholars.

3.3.2 Contributions

This study contributes to the literature in the following ways.

- Identification of the at-risk students via clustering based approach for blended learning environments.
- Explores this research direction further for finding out the basic characteristics, objectives and reasons for at-risk behaviour of low performer students.
- Identifies whether the 21^{st} century learners are real strugglers or are willing to "risk" their academic performance to enhance their newly evolved 21^{st} century skill-set and achieve their long-term goals.
- Suggesting design reflections for blended learning environments.

3.3.3 Research Objectives

Following are the research objectives with respect to the perceptions of at-risk students.

RQ1: What are the learning perceptions and behaviour of at-risk students in blended learning environments?

RQ2: What are the reasons for not actively participating in the courses?

RQ3: What are their major objectives behind completing the courses?

RQ4: What are the possible design reflections and insights for fulfilling at-risk student's study needs, in blended learning environments.

3.3.4 Methodology

This study was conducted in one of the top ten engineering universities of the country. Here, the academic year is divided into two six-month semesters. There are pre-decided fixed courses or subjects for each semester that are mandatory for all the students, except for some electives that are introduced at later years of the under-graduation. Each course further comprises of certain credits which contribute to the overall CGPA of the final degree obtained at the end of four-year engineering program. Each course unit carries an overall weightage of 100 marks. These marks are further divided into continuous evaluation components like quizzes, lab evaluations, tutorials, mid semester examinations and end semester examinations. These are appropriately distributed with respect to time and marks and are conducted within a certain time span throughout the six-month semester. The sequence of conductance of the evaluation components is shown in Figure 3.3.

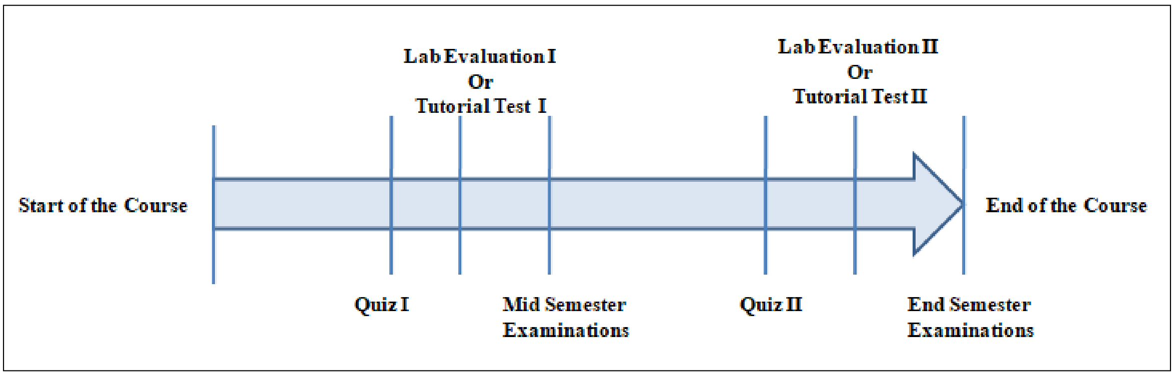


Figure 3.3: Distribution of evaluation components across the course

The present study was conducted on fifth semester (third year) students, studying the course of Advanced Data Structures and Algorithms (ADS) in the Computer Science and Engineering (CSE) department of the university having blended learning environments. The course content, practice questions *etc.* were delivered to the students via a Learning Management System (LMS). Apart from the basic activity parameters provided by the online LMS for tracing the student activities, the in-class behaviour was also traced. It included the students' class attendance, hands raising, number of doubts asked *etc.* So, three major areas of inputs were: measurement of the overall class attendance of the students, their overall interaction during the classrooms including doubt clearing and tracing their overall performance.

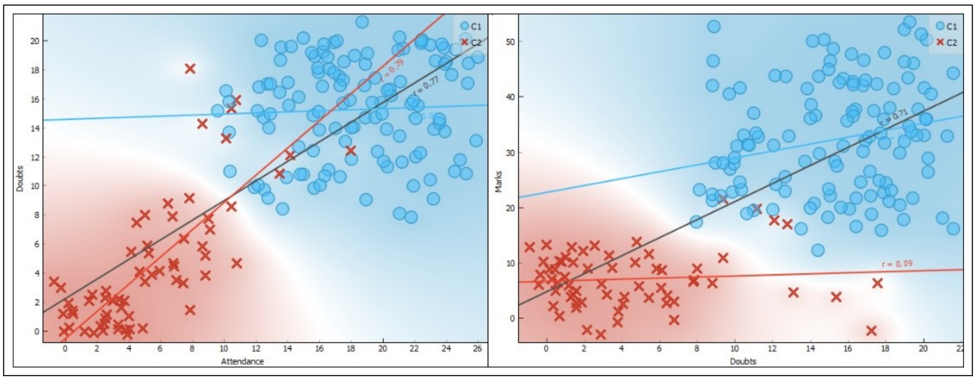


Figure 3.4: Two major identified clusters using k-means clustering

The students were bi-monthly tracked on the above three major parameters with the help of an early warning system using k-means clustering at the backend. However, their at-risk of failure or being a low performer behaviour was confirmed after analysing their overall performance in the Quiz-I, Lab Evaluation-I and Mid Semester Examinations, carrying an overall weightage of 50 percent of the entire course evaluation scheme. The system identified two major clusters of students as shown in Figure 3.4. Cluster one was identified with active students. Students who were having high attendance, were actively engaged in clearing their doubts and as a result yielded good marks. However, cluster two was identified as the cluster of at-risk students. Students who were mostly absent during the classrooms, poorly engaged and were low performers. The box plots for the three major input areas namely overall attendance, overall doubts clearing and overall performance (marks), with respect to the clusters is shown in Figure 3.5.

The students belonging to cluster two, were considered and asked to fill a form requiring their information like the student's basic information (gender, overall CGPA), marks and grade in pre-requisite course, overall number of failures in all courses versus domain based courses, reasons for not being an active learner and objective behind completing the course. The complete procedure carried out for data collection and analysis is shown in Figure 3.6.

After this, each student was interviewed for about fifteen to twenty minutes for analyzing the reasons that they have documented and relevant points were jotted down. The analysis of the inputs received from these students helped to identify the main reasons of at-risk behaviour and also addressed many issues of the blended learning environments that can be summarized as numerous emergent themes. However, since the questions were open ended, the final reasons identified were found to be overlapping as one student can give multiple reasons unboundedly.

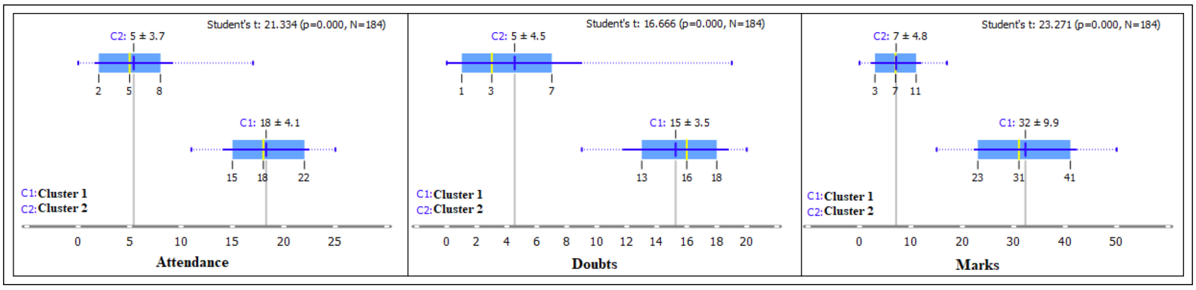


Figure 3.5: Box plots across different input parameters for two identified clusters

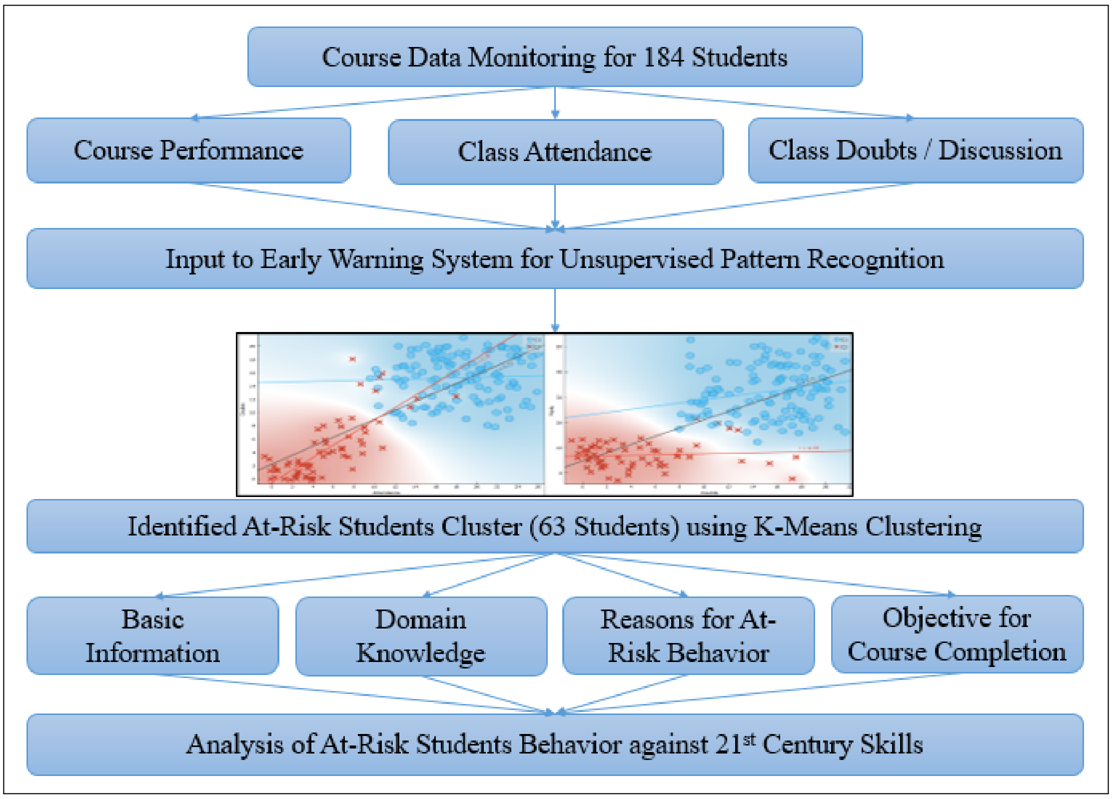


Figure 3.6: Data collection flowchart

3.3.5 Data Analysis

Out of the 184 class students, the overall count of at-risk, low performer students as identified by at-risk student's cluster, was 63. Four students were not considered for the study as they had already dropped out from the course till the time of the interview, so actual count considered was 59. Out of these 59 students, on the basis of gender, 8 students considered were female and 51 were male. The percentage for the gender based diversification is shown in Figure 3.7(a). There were no diversifications found amongst the students on the basis of age as all students belonged to same age group of 17-20 years. The students were taught by the same instructor hence no variations prevailed in, with respect to the teaching or other pedagogical approaches adopted. The diversification with respect to their present overall grades is shown in Figure 3.7(b). Most students belonged to average or above average category, based on their grades.

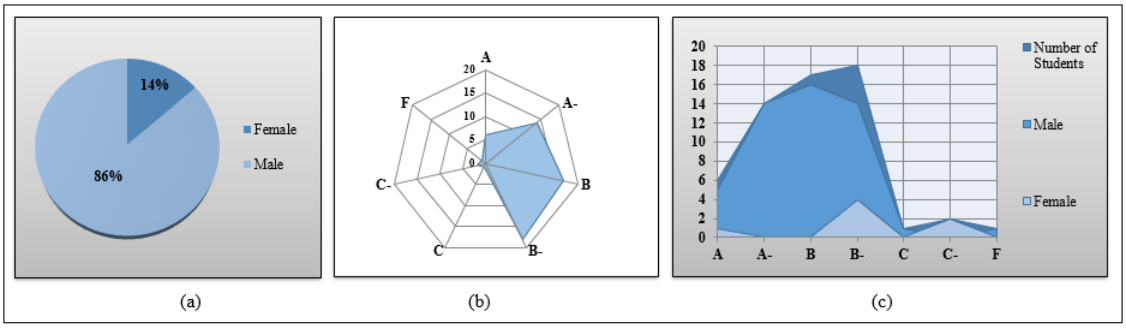


Figure 3.7: (a) Male and female student composition (b) Frequency composition for overall current grades (c) Distinguished frequency with respect to the gender for knowledge representation in pre-requisite course

Further analysis was done, in order to identify whether the students had enough required pre-requisite core course knowledge (Data Structures), on the basis of their marks obtained in the pre-requisite course. The details of their pre-requisite course grades with respect to the gender along with their numbers is shown in Figure 3.7(c). Majority students were found to have good or average knowledge in the pre-requisite subject. The students considered were further analyzed on the basis of their comfortableness and understanding of the engineering branch by collecting the data regarding 'F' grade (failure) in any of the previous overall engineering based courses and CSE (domain) based courses studied till date. The information regarding the number of failures of the students across the courses considered for this study are shown in Figure 3.8(a). Extremely few students were found to have failure history. Figure 3.8(b) shows the overall CGPA obtained by the students obtained till the conduct of this study. Except five students, all were having a CGPA of above 6.

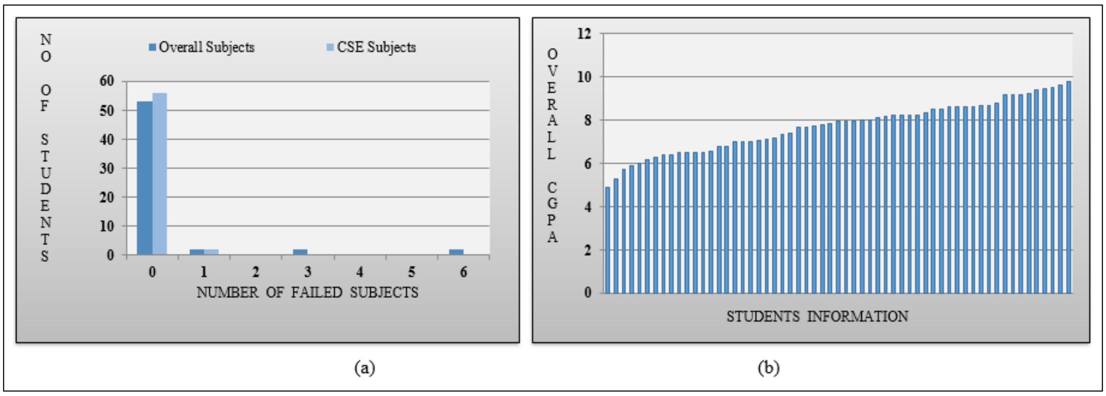


Figure 3.8: (a) Previous academic status of students representing the number of overall vs. CSE courses or subjects failure (b) Overall cumulative grade point averages (CGPA) of the students

3.3.6 Results

This section discusses the analysis results from different perspectives.

3.3.6.1 Blended Learning Perceptions and Behaviour: Based on the analysis of the actual behaviour of the at-risk, low performer students and in-line with the 21^{st} century skill-set, the learning behaviour is broadly categorized in five major categories: Research Based Behaviour, Job Oriented Behaviour, Independent Behaviour, Passionless Behaviour and Others. The relation of these along with the 21^{st} century skill-set is shown in Figure 3.9. The complete composition of different behaviour along with students' frequency is shown in Figure 3.10.

- *Research Based Behaviour:* With the goal of life-long learning, these students are focused to have a research based career and studying any other course except core is not on their priority list. The students are more dedicatedly involved in research work and writing research papers or working on research based projects and believe to learn concepts on the go. They follow the approach of learning tools, technology or concepts, as and when the need arises. Their CGPA was relatively high and they believed that they can just pass any course with one-night study based approach.

- *Job Oriented Behaviour:* Having high life and career goals, these students try to equip themselves with those skill-set which they think, make them market ready.

They follow a pattern of first searching for the current market skill-set trends, gain reviews from the peers regarding what can be the best qualities that can enhance their e-portfolios or resumes. Then they do a self-analysis of what are the regions or parameters in which they are lacking behind and start updating themselves willingly and accordingly. No outer intervention is actually required by these candidates as they are self-motivated. They work on the theory of passing the courses (other than core-domain based courses) with average or passing-by marks but in parallel try to maintain the minimum qualifying CGPA required for the high profile jobs.

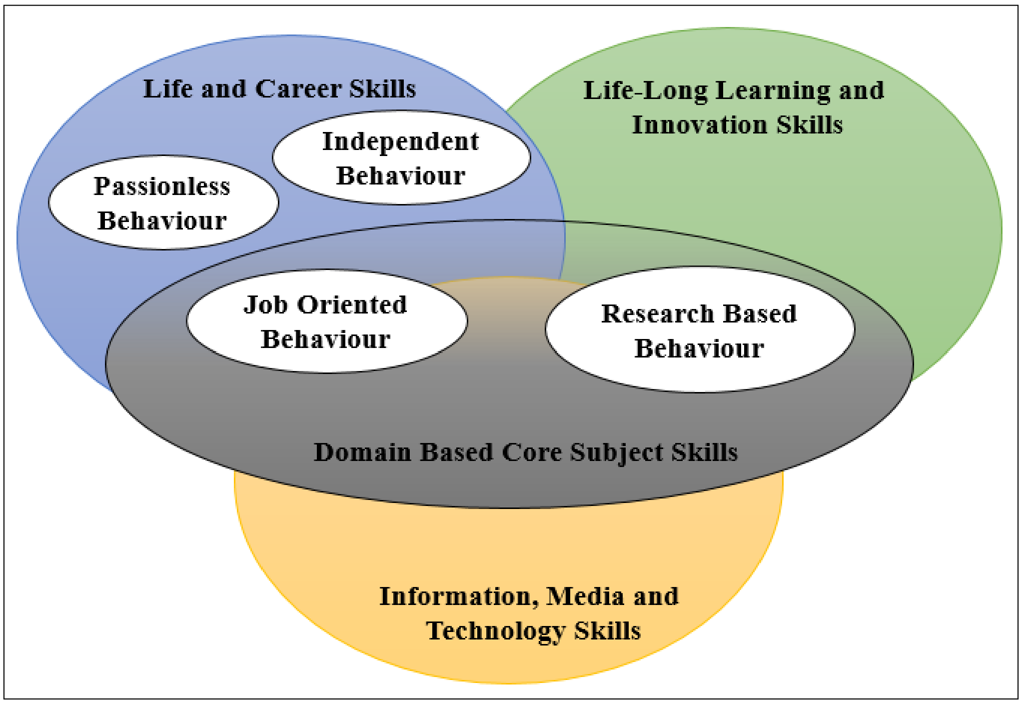


Figure 3.9: Relation between 21^{st} century skill-set and student behaviour

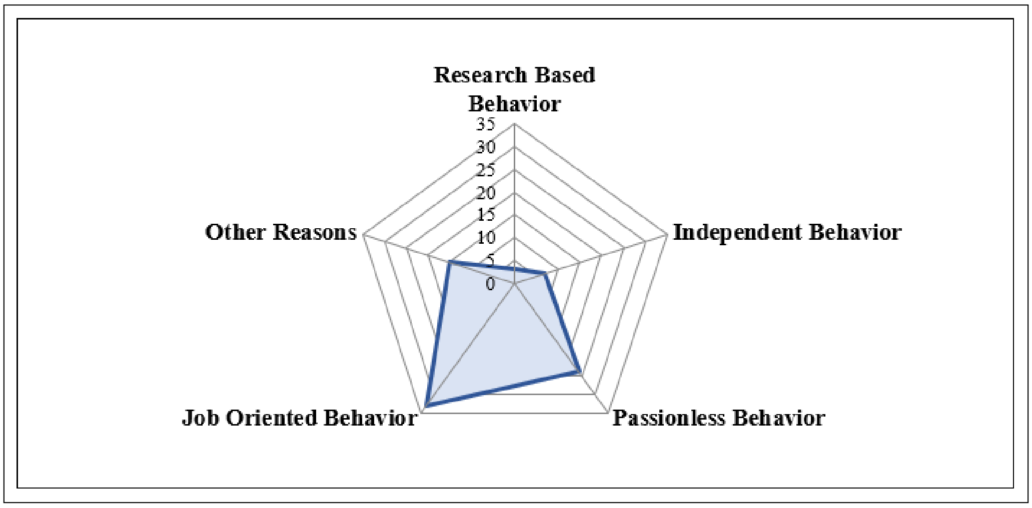


Figure 3.10: Five broadly identified learning behaviour

- *Independent Behaviour:* These students are having an independent nature and are tilted towards life goals. They are least concerned for the course activities, as they have alternative ways for their adjustment in the natural world. These students are either free-lancers or social activists involved in different types of socially beneficial activities. Their main objective of completing the courses is to just pass the examinations, as either they are determined to open their own start-ups at the end of their engineering degree or are planning to set up their own Non-Government Organizations (NGOs) for serving the society. They also comprise of students who believe in self-study and are confident enough that they don't need an instructor for clearing the examinations.

- *Passionless Behaviour:* These students are having a passionless nature and complained of timetable issues or accepted that they lack the skills of time-management. These students are not clear why they are actually studying the course and are often directionless. They follow their peers but on the competitive runways, they mostly lag behind as they don't have the required skill-set as well as motivation to pursue their peer's dreams. They are mostly characterized by having an average CGPA and their dangling learning behaviour.

- *Others:* This category involves students having genuine health or family based issues. They are not able to perform timely in the course either because of their own prolonged illness or infections or due to the deteriorating health or death of their near and dear ones. This in turn affects their academic studies. But these students are well aware of their strengths and weaknesses throughout the course and are clear with their targets.

3.3.6.2 Underlying Reasons: This section explores in detail each of the identified category in earlier section for the low performer and at-risk of failure students. Figure 3.11 summarizes all the in-detail reasons and low performer student engagements.

- Research Based Behaviour

  o *Research Work:* One reason for not actively participating in the current ongoing course was that the students were busy with the research work.

When further investigated, the objective of such students was to invest their time in doing some relevant research such that they may publish research papers and get further recognized internationally. According to them, this in turn will help them to enroll in top CSE universities across the world for their master's degree. The students acknowledged that they are already satisfying the minimum CGPA criterion and don't want to focus more on their CGPA now.

o *Preparation for Other Examinations:* Some of the students were found to engulf themselves in the preparation for National or International Level Examinations. However, this zone of students was identified to have diverse reasons. Either they were not satisfied by their current academic domain choice and wanted to switch over or were aspiring for underlying higher education opportunities. So, the students who wanted to drop off from the course were least concerned by their low grades and the students aspiring for higher education were having enough grades that can easily land them in a top university once they clear the qualifying examinations.

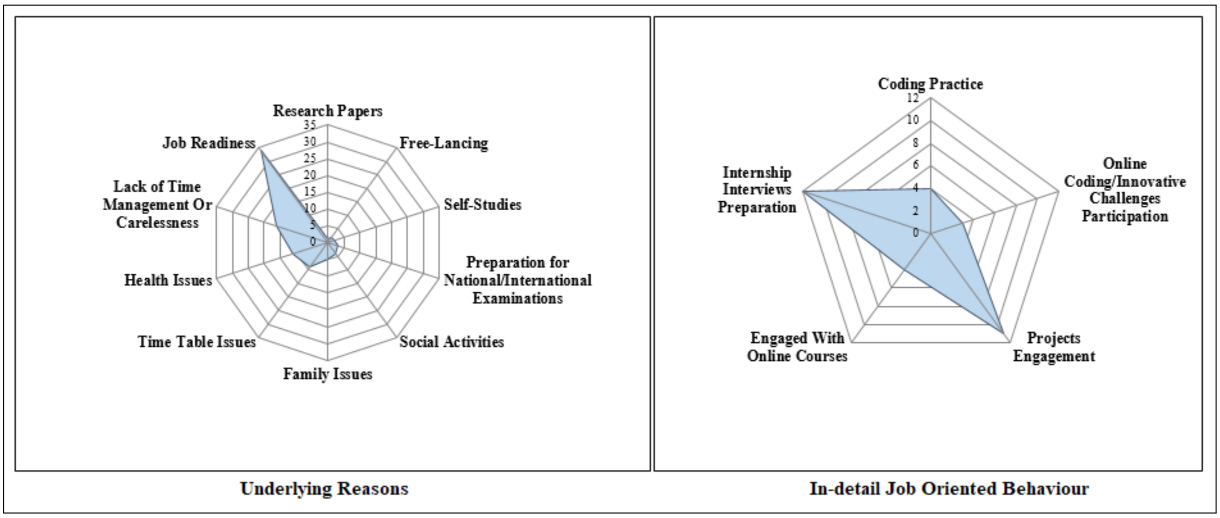


Figure 3.11: All reasons and engagements along with student frequency count for at-risk behaviour

- Independent Behaviour

o *Free-Lancing:* These students were engaged in free-lancing activities. The students in this zone were independent enough and interested in practical implementations. They were having their own independent existence on the web in the form of blogs, websites *etc.* They were investing their time in different real-time projects and believed to learn from there more practically as compared to their classes and classroom based activities. The students acknowledged that CGPA is not the criterion any more for them, and are satisfied with their work and want to just pass the course.

- *Self-Studies:* These students were more interested in self-study instead of attending and actively participating in the classes. The students for this zone quoted that "They came to the classes initially, but their mind is quite slow in grasping the concepts as compared to other students. So they prefer to study independently". So, they preferred to study at their own pace and time. However, they accepted that by studying on their own they were not able to match the pace of their other classmates and that resulted in their low performance.

- *Social Activities:* The students for this zone were involved in various social activities occurring within the university campus or even outside the university at district level. The students were actively involved in various events that have direct positive effect on the society. The activities ranged from setting up blood donation camps, yoga camps for healthy living, "education for all movement" that helped every little child of the district, belonging to the below poverty line community, to start its learning journey *etc.* The students were satisfied with their work and accepted that they just wanted to pass their examination for getting a bachelors engineering degree.

- Job Oriented Behaviour

  - *Job Readiness:* Most of these students were having a market based job oriented nature and were trying to earn themselves pre-placement offers. These students adopted pro-active approaches for getting themselves exposed to real-world environment based internships as well as pre-placement offers. They believed that this will increase their future job security. As otherwise according to them, the competition increases at the end of their engineering degree completion and they don't want to take risk and deal with unemployment at later stages. The students were further engaged in various activities which they thought were suitable to make them worthy enough of the job they were aspiring for.

- *Coding Practice:* These students devoted most of their study time in hands-on coding practice which they assumed is the heart of most of the job interviews.
- *Online Coding/Innovative Challenges Participation:* The students of this zone were self-confident in their coding part and were testing their skills by getting enrolled for different online coding competitions or innovative challenges. The students were crazy about their ranking displayed on the leader-boards as that acted as a motivation for them to work and progress further.
- *Projects Engagement:* Some students engaged themselves in real-world research projects that were ongoing under different professors within the university. When asked for reasons, one of the students reported that "In some internship interviews, I was rejected as I was not having a hands-on experience in the form of a project. That is why I am now working on real-world projects so that I can enhance my job profile and be market ready."
- *Online Courses Engagement:* The students of this category were weak in their core courses. After getting rejected from the internship interviews, the students focused more on increasing their core understanding of their basic concepts by getting enrolled in various international online courses. They preferred these online classes over the present ongoing semester classes. These students were having mediocre grades on their side, and aspired for getting a mediocre grade in present courses too, as their main objective was to strengthen their conceptual knowledge of core CSE based courses.
- *Internship Interviews Preparation:* The students of this category were devoted towards the preparation of internship interviews. These students were occupied with different types of activities, apart from the ones mentioned above. For example, one student stated that "Despite of having all the required skill-set I was rejected because I was not fluent in speaking English. So, I am now devoting most of my time in increasing my fluency in

English language". The other activities involved increasing the communication skills with the help of group discussion *etc.*

- Passionless Behaviour

  - *Time-Table Issues:* These students were disturbed with their timetable. They were not comfortable with the class timings. They felt either it was too early or the course study timings were too odd. One student reported that "One of my ADS class timings are from 8:00 a.m. to 9:00 a.m. in the morning whereas rest of the classes start from 11:00 a.m. after this. So, it is more comfortable for me to come directly at 11:00 a.m. and attending rest of the classes instead of wasting 2 hours in between". Whereas the other student reportedly said that "My class timings are odd. It mostly occurs late when I have studied all other courses and my mind is completely exhausted. ADS is a course that requires a fresh mind for easy understanding of concepts. So, it will be better if you can shift the ADS classes early in the morning for easy understanding of the concepts".

  - *Lack of Time Management:* The students lying in this zone confessed for lacking time management capabilities. They confessed that they studied late night and were unable to get up early in the morning for the classes which directly resulted in weaker concepts and low performance. These students demanded for appropriate interventions and assistance for managing their time.

- Others

  - *Health Issues:* The students of this zone wanted to actively participate in the classes and its activities but were unable to do so either due to their prolonged illness, surgical operations, low immunity power or other physical body health based restrictions. The students were not satisfied by their studies and longed to study more for covering up the loss.

  - *Family Issues:* Two students were identified who have either their mother or father suffering from severe illness. This resulted in their withdrawing nature from the studies as they were deeply affected by this. They were mentally prepared for the outcomes of their low performances and promised to get back on track once everything was back to normal from their family side.

3.3.6.3 Gender Based Differentiation: As only 14% female students were identified to be at-risk, this learning behaviour pertains that the female students are comparatively sincerer and conscious of their overall class ranking. Out of the 8 female students considered, two female students were having job readiness nature. They were having a CGPA of more than 9 and hence accepted to "risk" their CGPA for making themselves job ready. The other category of female students gave reasons like carelessness or health issues or both for not paying attention to the classes. They were concerned by their low performance in the course and promised to recover the loss soon.

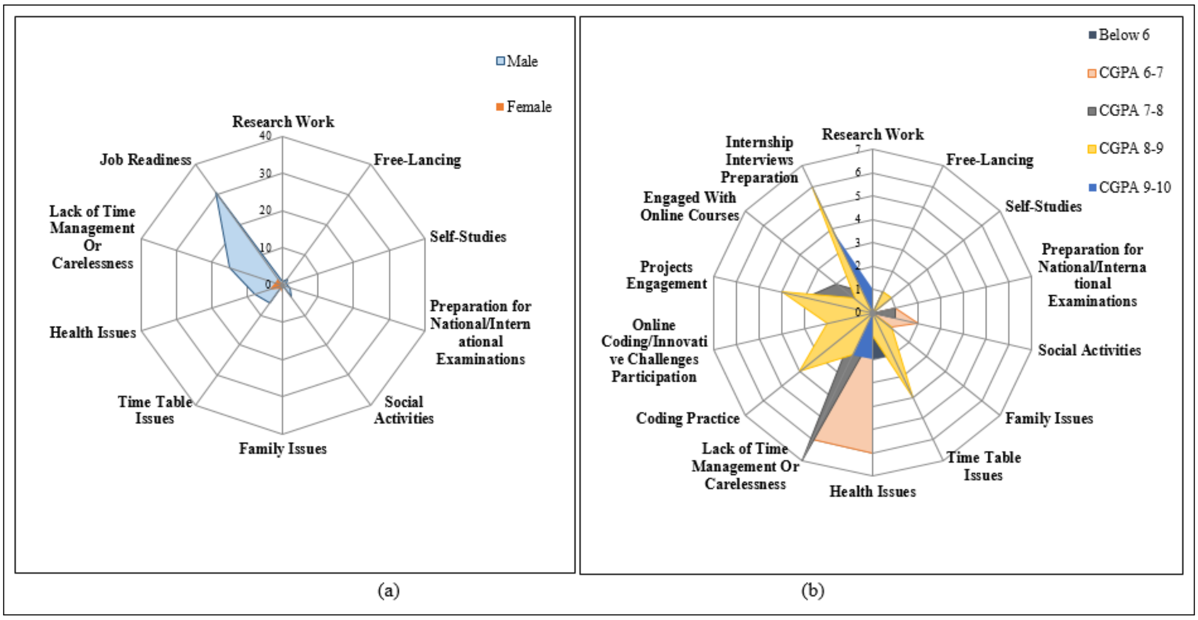


Figure 3.12: Comparative analysis of (a) gender and (b) CGPA based categorizations

As opposed to these, the male candidates were maximally oriented towards the job readiness nature. The second major disruption identified in case of male students was their careless nature. They were either disturbed because of the odd-timings of the classes or lack of their own time management because of late night studies. The third major reason in the row was the health or family based issues, because of which they were not able to pay much attention to the classroom activities.

Table 3.1: CGPA and gender based differentiation across the at-risk behaviour reasons

	CGPA Based						**Gender Based**		
	Below 6	CGPA 6-7	CGPA 7-8	CGPA 8-9	CGPA 9-10	MEAN (STD EV)	M	F	MEAN (STDEV)
Research Work	0	0	0	0	1	0.2 (0.45)	1	0	0.5 (0.71)
Free-Lancing	0	0	1	1	0	0.4 (0.55)	2	0	1 (1.41)
Self-Studies	0	0	0	1	0	0.2 (0.45)	1	0	0.5 (0.71)
Preparation for Examinations	0	1	1	0	0	0.4 (0.55)	2	0	1 (1.41)
Social Activities	0	2	1	0	1	0.8 (0.84)	4	0	2 (2.83)
Family Issues	1	1	0	1	0	0.6 (0.55)	0	3	1.5 (2.12)
Time Table Issues	2	0	1	4	0	1.4 (1.67)	6	1	3.5 (3.54)
Health Issues	2	6	1	1	2	2.4 (2.07)	8	4	6 (2.83)
Passionless Behaviour	0	6	7	2	2	3.4 (2.97)	15	2	8.5 (9.19)
Coding Practice	0	0	1	4	0	1 (1.73)	5	1	3 (2.83)
Online Challenges Participation	0	0	1	2	0	0.6 (0.89)	3	1	2 (1.41)
Projects Engagement	0	0	3	4	3	2 (1.87)	10	0	5 (7.07)
Engaged With Online Courses	0	1	2	1	0	0.8 (0.84)	4	0	2 (2.83)
Internship Interviews Preparation	0	0	1	6	4	2.2 (2.68)	9	0	4.5 (6.36)

After the analysis of the students on the basis of gender, the female students were found to have marks based criterion as priority as opposed to male students who were having the priority of obtaining the required skill-set for making them job ready and were running after future job security. The comparative analysis of gender based differentiation based on the reasons is shown in Figure 3.12(a) and Table 3.1.

3.3.6.4 CGPA Based Differentiation: The students were also categorized on the basis of their CGPA for identifying the exact learning behaviour. The students having a CGPA of more than 9 were least concerned about their class performance and grades. Their involvement in projects, interviews, coding competitions, research work, social activities *etc.* were found to be the main reason for their low attention. However, they were most reluctant to change their present routine or learning behaviour as they were ready to “risk” their grades for doing the things they want to do.

The students having CGPA between 7 to 9 were more complaining for their passionless behaviour. These groups complained of their lack of time management issues. Their main objective was to make themselves job ready, but they acknowledged that were lacking in one or the other skills required for their dream or desired jobs and hence devoted most of their time to fill in the existing gaps and convert them into their strengths. This complete process consumed most of their time and they worked for extended late hours. As a result, they were not able to attend their classes. They accepted that later on, when they tried to self-study those concepts, this consumed much of their time and hence, they modified their approach to the theory of selectivity. They started studying only selected topics within the allotted time they have kept for respective course. They believed that this approach will help them to pass the courses.

Students having CGPA below 7 were having major issues in the form of lack of time management, health issues or family based issues. These students were well aware of their present academic state and demanded for assistance in terms of how to better manage their time so that they may cover up the syllabus in the remaining time and end up with average marks in the considered course.

So, the students on the basis of their CGPA were differentiated into 3 different groups. First group of students were high profilers, then medium profilers and lastly, low profilers. Only low profile students were found to be struggling with the concepts. However, this was not because they were not able to understand the concepts, instead they were having other priorities that consumed most of their time. So they were interested in learning time management so that they may land up with average marks in the course considered for this study. The comparative analysis of CGPA based differentiation based on the reasons is shown in Figure 3.12(b) and Table 3.1.

3.3.6.5 Objectives behind Completing the Course: The objective of the students for studying the present course was identified to be majorly lying in 3 different categories: passing the course with a good score, obtaining average marks in the class and just pass the course. Majority of students were having the objective of obtaining average marks in the course. The secondly ranked objective was to just pass the course irrespective of the grade. Only five students opted for having their objective as passing the examination with a good score.

The five students who opted for passing the exam with good score were all male students and were having their CGPA between 6 to 10. For male as well as female students, obtaining average marks within the course was the most prevalent objective. The second major objective across the male fraternity was to just pass the course.

The group having CGPA between 9 to 10, was very clear with the objective of just passing the course examinations whereas groups having CGPA between 7 to 9 were highly targeting to get an average marks in the concerned course. Figure 3.13 shows the overall composition of the objectives along with their frequency across the students, their gender and CGPA based differentiations.

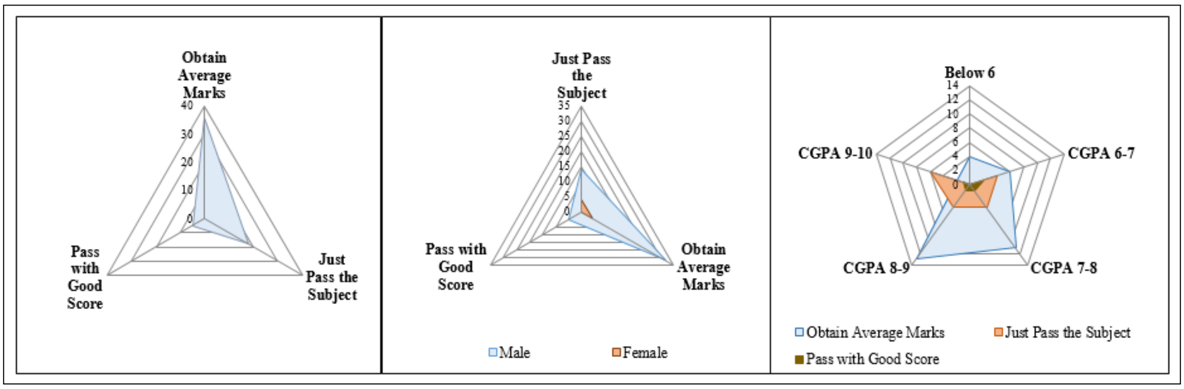


Figure 3.13: Overall and comparative analysis of student objectives behind completing the course

3.3.7 Discussion

According to the analysis conducted in this research study, the majority of the identified at-risk or low performer students of blended learning environments are those students, who are very well aware of their current status of the class. They are found to be ready to risk their academic performance for nominal or average marks, in order to achieve their long term 21^{st} century skills. The long term goals or lifelong skills are found to be important in framing their future. They have there own targets and are on the pathways of fulfilling them, even at cost of nominal or average marks. As discussed earlier, these evolved skills of life-long learning, information and technological updations and life and career skills are being easily adopted by these undergraduates in order to keep them "on-track" while building of an efficient knowledge based society. This study goes with the Bahadir's research study (2020), and suggests that success is a relative concept [292].

It depends on the student's knowledge, intelligence, background and societal influences, that what parameters one considers for measuring his success, in order to make himself "future ready".

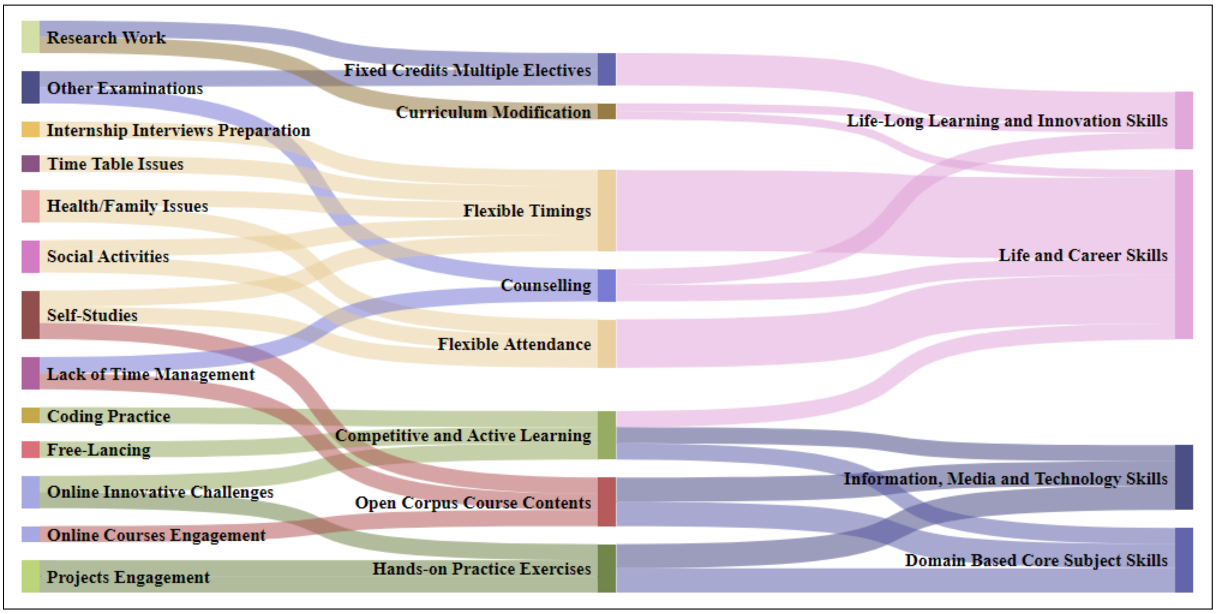


Figure 3.14: Relationship between at-risk behaviour reasons, design reflections and 21^{st} century skill-set respectively

After analysis of the reasons, various solutions were also discussed with the students which they wanted to be in-place within the system, for effective functioning of the blended learning environments. As the major objective of the students was just to pass the course or obtain average marks, they suggested various design reflections that may help them in developing the required skill-set along with their routine studies. For example, students who mainly focussed on doing the research work, suggested fixed credits multiple electives approach along with curriculum modification. As they followed a life-long learning approach, they wanted to be focussed from the starting of the under-graduation and demanded to have the freedom to choose their own career pathway or area of interest. This will help them to study only those courses that are relevant to them in their respective fields. Also, the practical research aspect must be inculcated within the curriculum, in order to give them a deeper insight into the respective field.

The various other design reflections suggested by the students are flexible class timings, flexible attendance within the class, timely guidance and counselling, hands-on practice exercises, competitive and active learning for better understanding of the course concepts as well as healthier learning environment and open corpus course contents for standardized and generalized concepts. Last section of this chapter discusses these design reflections in detail. The in-depth linking of the reasons given by the students for at-risk behaviour, suggested design reflections and their association in further development of 21^{st} century skill-set are shown in Figure 3.14.

3.4 Gender and Status based Behavioural Analysis

This research case study relates to the feedback based behaviour of different gender and socio-economic status students in normal classroom environments.

3.4.1 Overview

Under-representation of women and low socio-economic classes, as students and as teachers, has been a common phenomenon in most countries. For instance, in Indian educational environments, women constituted 46.7% of all undergraduate students in the academic year 2015–2016, but less than 30% were taking programs in engineering and technology [218]. Similarly, only 40% of teachers in stand-alone technical institutions were female, and only an average of 11.6% of teachers came from low socio-economic classes [218]. This varies across engineering programs. For example, in one of the top 20 Indian universities considered in this study, female teachers constituted just 5% of the mechanical engineering faculty as compared to 43% of the computer science and engineering faculty. Gender differences have also been found in teachers' career progression, with men advantaged over women in engineering [248]. The situation of low socio-economic status students is an area of major concern in education, with various policies and measures being undertaken internationally to raise their standing, equity and success [154].

Despite the vast literature available on the role of gender in higher education, very few studies evaluate the role of gender in student evaluations of teaching within different professional engineering disciplines. Similarly, few studies examine the socio-economic diversification effects in these student ratings in higher education.

The goal of this study is to provide a deeper insight into these aspects by exploring student ratings of teachers across various disciplines at a large Indian university. An analysis is made of complete ratings datasets, by gender and socio-economic level, for both students and teachers, to understand the differences in these ratings found in higher education.

In India, according to a 2011 census report [131], there are 940 females per 1000 males, but a skewed distribution of women is still seen in the field of education [218]. Similarly, many people live below the poverty line (BPL), have no access to educational facilities, and are distinguished as having low economic status in society. Society is also divided by social status. For over five millennia, Indian society has been an agglomeration of several castes that have striking differences in skill-set, occupations, dress, religious observation, and so on, with an individual's way of earning a living being determined by heredity [4]. Scheduled Castes (SC), Scheduled Tribes (ST), Other Backward Classes (OBC) and the like are considered of lower social status than other castes. The term 'low socio-economic status' (LSES) includes both of these classes, thus having low economic status and low social status. Other classes are grouped in a general (GEN) category.

To raise the standard of living and promote equity across the population, the authorities have taken various measures to improve the lot of women and low socio-economic class students in education via its various "reservation policies". These policies provide an opportunity to promote women and low socio-economic status class students by reserving a specific number of seats for them in the field of education. The effects of these policies are investigated here through ratings given by students, of both genders and of various socio-economic groups, to teachers, also of different gender and socio-economic groups, in engineering and non-engineering disciplines at a large Indian university.

Student Response Survey (SRS): At the end of each six-month semester, students evaluate their faculty on an online Student Response Survey (SRS). The SRS consists of 16 statements on instructors' teaching and practical traits; sample SRS statements are shown in Table 3.2. Students rate the instructor on a scale of 1 to 5 (1 being 'strongly disagree' and 5 being 'strongly agree'). These SRS parameters can be easily mapped to the well-known 23-item CEQ (Course Experience Questionnaire) parameters devised by Ramsden [16], although the SRS has 16 items, and includes a parameter of Practical Skills instead of Appropriate Workload [16].

Table 3.2 Sample survey statements for student response survey

Code	Aspect	Sample Statement
CC	Content Coverage	Covered the topics in a logical sequence.
AS	Assessment Skills	Was fair in evaluation of exams.
MS	Motivational and Supportive	Displayed motivation and ability to create interest in the subject.
PS	Practical Skills	Experiments/programming exercises/ workshop tasks assisted in improving problem-solving skills.
GS	Generic Skills	Was approachable outside lecture hours.

3.4.2 Contributions

This study contributes to the literature in following ways.

- Confirming the existence of biases in gender and socio-economic diversified higher educational environments, of differential evaluation ratings given by students to their teachers.
- Extending the research further by analyzing the after-effects of such policies and frameworks and exploring student ratings for the existence of any status bias for these low socio-economic status teachers in higher education.

3.4.3 Research Objectives

This research study is conducted for checking the existence of gender and socio-economic biases through students feedback, for blended learning environments of higher education. It examines data from five disciplines, three engineering and two non-engineering, selected according to their 'appropriateness' based on gender, as per the public perception [130]. Amongst the three engineering disciplines, computer science and engineering (COE), represented a field considered to be most 'appropriate for women' and civil engineering (CIE) a field most 'appropriate for men'. Electrical engineering (ELE) was less extreme, leaning towards more 'appropriate for men'. In non-engineering disciplines, mathematics (SOM) was chosen as an under-represented area for women, and humanities and social sciences (HSS) as an underrepresented area for men [50]. The study aimed to investigate differences persisting in the educational environment due to differences in gender and socio-economic status between teachers and students across five engineering and non-engineering disciplines. The study addresses the following research questions.

RQ1: Does the gender and socio-economic diversity of the teaching-learning context affect students' ratings across the disciplines on the SRS?

RQ2: Do male and female teachers receive different ratings from their students?

RQ3: Do male and female students give different ratings to their teachers?

RQ4: Do students give different ratings to teachers of the same gender as themselves as compared to the other gender?

RQ5: Does a teacher's socio-economic status affect their ratings from their students?

RQ6: Does a student's socio-economic status affect how they rate their teachers?

RQ7: Do students rate teachers of the same socio-economic class as themselves differently to teachers of other classes?

3.4.4 Methodology

The academic year is divided into two six-month semesters. The course units making up each program were all taught for a single semester, with the online SRS being administered at the end of each course unit. The various required parameters, such as gender or category, were linked to the student and teacher profiles at the backend and extracted from there. The response rate for the online SRS was 100%, being mandatory before taking final exams. Student ratings of instructor and teaching quality on courses across the five disciplines (COE, ELE, CIE, SOM, and HSS) were obtained from the online SRS system.

3.4.5 Data Analysis

A multivariate analysis of variance was carried out on the students' ratings on the five scales of the SRS. Although each student may have contributed responses on several course units over consecutive years, the datasets were anonymized, so each set of scores was treated as an independent observation. The independent variables for analysis were the student's study discipline, the teacher's gender, the student's gender, the student's category, the teacher's category, the student's course unit, and the semester in which the unit was taught. The course units were further nested within the disciplines. All possible interactions were computed between the student's discipline, the teacher's gender, the student's gender and between the student's discipline, the teacher's category and the student's category. Some departments had no low socio-economic teachers. This resulted in two separate datasets: one with five disciplines for gender, and another with two disciplines (ELE and SOM) for socio-economic status, since only those two departments had the necessary category ratings for both students as well as teachers.

Multivariate and univariate general linear models of Statistical Package for the Social Sciences (SPSS) were used to derive the relevant results and graphs [1]. Wilk's Λ, a direct measure of the proportion of variance in combination of dependent variables that is unaccounted for by the independent variable, was used to evaluate the multivariate statistics along with its associated F-test. These were followed by univariate tests on each of the five SRS scales. Statistically significant interactions were analyzed further by tests on simple main effects. For effect size, partial eta squared (η^2) was used. Partial η^2 is the proportion of the total variance from which variations due to other factors and interactions are excluded. Partial η^2 values of 0.0099, 0.0588, and 0.1379 reflect "small," "medium," and "large" effects, respectively, as proposed by Cohen [2].

3.4.6 Results

This section discusses about the results analysis based on gender and category.

3.4.6.1 Based on Gender: The gender data covered, overall, 448 course units (231 unique course units) presented to the students over five semesters across five disciplines between 2014-15 and 2016-2017. The overall average of male and female students across the five disciplines was 78.1% and 21.9% respectively.

The overall average of male and female teachers across the disciplines is 57% and 43% respectively. The detailed gender distribution is shown in Figures 3.15 and 3.16. There were 112,919 complete responses to the SRS, of which 31,886, 34,047, 19,491, 12,621 and 14,874 were from students taking CIE, COE, ELE, HSS and SOM course units respectively. Of these, 24,734 responses were from female students and 88,185 from male students. 48,302 responses were from students taught by female teachers and 64,617 sets from students taught by male teachers.

A. Discipline by Teacher's Gender

There was a small but highly significant multivariate effect of the discipline, Wilks' $\Lambda =$

.906, $F(4, 112899) = 568.04$, level of significance: $p < 0.001$, partial $\eta^2 = 0.024$. Here, p is rounded to three decimal places. There was also a small but highly significant multivariate effect of the teacher's gender, Wilks' $\Lambda = .999, F(5, 112899) = 12.443, p < 0.001$, partial $\eta^2 = 0.001$. Further univariate analysis showed significant difference on Practical Skills scale, $F(1, 112899) = 40.611, p < 0.001$ and partial $\eta^2 = 0.000$. None other univariate tests were found significant. Table 3.3 gives the SRS mean ratings with standard errors by discipline and teacher's gender.

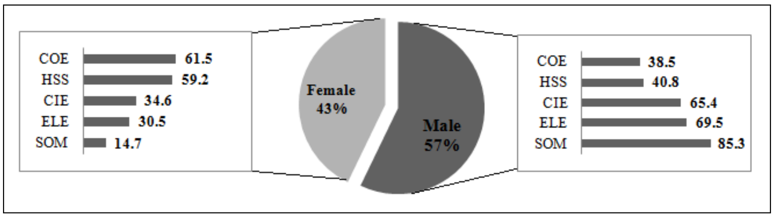


Figure 3.15: Teacher's gender distribution across disciplines for 448 course units

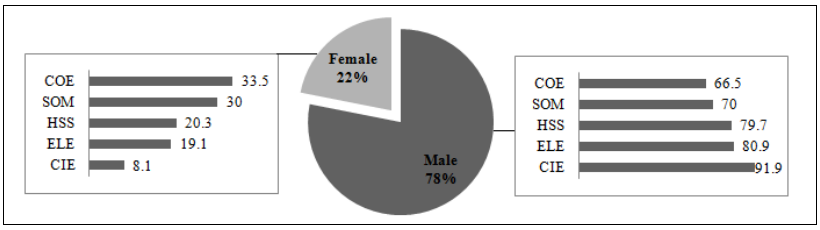


Figure 3.16: Student's gender distribution across disciplines for 448 course units

Post hoc tests on simple main effects showed that female teachers were rated higher on the Practical Skills scale as compared to male teachers with mean difference of $0.082, p < 0.001$. However, these effects were qualified by a small but highly significant multivariate interaction between the effects of the discipline and teacher's gender, Wilks' $\Lambda = .998, F(4, 112899) = 13.522, p < 0.001$, partial $\eta^2 = 0.001$. There were significant univariate interactions on all five aspects of the SRS, namely Content Coverage, Assessment Skills, Motivational and Supportive, Practical Skills and Generic Skills with its $F(4, 112899) > 17.756, p < 0.001$, partial $\eta^2 = 0.001$.

Further post hoc tests showed that on Content Coverage and Assessment Skills scale, female teachers were rated higher than male teachers by COE and SOM students with $F(1, 112899) > 21.197, p < 0.001, partial \eta^2 = 0.000$ whereas the male teachers were rated higher by HSS students, $F(1, 112899) > 21.658, p < 0.001, partial \eta^2 = 0.000$. On the Motivational and Supportive scale, female teachers were rated higher than male by CIE and SOM students, $F(1, 112899) > 18.258, p > 0.001$ and partial $\eta^2 = 0.000$ whereas male teachers received higher ratings by ELE and HSS students with $F(1, 112899) > 12.624, p < 0.001$ and partial $\eta^2 = 0.000$. COE and SOM students gave higher ratings to the female teachers on the Practical Skills scale with $F(1, 112899) > 42.426, p < 0.001$ and partial $\eta^2 < 0.001$ whereas in ELE, male teachers received higher rating than female teachers with $F(1, 112899) = 11.118, p = 0.001$ and partial $\eta^2 = 0.000$. On the Generic Skills scale female teachers received higher ratings than male teachers in CIE, COE and SOM with $F(1, 112899) > 20.717, p < 0.001$ and partial $\eta^2 = 0.000$. However, again in HSS male teachers were rated higher than female teachers with $F(1, 112899) = 39.889, p < 0.001$ and partial $\eta^2 = 0.000$.

Table 3.3 SRS mean ratings with standard error by discipline and teacher's gender

	FEMALE TEACHER		**MALE TEACHER**		
Scale	**M**	**SE**	**M**	**SE**	**p**
Civil Engineering					
CC	2.888	0.015	2.949	0.011	0.06
AS	2.938	0.013	2.980	0.010	0.04
MS	4.114	0.015	3.996	0.011	0.12
PS	2.599	0.013	2.643	0.010	0.04
GS	4.036	0.013	3.915	0.009	0.12
Computer Science and Engineering					
CC	3.991	0.011	3.907	0.014	0.08
AS	4.095	0.010	4.007	0.012	0.09
MS	3.888	0.011	3.851	0.014	0.04
PS	3.885	0.010	3.768	0.012	0.12
GS	4.092	0.009	4.017	0.012	0.08
Electrical Engineering					
CC	3.528	0.019	3.594	0.014	0.07
AS	3.796	0.017	3.921	0.012	0.13
MS	3.551	0.019	3.698	0.014	0.15
PS	3.577	0.017	3.687	0.012	0.11
GS	3.856	0.017	3.961	0.012	0.11

Main Findings: To address Research Question 1, the pattern of ratings given by the five discipline students varied largely on different SRS scales. In COE and SOM, female teachers were rated more highly than their male counterparts on Content Coverage, Assessment Skills, Practical Skills and Generic Skills scales of the SRS. Similarly, in CIE female teachers were rated higher than the male teachers on Motivational and

Supportive and Generic Skills scales. Whereas in HSS, male teachers received higher rating then their female counterparts on Content Coverage, Assessment Skills, Motivational and Supportive and Generic Skills scale of SRS. COE, SOM and CIE disciplines represent fields of underrepresentation of women as compared to HSS, where there is underrepresentation of men [50]. This study via this differentiation in ratings across the disciplines, reveal gender atypical behaviour confirmation of the students *i.e.*, the students tend to give higher rating to the teachers in discipline that are less typical to their gender, as compared to the disciplines, that are more typical to their gender [3, 17, 19, 29].

However, a gender-typical behaviour is also seen in ELE discipline across two SRS scales *i.e.*, Motivational and Supportive and Practical Skills in which male teachers were rated higher than female teachers. Motivational and Supportive is the SRS parameter termed more 'female specific', compared to Practical Skills that is termed to be more 'male specific'. However, differential rating along with the preference of male teachers over female in both these parameters may account for other factors not considered in this study—like the teaching methodology adopted, or the teacher's skill-set, attitude towards students and personality—traits which are generally termed 'teacher specific' and not 'gender specific'.

To answer Research Question 2, different gendered teachers receive different ratings on the Practical Skills scale of SRS, with female teachers being rated higher than their male counterparts. Practical Skills is an aspect of SRS that deals with the application of theoretical knowledge to the practical world and is found to be more 'male specific'. Higher rating of female teachers in this aspect nullifies earlier notions regarding perception of female teachers in more theoretical works [17, 19] and support 'gender atypical' nature.

B. Discipline by Student's Gender

There was a small but highly significant multivariate effect of the student's gender, Wilks' $\Lambda = .998, F(4, 112899) = 34.445, p < 0.001$, partial $\eta^2 = 0.002$. Further univariate analysis showed significant difference on all SRS scales, $F(1, 112899) > 29.857, p < 0.001$ and partial $\eta^2 < 0.001$. However, these effects were qualified by a small but highly significant multivariate interaction between the effects of discipline and student's gender, Wilks'$\Lambda = .999, F(4, 112899) = 5.595, p < 0.001$, partial $\eta^2 = 0.000$. Table 3.4

shows the SRS mean ratings with standard error by discipline and the student's gender. There were significant univariate interactions on four scales of SRS, Assessment Skills, Motivational and Supportive, Practical Skills, Generic Skills with $F(4, 112899) > 6.266, p < 0.001$ and partial $\eta^2 < 0.001$. Further Post Hoc tests showed that in all four scales, female students gave higher rating than male students: on the Assessment Skills scale, in CIE, COE, ELE and SOM, with $F(1, 112899) > 25.130, p < 0.001$ and partial $\eta^2 < 0.001$; on the Motivational and Supportive and Generic Skills scale, in COE, ELE and SOM, with $F(1, 112899) > 16.713, p < 0.001$ and partial $\eta^2 = 0.000$; and on the Practical Skills scale, in COE and SOM, with $F(1, 112899) > 21.032, p < 0.001$ and partial $\eta^2 = 0.000$.

Table 3.4: SRS mean ratings with standard error by discipline and student's gender

	FEMALE TEACHER		**MALE TEACHER**		
Scale	**M**	**SE**	**M**	**SE**	**p**
Humanities and Social Sciences					
CC	3.997	0.018	4.193	0.022	0.20
AS	4.119	0.016	4.316	0.020	0.20
MS	4.018	0.018	4.197	0.022	0.18
PS	4.042	0.016	4.017	0.019	0.03
GS	4.143	0.016	4.342	0.019	0.20
Mathematics					
CC	3.876	0.033	3.639	0.014	0.24
AS	4.326	0.030	4.101	0.013	0.22
MS	4.161	0.034	3.887	0.014	0.27
PS	4.148	0.030	3.833	0.012	0.32
GS	4.370	0.029	4.132	0.012	0.24

**Values of p are rounded to two places of decimal and indicate the significance of differences between the mean scores of gender diversified teachers

Main Findings: To answer Research Question 3, female students gave higher ratings than male students on all five SRS scales, Table 3.5. For most of the ratings, female students gave higher mean ratings to their teachers than male students with a considerable significance level (p), for all aspects of SRS and across all disciplines. So, where female students are underrepresented, if given an opportunity, they are found to be more receptive, perceptive and appreciative than their male counterparts, which is partially consistent with a previous study [50].

C. Discipline by Teacher's Gender and Student's Gender

There was not a highly significant multivariate interaction between the effects of the discipline and teacher's gender and student's gender with Wilks' $\Lambda = 1.000, F(4, 112899) = 2.1888, p = 0.002$, partial $\eta^2 = 0.000$. Further univariate interactions showed only small variations in the Practical Skills scale with $F(1, 112899) = 6.436, p < 0.000$ and partial $\eta^2 = 0.000$. No other univariate tests were found significant. Table 3.5 and Figure 3.17 show the SRS mean ratings with standard deviations by discipline and teacher's gender and student's gender.

Table 3.5: SRS mean ratings and standard deviations by discipline, teacher's gender and student's gender

Scale	FEMALE STUDENT				MALE STUDENT			
	FEMALE TEACHER		MALE TEACHER		FEMALE TEACHER		MALE TEACHER	
	M	SD	M	SD	M	SD	M	SD
Civil Engineering								
CC	3.09	1.74	3.00	1.70	2.87	1.72	2.94	1.72
AS	3.18	1.63	3.03	1.61	2.92	1.60	2.98	1.62
MS	4.12	2.10	3.93	2.16	4.11	2.23	4.00	2.19
PS	2.79	1.66	2.59	1.63	2.58	1.70	2.65	1.66
GS	4.13	1.30	3.97	1.34	4.03	1.38	3.91	1.45
Computer Science and Engineering								
CC	4.08	1.30	4.01	1.37	3.95	1.41	3.85	1.49
AS	4.16	1.21	4.10	1.30	4.06	1.32	3.96	1.43
MS	3.94	1.19	3.90	1.26	3.86	1.25	3.82	1.33
PS	3.91	1.19	3.84	1.27	3.87	1.26	3.73	1.38
GS	4.18	1.20	4.13	1.28	4.05	1.33	3.96	1.43
Electrical Engineering								
CC	3.68	1.47	3.66	1.49	3.49	1.61	3.58	1.59
AS	3.97	1.28	4.00	1.26	3.76	1.51	3.90	1.43
MS	3.71	1.17	3.76	1.18	3.51	1.43	3.68	1.37
PS	3.67	1.22	3.73	1.19	3.56	1.40	3.68	1.36
GS	3.98	1.27	4.02	1.25	3.83	1.48	3.95	1.41
Humanities and Social Sciences								
CC	4.09	1.31	4.19	1.27	3.98	1.42	4.19	1.31
AS	4.16	1.22	4.35	1.08	4.11	1.32	4.31	1.20
MS	4.01	1.16	4.14	1.07	4.02	1.20	4.21	1.10
PS	4.03	1.11	3.99	1.19	4.04	1.19	4.03	1.25
GS	4.17	1.22	4.35	1.09	4.14	1.29	4.34	1.15
Mathematics								
CC	4.01	1.45	3.79	1.54	3.81	1.50	3.58	1.62
AS	4.48	0.94	4.33	1.11	4.25	1.14	4.01	1.39
MS	4.32	0.96	4.10	1.15	4.09	1.07	3.80	1.32
PS	4.29	0.98	4.03	1.14	4.08	1.11	3.75	1.36
GS	4.53	0.89	4.32	1.11	4.30	1.10	4.05	1.36

Post hoc tests with simple main effects showed that female teachers received higher ratings by female students on the Practical Skills scale in CIE, $F(1, 112899) = 15.672, p < 0.001$, partial $\eta^2 = 0.000$, whereas male teachers received higher ratings by female students in COE and SOM with $F(1, 112899) > 20.302, p < 0.001$ and partial $\eta^2 < 0.001$.

Further post hoc tests with simple main effects showed that male students rated male teachers higher than female teachers on the Practical Skills scale in CIE and ELE with $F(1, 112899) > 13.699, p < 0.001$ and partial $\eta^2 = 0.000$. Male students gave higher ratings to female teachers in COE and SOM with$F(1, 112899) > 58.217, p < 0.001$ and partial $\eta^2 < 0.001$.

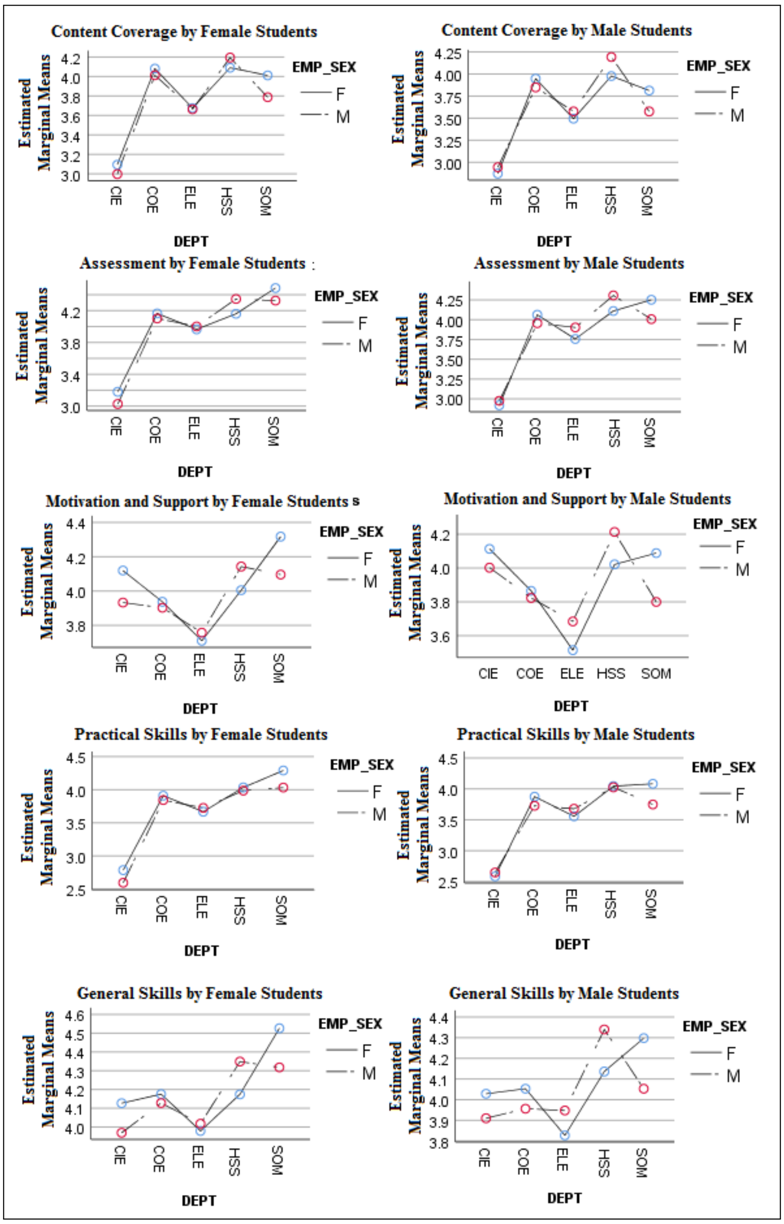


Figure 3.17: Graphs for SRS mean ratings across disciplines by teacher's gender and student's gender

Main Findings: The results of the two-way interaction of teacher's gender and student's gender were not statistically significant, nor were any of the univariate results found to be significant, which answers Research Question 4. However, three-way interactions showed some variations in the Practical Skills scale across the disciplines, where same-gender bias was found in CIE as students gave comparatively higher ratings to the same gender teacher, and cross-gender bias was found in COE and SOM where students gave higher ratings to the opposite gender teacher. The differential level of understanding and teaching methodology adopted by the teachers to explain the practical aspects of the experiments involved in a 'male dominated' field of study, may be a reason for same-gender bias in CIE. Cross-gender bias in COE and SOM may be due to factors outside the scope of this study, such as age, teaching philosophy, or physical attractiveness, that were found to be relevant in some previous studies [12, 134, 196, 214].

Next section discusses about the analysis results for category.

3.4.6.2 Based on Category: The socio-economic data covered 72 course units spanning over 6 semesters across two disciplines between 2013-14 and 2015-2016. Of the 72 course units, 10% were taught by teachers of low socio-economic status (LSES) and 90% by teachers of the general category. There were 16,354 complete sets of responses to the SRS, out of which 11,916 and 4,438 sets were provided by the students taking ELE and SOM course units respectively, 14,630 sets were provided by the general category students and 1,724 sets were provided by students of low socio-economic status. A total of 15,442 and 912 sets were provided to general and low socio-economic status teachers respectively.

A. Discipline by Teacher's Category

The multivariate interaction between the effects of the discipline as well as discipline by teachers' category was not statistically significant, Wilks' $\Lambda = 1.000, F(1, 16346) = .213, p = 0.957$, partial $\eta^2 = 0.000$ and Wilks' $\Lambda = 1.000, F(1, 16346) = 1.497, p = 0.187$, partial $\eta^2 = 0.000$ respectively, and none of the univariate interactions were significant. Table 3.6 gives the SRS mean ratings by discipline and teacher's category.

Main Findings: None of the multivariate and univariate interactions between the effects of discipline and discipline by teacher's category were found to be statistically significant, which answers Research Question 5.

Table 3.6: SRS mean ratings with standard error by discipline and teacher's category

Scale	GENERAL TEACHER		LSES TEACHER		
	M	SE	M	SE	p
			Electrical Engineering		
CC	3.63	0.02	4.02	0.24	0.39
AS	3.63	0.02	4.03	0.24	0.40
MS	3.61	0.02	4.03	0.24	0.42
PS	3.80	0.02	3.46	0.24	0.34
GS	3.61	0.02	4.00	0.24	0.39
			Mathematics		
CC	3.94	0.05	3.77	0.08	0.17
AS	3.94	0.05	3.82	0.08	0.12
MS	3.92	0.05	3.78	0.08	0.14
PS	3.66	0.05	3.40	0.08	0.26
GS	3.84	0.05	3.78	0.08	0.06

**Values of p are rounded to two places of decimal and indicate the significance of differences between the mean scores of socio-economic diversified teachers

B. Discipline by Student's Category

There was a small but highly significant multivariate effect of the student's category, Wilks' $\Lambda = 0.999, F(1, 16346) = 4.661, p < 0.001$, partial $\eta^2 = 0.001$. Further univariate analysis showed significant difference on four SRS scales, namely Content Coverage, Assessment Skills, Motivational and Supportive and Generic Skills.

Post hoc tests with simple main effects confirmed that students of low-SES tend to give comparatively higher ratings than general category students, with the $F(1, 16346) > 14.381, p < 0.001$ and partial $\eta^2 = 0.001$ on the Content Coverage, Assessment Skills, Motivational and Supportive and Generic Skills scale. However, these effects were qualified by a small but highly significant multivariate interaction between the effects of the discipline and student's gender, Wilks'$\Lambda = .999, F(1, 16346) = 4.791, p < 0.001$, partial $\eta^2 = 0.001$.

Table 3.7 gives the SRS mean ratings with standard errors by discipline and student's category. There were significant univariate interactions on four scales of the SRS, Content Coverage, Assessment Skills, Motivational and Supportive and Generic Skills with $F(1, 16346) > 13.364, p < 0.001$ and partial $= 0.001$.

Further post hoc tests showed that on all four SRS scales, general category students gave higher ratings than students of low-SES in the ELE discipline,

$F(1, 16346) > 18.842, p < 0.001$, partial = 0.001. No other discipline results were found significant.

Main Findings: A student category bias exists on four SRS scales, Content Coverage, Assessment Skills, Motivational and Supportive and Generic Skills, where low-SES students gave higher ratings than the general category students. According to previous studies, low-SES students are found to be passive recipients of the general culture and discourse of their university, although one study [154] rejected this notion, arguing that these students often engage actively, adapt well to the general and university cultures, and can even attempt to challenge them.

This study is consistent with, and answers, Research Question 6, with the addition that low-SES students are found to be better respondents and appreciators of the new culture as compared to their general category counterparts.

Table 3.7: SRS mean ratings with standard error by discipline and student's category

Scale	GENERAL STUDENT		LSES STUDENT		
	M	SE	M	SE	p
Electrical Engineering					
CC	3.30	0.05	4.36	0.23	1.06
AS	3.30	0.05	4.36	0.24	1.06
MS	3.29	0.05	4.35	0.24	1.06
PS	3.57	0.05	3.69	0.24	0.12
GS	3.26	0.05	4.35	0.24	1.09
Mathematics					
CC	3.90	0.03	3.81	0.09	0.10
AS	3.85	0.03	3.92	0.09	0.07
MS	3.80	0.03	3.91	0.09	0.11
PS	3.70	0.03	3.36	0.09	0.33
GS	3.78	0.03	3.84	0.09	0.05

**Values of p are rounded to two places of decimal and indicate the significance of differences between the mean scores of socio-economic diversified students

C. Discipline by Teacher's Category and Student's Category

There was a small but highly significant multivariate interaction between the effects of the teacher's category and student's category, Wilks' $\Lambda = .998, F(4, 112899) = 5.154, p < 0.001$, partial $\eta^2 = 0.002$. Further univariate interactions showed significant variations in Content Coverage, Assessment Skills, Motivational and Supportive and Generic Skills with $F(1, 16346) > 19.446, p < 0.001$, partial $\eta^2 = 0.001$. Table 3.8 and Figure 3.18 show the SRS mean ratings along with standard deviations by discipline and teacher's category and student's category.

Post hoc tests with simple main effects found that teachers of low-SES received higher ratings from students of low-SES as compared to the general category students on Content Coverage, Assessment Skills, Motivational and Supportive and Generic Skills scale with $F(1, 16346) > 17.495, p < 0.001$, partial$\eta^2 = 0.001$. Further post hoc tests with simple main effects showed that general students rated general teachers higher than low-SES teachers on Content Coverage, Assessment Skills, Motivational and Supportive, and Generic Skills scales with $F(1, 16346) = 58.811, p < 0.001$, partial $\eta^2 = 0.004$.

Table 3.8: SRS mean ratings and standard deviations by discipline, teacher's category and student's category

Scale	GENERAL TEACHER				LSES TEACHER			
	GENERAL STUDENT		LSES STUDENT		GENERAL STUDENT		LSES STUDENT	
	M	SD	M	SD	M	SD	M	SD
Electrical Engineering								
CC	3.55	1.37	3.71	1.38	3.04	1.51	5.00	0.00
AS	3.54	1.38	3.71	1.37	3.06	1.51	5.00	0.00
MS	3.52	1.39	3.70	1.41	3.07	1.48	5.00	0.00
PS	3.73	1.33	3.88	1.30	3.41	1.49	3.50	0.54
GS	3.51	1.39	3.70	1.38	3.00	1.54	5.00	0.00
Mathematics								
CC	4.10	1.09	3.78	1.37	3.70	1.33	3.83	1.07
AS	4.06	1.13	3.83	1.32	3.64	1.33	4.00	0.93
MS	4.03	1.15	3.81	1.34	3.57	1.39	4.00	0.91
PS	3.77	1.31	3.54	1.42	3.61	1.29	3.18	1.42
GS	3.99	1.20	3.69	1.39	3.58	1.41	3.98	0.89

The three-way multivariate interaction between the effects of the students' discipline, teachers' category and student's category was not statistically significant, Wilks' $\Lambda = 1.000, F(1, 16346) = 1.467, p = 0.197$, partial $\eta^2 = 0.000$, and none of the univariate interactions was significant.

Main Findings: A same-status bias exists where students prefer teachers of same status and rate them higher than other classes on four scales of SRS, Content Coverage, Assessment Skills, Motivational and Supportive and Generic Skills, across ELE and

SOM, which answers Research Question 7. The unbiased behaviour in Practical Skills, and biased behaviour shown in the other four aspects (Content Coverage, Assessment Skills, Motivational and Supportive and Generic Skills), may show that students tend to rate a same-status teacher higher in parameters unrelated to the teacher's knowledge or practical skills, but rather evaluate the teacher's class behaviour, assessments, motivation and general skills based on direct student-teacher interactions.

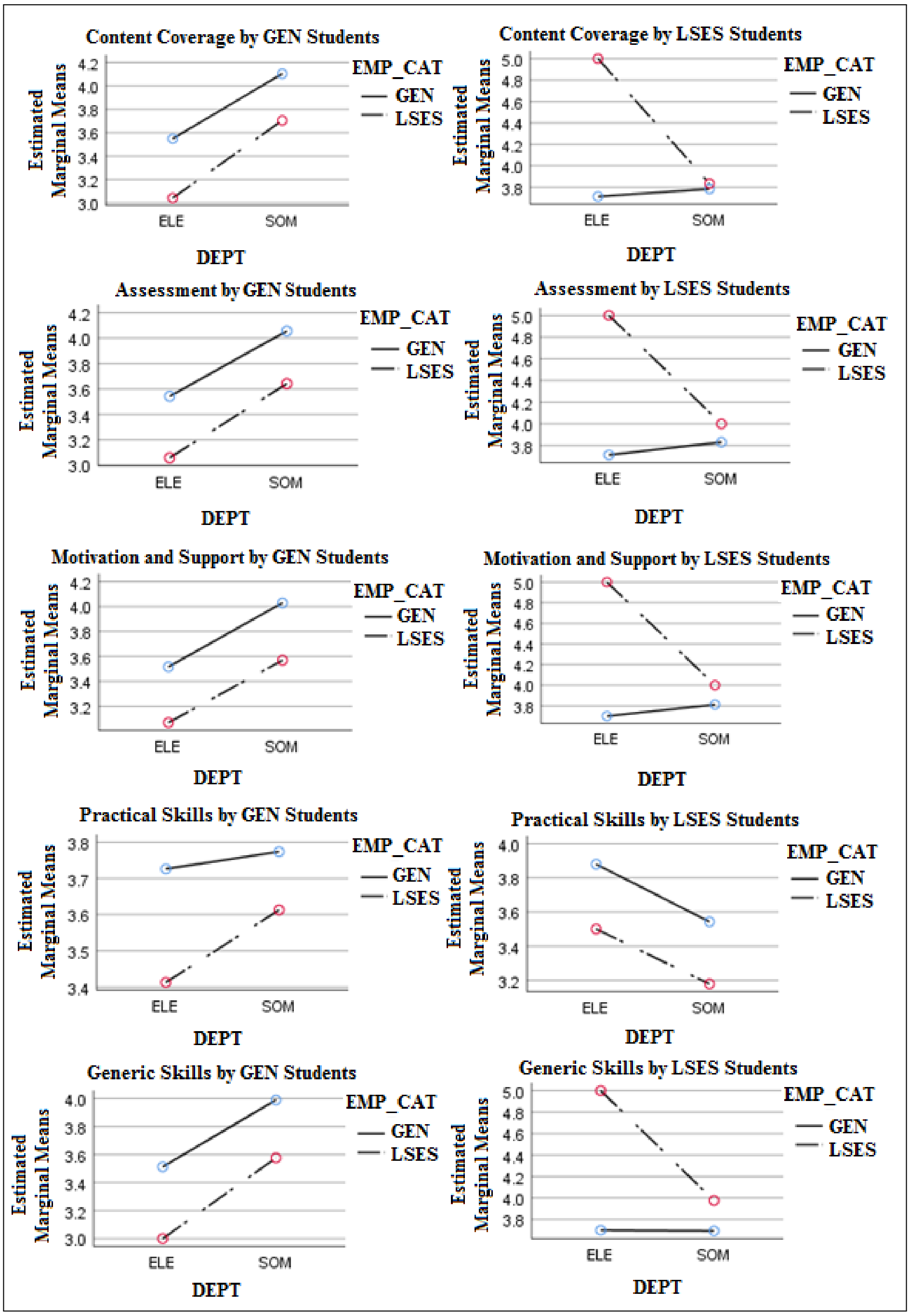


Figure 3.18: Graphs for SRS mean ratings across disciplines by teacher's category and student's category

However, the statistical differences obtained in this study that reveal gender and socio-economic status biases are only small effects that gained statistical significance because of the large sample size (N=112,919 and N=16,354). Each scale rating accounted for less than 1/100th of the variance where effects of other variables and interactions had been significantly controlled.

3.4.7 Discussion

The summary of responses to the research questions are in Table 3.9. This study found that, according to their gender and socio-economic status, students tend to give differential ratings to their teachers. This study revealed, across the disciplines, the existence of gender-typical and gender-atypical behaviour, of same-gender bias where students gave higher rating to same gender teacher, and of cross-gender bias where students gave higher ratings to opposite gender teacher. Students also gave higher ratings to teachers of their own status than to teachers of other status in all aspects of SRS that involved a higher interaction of teachers with students, except when practically judging the knowledge or practical skills of the teacher.

Table 3.9: Summary of findings of the present study

R. No.	Research Questions	Findings
RQ1	Does the gender and socio-economic diversity of the teaching-learning context affect students' ratings across the disciplines on the SRS?	Yes
RQ2	Do male and female teachers receive different ratings from their students?	Yes
RQ3	Do male and female students give different ratings to their teachers?	Yes
RQ4	Do students give different ratings to teachers of the same gender as themselves as compared to the other gender?	No/Yes**
RQ5	Does a teacher's socio-economic status affect their ratings from their students?	No
RQ6	Does a student's socio-economic status affect how they rate their teachers?	Yes
RQ7	Do students rate teachers of the same socio-economic class as themselves differently to teachers of other classes?	Yes

**2-way interactions of teacher and student were not significant but 3-way interactions of teacher, student and discipline revealed some biases.

To increase equity amongst the population internationally, some countries have introduced various reservation policies or affirmative action policies to support low socio-economic students in education. Although small in magnitude, the socio-economic status bias detected in this study suggests that the authorities must also pay attention towards the biased after-effects of these policies. A proactive approach with efficient methodologies and frameworks should be instituted in these initiatives to bridge this socio-economic variance.

These student ratings are now being used in important decisions like recruitment, promotion, tenure, and rewarding faculty members across the disciplines. The differences in ratings, behaviour and biases across various disciplines revealed in this study may be useful in judging the utility of these ratings for such important decisions. However, this study redirects to the decision that while designing for efficient pedagogies and other course specific teaching decisions, along with feedback other factors also need to be taken into consideration. Involving other factors and in-detail study of vertical target groups diversifications (instead of natural diversifications of gender and low-socio economic status) like at-risk students (based on marks) can help to give more clarity about the course expectations, pedagogical designs, and reliable parameters.

3.5 Limitations

This section presents the limitations of these two case studies. The first case study was conducted on students of a particular domain for blended learning environments. For generalization of the present needs and reasons for at-risk behaviour of 21^{st} century students, more studies comprising of different domain as well as institutions must be conducted. The study was conducted on fifth semester undergraduate students. The fifth semester students are much more matured and clear with their needs and objectives as opposed to sophomores and hence the needs and reasons may vary across different year students at higher education level. Students across different geographic regions may also present different motivations, objectives and learning behaviour. The study was conducted only for blended learning environments which may not be the case for online based learning environments or traditional learning environments.

The second case study was conducted on a single Indian university. Analogous studies from other institutions can be also leveraged upon for comparison and more generalization. This study considered all parameters as independent observations, but the parameters in real world scenarios are all related and are of great interest for educators, as they reveal relevant information on the learning behaviour of students and the norms followed by the teacher. Due to the anonymization of the datasets used in the study, any correlations between these parameters were not leveraged.

The future scope lies in conducting the analysis across different institutions, domains, levels and types of learning environments for better generalizability of the results.

3.6 Major Outcomes

After the combined behavioural analysis of reasons and objectives of both the studies, the following factors have been identified that can contribute towards the search of reliable parameters. These might be helpful for efficient pedagogy designing and also help in early identification of at-risk students for blended learning environments.

- *Feedback Reliability:* This study found that, according to their gender and socio-economic status, students tend to give differential ratings to their teachers. This study revealed the existence of gender-typical, gender-atypical behaviour and cross-gender bias for gender as well as status diversifications. This redirects not to blindly rely on feedback for effective parameter search. For efficient course and discipline specific pedagogical designing, parameters other than direct feedback also needs to be taken into consideration.

- *Flexible Timings:* For small sized classrooms, the students may be collectively allowed to choose and freeze their own course timings along with the consultation of the instructor, instead of providing them pre-decided timetable planned according to the institution's convenience. For large sized classrooms, before planning of the timetable, all factors like sequential placement of courses, difficulty level, complementing the lectures with appropriate laboratory assignments with minimum in between time lag *etc.* may help the students to arouse interest and retain focus in the courses they are studying.

- *Flexible Attendance:* For the present-day students, the role of the instructors has shifted to the facilitators. So, they don't consider it important to attend each and every lecture of the instructor, since they can find the course material of international levels and standards on the internet in the form of Open Learning Initiatives or Massive Open Online Courses. The students may be given a little flexibility in attendance while considering such scenarios, subjective to the respective course requirements. However, with the flexibility, they must be monitored and traced via their online learning behaviour so that they may not get off track from the course.

- *Competitive and Active Learning:* Innovative pedagogies that support active learning must be incorporated within the blended learning environments as the 21^{st} century learners are technology freaks and lack of practical tools and technologies lead to early loss of interest in the respective courses. For example, pedagogy supporting the use of clicker technology with the help of peer instructions can increase the understanding level of the students as well as the decrease the response time of the students for any domain [298]. Project based learning, scenario based learning, competitive and cooperative learning environments can prove to be more appropriate and fruitful and can largely effect the students' productivity [151, 203, 286].

- *Open Corpus Course Contents:* Open Corpus International standard course contents links can also be a good option as the students find it difficult to blindly follow the instructor's course material. The students are looking for generalized concepts that can be applied anywhere. Secluded and restricted course content available in the form of notes or e-content is no more the norm. The students, who do not attend the classes, are usually found to explore multiple options online and are likely to follow those from where they understand that concept in an easy way. So, suggesting standardized course material available online by the instructor can help to increase the quality of the study, win the trust and save the time of the students.

- *Hands-On Practice Exercises:* Hands-on practice exercises must be provided to the students so that even if they go for self-study at later stages, they may practice those exercises which in turn can help them to understand the concepts. The exercises may involve small tasks, virtual examples, simulations, quizzes, projects or may include gamification of education [153, 306]. These practice problems can help them to quench their thirst for practicality of education and give them the required exposure, that they are longing for in real-world scenarios.

- *Counselling:* While entering for Higher Education and choosing their career paths or fields, students must be counselled for providing an efficient mapping between the possessed and desired skill-set, interests as well as their internal motivations, inbuilt strengths *etc.* This can be done through manual appointments or automated decision support systems can be put in place [300]. Once this mapping is done correctly, the students can largely unleash their underlying potential and come out with flying colours in the respective interest fields at the end. On the other hand, a mis-mapped case can lead to inefficiency. This student will lack the necessary motivation that will in-turn lower the student's self-confidence and will affect other aspects of his life too.

- *Curriculum Modification:* Modifying the curriculum with special focus to outcome based approach can enhance the core competencies of the present day students. Inculcating research based projects or real-world capstone projects displaying the utility of each and every course they are studying can be a possible solution [20, 263]. Early inclusion of real-world projects like capstone projects within the syllabus can help students to get an early exposure of the real-world scenarios that the students are yearning for.

- *Fixed Credits Multiple Electives:* Apart from the core courses of the engineering domain, the students must be set free to choose their courses according to their interests instead of blindly following the pre-set course pathways. Selective electives along with the basic core courses must be introduced early, for catching the attention of the students in their desired fields and that may help to increase the retention rate of the course [295]. Revelation of the significance of each elective with respect to the industry along with its future prospects, may help the students to streamline their line of action and retain their focus throughout their career pathway.

Chapter 4

AT-RISK MODEL GENERATION

4.1 Overview

In earlier phase, efforts were put to identify the effective approaches and probable parameters that may work effectively for blended learning environments. The design reflections were obtained via student feedback and interviews that mapped theoretically well to the blended learning teaching environments. The technical aspect of the applicability of probable parameters obtained through active learning like activity logs, assessment logs *etc.*, still need to be checked and verified. So, the target of the present phase is to look into the practical aspects with necessary validations of the available educational parameters, in early identification of at-risk students. Here, two case studies were conducted focussing on the importance of activity logs and assessment logs, respectively. However, as per the limited availability of educational blended learning environment datasets, the studies were conducted on publically available educational datasets, for online and distance educational environments. As an output, effective parameters from behavioural analysis from earlier phase, and technical effectivity with validations from present phase, were analyzed. Further follow up for embedding and validations of effective parameters (theoretically effective and technically validated) for blended learning environments was done. The details of efficient implementation of identified parameters for blended learning environments of higher education are discussed in detail in next chapter.

In this Internet era, web based education is gaining its popularity. Online and blended learning environments are replacing traditional classrooms. This is generating large amount of big educational data through instructors and students' online interactions. The smart technology-enhanced platforms that include LMS, Content Management Systems (CMS), Virtual Learning Environments (VLE), MOOC platforms and other web based educational systems, capture these interaction logs, clickstream data, performance parameters *etc.* This generated data being associated with a course, is termed as course specific data. This data can be of interest to an instructor for measuring course analytics which may include identification of at-risk students, student performance prediction *etc.* It can also be of interest for the students, as one may be interested in predicting his own rank from the current respective class performance scenario. Further traversing up the granularity ladder, as the same student may be associated with multiple courses, this data can be relevant at department or institution level. This may involve department or institution level analytics that includes analysis regarding trending courses, poorly performing courses, prediction of student dropout rate at undergraduate level, investing in region based trending career *etc.*

Amongst these, one of the prevalent research area is the Early Warning System (EWS). Due to the online drift of education and lack of individual accountability and motivation for the learner, the dropout and failure rates are high for online educational environments. In order to retain the learner population, the stakeholders are investing in those systems that help them in timely classification of students that are at-risk of failure or dropout or both. EWS help them via their early predictions. These systems feed upon the Big Educational Datasets (BED) generated by the technology-enhanced platforms or any additional information provided by the instructors. This BED comprises of various types of course logs. These can include clickstream data logs, course assessments data, discussion-forum participation data logs, student demographics data, contextual data, and many more, depending on the course layout. This chapter discusses about two such studies where the experimentations regarding the building of efficient at-risk model differentiated on the fed input parameters, have been discussed.

4.2 Chapter Flow

With the target of building efficient EWS at-risk model, the research consisted of two experiments. In both the experiments the common point was the sequential nature of the educational data. As educational data is of sequential nature and is generally relative to the students involved, so this was explored throughout the two experiments. For first experiment, the activity logs were taken as input parameters. So, the sequential nature of big activity logs were explored using the sequential deep learning models. For second experiment the sequential nature of performance logs were explored and at-risk model was generated using sequential hidden markov model. For these the deep learning models were not used as the data was comparatively less and the models were overfitting. For both the experiments, online public datasets were used as per the availability of the required input parameters. As an outcome of the two research studies, two generalized efficient models were generated using activity logs and clickstream logs respectively. Figure 4.1 represents the complete workflow for the at-risk model generation using online public datasets.

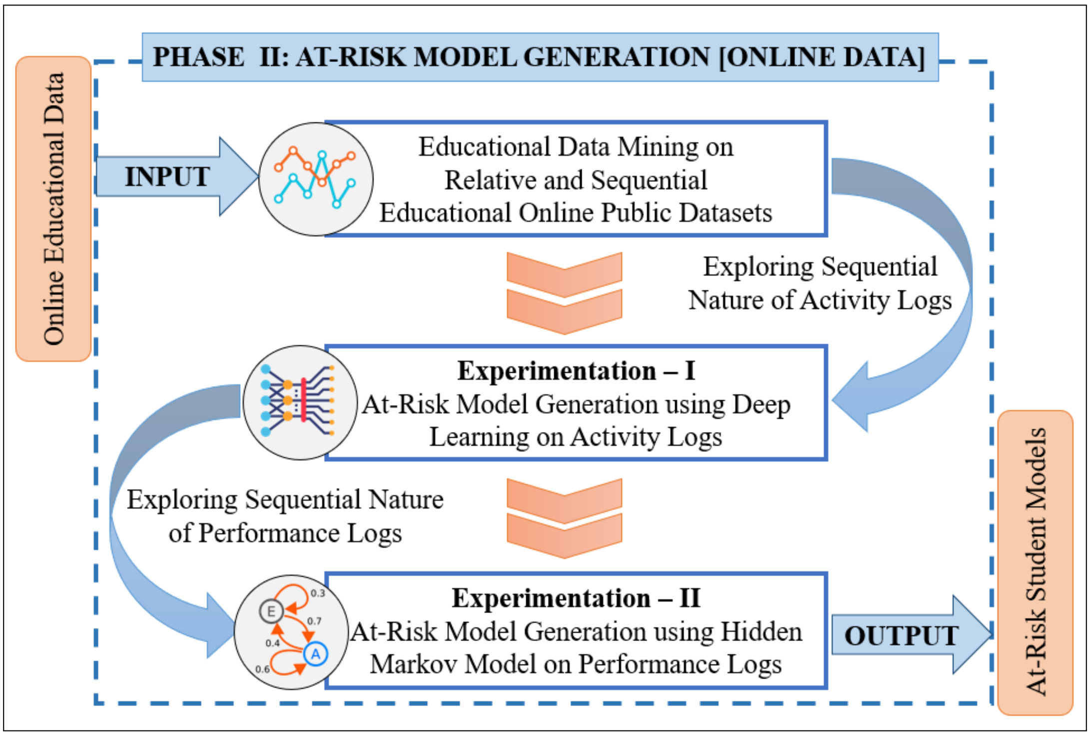


Figure 4.1: Adopted research workflow for at-risk model generation

4.3 At-Risk Model with Clickstream Data

This section discusses about the research study that uses clickstream logs for building the at-risk student model.

4.3.1 Overview

With the objective of student retention in various educational environments, the researchers focus on the early identification of at-risk students. At-risk students are those who are either at-risk of dropout or at-risk of failure from the course. Early identification of these at-risk students in a course can result in timely intervention from the instructor side and may help in student retention. The predictive systems developed for the early identification of at-risk students often lie in two categories. Some studies focus on predicting the continuous performance score of the students [296]. Others treat it as a binary classification problem, where the system needs to detect and provide binary output in the form of yes or no, *i.e.*, whether the student is at-risk or not [258]. These predictive systems either treat educational data parameters as independent and use various machine learning models or consider the educational data of sequential nature and use various sequential models for the predictions. As per the latest trends, a variety of deep learning models are being used for making these efficient predictions that are discussed in detail in the literature survey section [156, 178, 309].

As per the vast range of research studies for the early identification of at-risk students, there have been some research gaps. Most of the systems developed for early identification are context-specific, in terms of types of data logs or models used for their development. It leads to a lack of applicability of such systems across the courses and hence lack generalizations. Secondly, most of the systems are trained and tested on the same data through validation splits. Whereas, in real-world scenarios, the at-risk analysis needs to be performed on the newer batch whose data is unseen by the system. Thirdly, an optimal time needs to be identified when these systems can be deployed for timely interventions, as doing at-risk analysis at the end of the course is of no further utilization.

In lieu of the above research gaps, this study focuses on developing a binary predictive generalized model that can be easily applicable by the instructors for their respective courses across the platforms or institutions. The proposed generalized model uses the commonly available clickstream data only and utilizes its temporal and sequential nature for efficient at-risk analysis. It builds upon the sequential deep learning models for temporal pattern identification and extraction and provides binary classified outcomes. The model is trained and tested on publically available two diversified big educational datasets from different institutions. For realistic results, unseen testing data is used during the model validation. To analyze the optimal time for implementation of the proposed generalized system, a quarterly analysis is performed, and results are discussed.

4.3.2 Contributions

As per the limited availability of the different types of logs across the diversified educational datasets from different platforms or institutions, this study contributes to the literature in the following ways.

- It relies only on the independent clickstream data of the course under consideration, which helps in easy implementation for the instructors.
- Feature selection through correlation analysis contributes to the input parameters effectiveness.
- Three-dimensional sequential data modelling across different time windows contributes effectively towards the early identification of at-risk students.
- It proposes a generalized deep learning architecture for at-risk student prediction.
- The proposed model is validated and tested on unseen data relating to the actual real-world scenarios.
- Validation is performed on two big data educational datasets from diversified institutions, educational environments, number of courses, course lengths, course domains, *etc.*
- Through the proposed model, an optimal time is suggested that can help the instructors in early and timely interventions for at-risk students.

4.3.3 Research Objectives

As per the literature survey, the following research gaps have been identified.

- Context-specific systems lack applicability across the educational data and models.
- Models are trained and tested on same data. Real-world testing on unseen data is lacking.
- Need for identification of optimal time for early identification of at-risk students across the systems for timely interventions.

To bridge the gap within the existing literature, this research study experiments with the sequential and temporal nature of clickstream data through deep learning models. It analyses their role in early predictions of at-risk students and poses the following research questions.

RQ1: Can the sequential nature of clickstream data assist in the early identification of at-risk students across the diversified educational environments?

RQ2: What is the optimum time for the prediction of at-risk students using sequential clickstream data?

4.3.4 Proposed Architecture

This section discusses the proposed generalized model for the early identification of at-risk students. The proposed architecture consists of different phases. These phases include 3-Dimensional (3-D) temporal data modelling, data pre-processing including duplicate data removal and data transformation, sequential pattern identification using deep learning models, output vector concatenation, and finally, generalized binary predictions using dense layer computations. A detailed description of each phase is given below.

4.3.4.1 3-D Data Modelling: The clickstream data consisting of enrolled students' information, events as features, and a number of clicks for each feature on distinct course dates, is modelled as 3-D data. The three dimensions include features as one dimension, students as the second dimension, and time window as the third dimension. Here, the time window represents the time period for which the number of clicks for a particular feature is considered. The time window is of three types: daily, weekly and monthly.

The sum of clicks is used as the statistical measure for calculating the number of clicks for a particular time window. Figure 4.2 shows the pictorial representation of the methodology adopted for calculating the sum of clicks for different features across the time windows for a specific student. For example, in the case of the daily time window, for four different features, feature one has a total of 2 clicks, feature two and four have zero clicks, feature three has one-click throughout a specific day for the student under consideration. Hence, students' clickstream data values of 2, 0, 1, and 0 will be considered for four features, respectively, for that specific day.

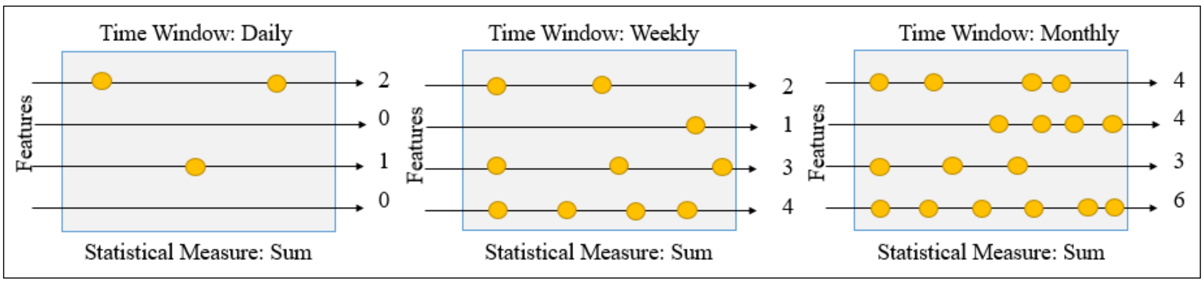


Figure 4.2: Sum of clicks calculation for a student across different time windows

Daily 3-D clickstream data contains information about the daily sum of clicks that student have made against the respective events or features. Similarly, weekly, and monthly 3-D clickstream data contains information about the weekly and monthly sum of clicks of the student against the features, respectively. Figure 4.3 shows the generalized 3-D clickstream data model with three different time windows.

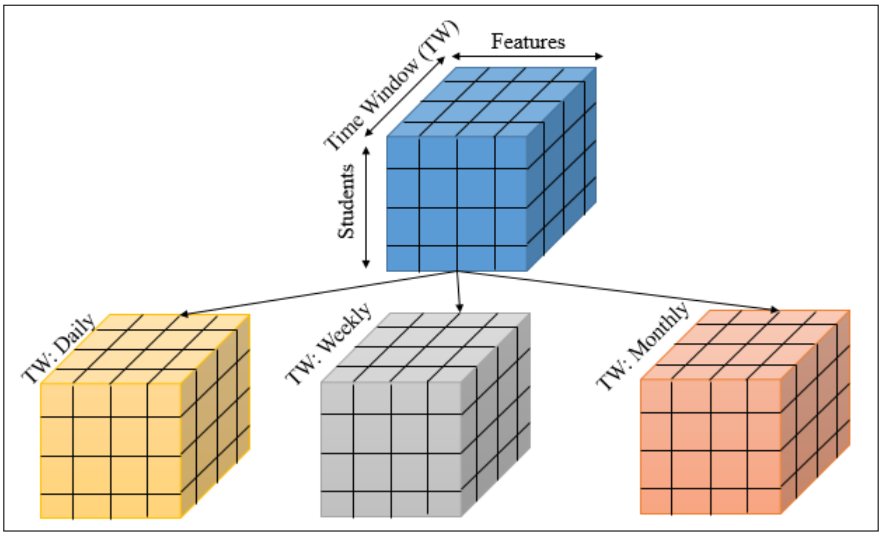


Figure 4.3: Generalized 3-D data modelling with three different time windows

4.3.4.2 Data Pre-processing: After 3-D clickstream data modelling, the data was pre-processed for duplicate data removal and data transformation.

- **Duplicate Data Removal:** The 3-D data is checked for duplicate values. If students have the same data values across the features and time windows, then duplicate student records are removed. Also, the majority class (at-risk or safe) for the removed records is considered as the final truth class.

- **Gaussian Transformation:** The unique and refined data received after the removal of duplicate data values is now processed further by mapping it to the Gaussian distribution or Normal distribution [36]:

$$g(x) = \frac{1}{\sigma\sqrt{2\pi}} exp(-\frac{1}{2}\frac{(x-\mu)^2}{\sigma^2})$$

  Here μ is the mean and σ is the standard deviation. Normalizing was done for the sum of clicks across the days and courses. It can be easily identified that the number of clicks largely varied within and across the courses of different datasets.

Considering data without any transformation may lead to suboptimal results due to large differences in clickstream data numbers as well as the existence of extreme outliers. So, the data is normalized and mapped to the normal distribution using the Box-Cox method [18]. The transformed data represents a normalized bell-shaped curve in which the lower left tail contains students with extremely low activity, whereas the upper right tail contains students with extremely high activity. Figure 4.4 shows the summary of the 3-D clickstream data pre-processing phases.

4.3.4.3 Sequential Pattern Identification: The objective of this phase is to identify the underlying sequential patterns in the differential periodic transformed data. In this phase, the daily, weekly, and monthly transformed data obtained from the earlier phase is fed into the sequential deep learning model. The deep sequential model consists of three LSTM layers and two in-between dropout layers. The basic equations for the forward pass of the LSTM unit along with a forget gate are given below:

$$f_t = \sigma_g(W_f x_t + U_f h_{t-1} + b_f)$$

$$i_t = \sigma_g(W_i x_t + U_i h_{t-1} + b_i)$$

$$o_t = \sigma_g(W_o x_t + U_o h_{t-1} + b_o)$$

$$\tilde{c}_t = \sigma_c(W_c x_t + U_c h_{t-1} + b_c)$$

$$c_t = f_t \ o \ c_{t-1} + i_t \ o \ \tilde{c}_t$$

$$h_t = o_t \ o \ \sigma_h(c_t)$$

Here: vector notation is used, and variables with lowercase represent vectors. $x_t \in \mathbb{R}^d$ is input vector to LSTM unit, $f_t \in (0,1)^h$ is forget gate's activation vector, $i_t \in (0,1)^h$ is input/update gate's activation vector, $o_t \in (0,1)^h$ is output gate's activation vector, $h_t \in (-1,1)^h$ is hidden state vector or output vector of the LSTM unit, $\tilde{c}_t \in \mathbb{R}^h$ is cell input activation vector, $c_t \in \mathbb{R}^h$ is the cell state vector, $W \in \mathbb{R}^{hxd}$, $U \in \mathbb{R}^{hxd}$, and $b \in \mathbb{R}^h$ are the weight matrices and bias vector parameters learned during training with superscript d and h as the number of input features and hidden units, respectively. σ_g : sigmoid function, σ_c and σ_h : hyperbolic tangent function. The initial values are taken as

$c_0 = 0$ and $h_0 = 0$, and the operator o denotes the element-wise product. The subscript t indexes the time step.

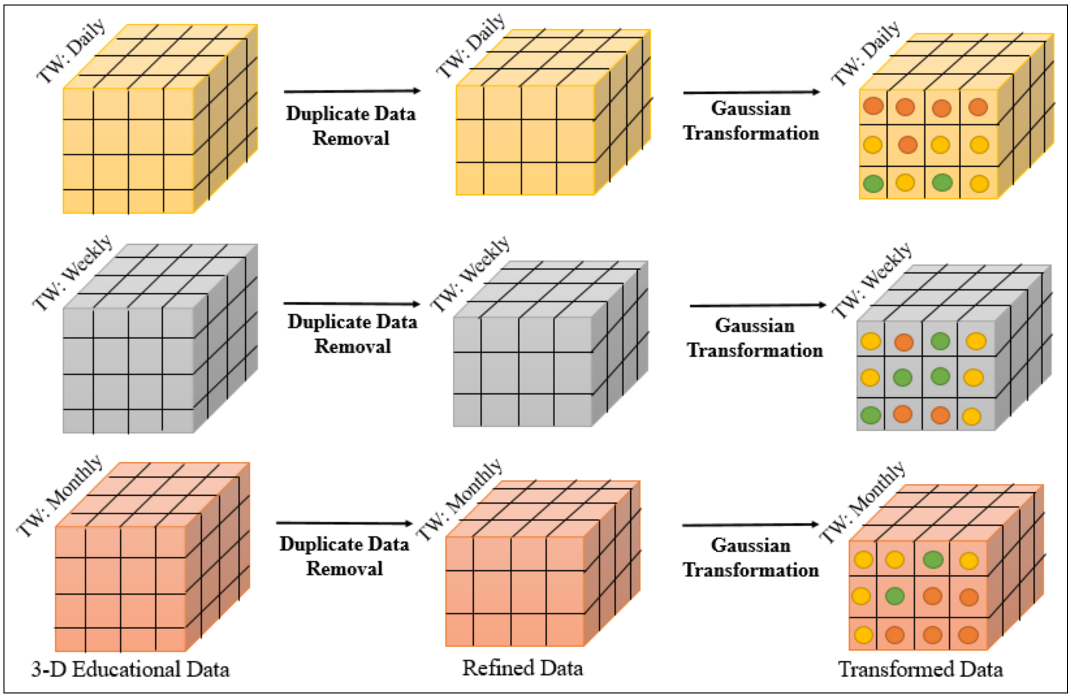


Figure 4.4: 3-D clickstream data pre-processing phases

According to available literature and experimentation with different numbers of LSTM layers, three layers are considered as these obtained optimal results. These are expected to identify the existing deep sequential patterns lying within the differential periodic activities of the students. However, less or more than three LSTM layers resulted in suboptimal results. Two dropout layers are introduced in between for making the network more robust and avoiding overfitting. The daily, weekly, and monthly transformed data are fed into the sequential deep learning network independently. So, for the identification of 3 different time period based sequential patterns, three sequential deep learning networks are considered. The output for this phase is the three vectors carrying information about the underlying identified sequential patterns.

4.3.4.4 Concatenation: The three different output vectors containing the information about the periodic sequential patterns obtained from the earlier phase are concatenated in this phase. The reason regarding the independent treatment of differential periodic data is because, in the real world, courses of different lengths are encountered—some range from as short as one month to longer periods approximating one year. So, the sequential pattern identification may also be varying across the time periods. For example, for a thirty days' course, daily sequential pattern identification may outnumber the weekly and monthly sequential patterns. However, for longer cases, vice versa may exist. So, for optimal results, all types of periodic sequential pattern identification are taken into consideration in this phase and further concatenated into a single vector.

Algorithm 4.1: Proposed generalized model training algorithm

INPUT: Training Clickstream Data
OUTPUT: Trained Model
MODEL TRAINING ALGORITHM:
Step 1: *3-D Data Modelling:* Represent sum of clicks into 3-D: Students, selected Features and Time-window.
Step 2: *Data Pre-processing:* 2.1 *Duplicate Data Removal:* Remove redundant data. 2.2 *Gaussian Transformation:* Apply gaussian transformation across the features. $$g(x) = \frac{1}{\sigma\sqrt{2\pi}} exp(-\frac{1}{2}\frac{(x-\mu)^2}{\sigma^2})$$
Step 3: *Sequential Pattern Identification:* Identify three different types of sequential patterns: 3.1 *Model Creation:* Create 3 models with 3 LSTM model layers and 2 in-between dropout layers. $$f_t = \sigma_g(W_f x_t + U_f h_{t-1} + b_f)$$ $$i_t = \sigma_g(W_i x_t + U_i h_{t-1} + b_i)$$ $$o_t = \sigma_g(W_o x_t + U_o h_{t-1} + b_o)$$ $$\tilde{c}_t = \sigma_c(W_c x_t + U_c h_{t-1} + b_c)$$ $$c_t = f_t \ o \ c_{t-1} + i_t \ o \ \tilde{c}_t$$ $$h_t = o_t \ o \ \sigma_h(c_t)$$ 3.2 *Data input:* Feed daily, weekly, and monthly transformed data into above three created models.
Step 4: *Concatenation:* Concatenate three different output vectors obtained from earlier phase.
Step 5: *Dense Computation:* Identify relevant patterns as obtained in concatenated vector from earlier phase. 5.1 *Pattern Identification:* Feed concatenated vector into the first fully connected dense layer. 5.2 *Probabilistic Output:* Generate probabilistic output through sigmoid function of second dense layer.
Step 6: *Trained Model:* Repeat Steps 3, 4 and 5 till training of the model converges.

4.3.4.5 Dense Computation: The objective of this phase is to identify the concatenated relevant patterns obtained from the earlier phase, perform dense computations and provide the predictions. The single concatenated vector obtained from the earlier phase is fed into a fully connected dense layer. This phase consists of two dense layers. The first one is a fully connected dense layer. The second dense layer has a sigmoid activation function. The output of the first layer is fed into the second dense layer with a sigmoid activation function that gives the prediction output.

4.3.4.6 Prediction Generation: The output of the second dense layer produces probabilistic output. The probabilistic output is further converted to binary output. 0 (zero) if the student is safe and 1 (one) if the student is at-risk of failure or dropout. For the binary classification, different thresholds were taken into consideration. For experimentation purpose, the threshold values varied between 0.2, 0.4, 0.5, 0.6 and 0.8. The binary classification produced optimal results with the threshold value of 0.5. So, for the conversion, the standard threshold value of 0.5 was finalized. If the probability is less than 0.5, then the student is categorized as safe. Otherwise, the student is categorized as at-risk. Thus, the final binary predictions are obtained as an output of this phase. Algorithm 4.1 and 4.2 represent the complete proposed generalized model's training and testing phases in algorithmic form.

Algorithm 4.2: Proposed generalized model testing algorithm

INPUT: Unseen Testing Clickstream Data
OUTPUT: Binary At-Risk Predictions
MODEL TESTING ALGORITHM:
Step 1: *3-D Data Modelling:* Represent sum of clicks into 3-D: Students, selected Features and Time-window.
Step 2: *Data Pre-processing:* 2.1 *Duplicate Data Removal:* Remove redundant data. 2.2 *Gaussian Transformation:* Apply gaussian transformation across the features. $$g(x) = \frac{1}{\sigma\sqrt{2\pi}} exp(-\frac{1}{2}\frac{(x-\mu)^2}{\sigma^2})$$
Step 3: *Import Trained Model:* 3.1 *Model Import:* Import trained model from earlier training phase. 3.2 *Data Input:* Feed daily, weekly, and monthly transformed data as per the model specifications. 3.3 *Probabilistic Output:* Generating probabilistic output through the trained model on testing data.
Step 4: *Prediction Generation:* The probabilistic output is converted to binary with optimal threshold value.

For calculating the overall time complexity of the proposed model: Sequential pattern identification phase involves 3 LSTM layers. For each time step per weight, a LSTM has time complexity of O(1) [27]. So, the time complexity of 3 LSTM models per time step is:

$$O(W_1 + W_2 + W_3)$$

where $O(W_1)$, $O(W_2)$ and $O(W_3)$ being the time complexities for 1^{st} , 2^{nd} and 3^{rd} LSTM models. Similarly, the time complexity for dense computations phase is:

$$O(W_{d1} + W_{d2})$$

where $O(W_{d1})$ and $O(W_{d2})$ are the time complexities for 1^{st} and 2^{nd} deep neural networks. The overall time complexity per time step for the proposed architecture can be computed as the sum of both phases complexity:

$$O((W_1 + W_2 + W_3) + (W_{d1} + W_{d2}))$$

During the training phase input length and epochs are also taken into consideration. So, for the complete training process the complexity is:

$$O((W + W_d) * n * e)$$

where $W = (W_1 + W_2 + W_3)$, $W_d = (W_{d1} + W_{d2})$, n is the input length and e represents the number of epochs [255]. The complete proposed generalized architecture or model is shown in Figure 4.5.

4.3.5 Methodology

This section discusses the detailed steps carried out using the proposed generalized architecture with respect to the two datasets involved.

4.3.5.1 Dataset Description: This section describes the basic information about two public datasets, along with the datasets curation and transformation.

- **KDDCUP15:** KDDCUP15 dataset belongs to the XeutangX platform, which is one of the largest MOOC platforms in China. This public dataset was launched as a competition where participants needed to predict whether a particular learner will drop out from the course or not within the next 10 days, based on his or her prior activities [182].

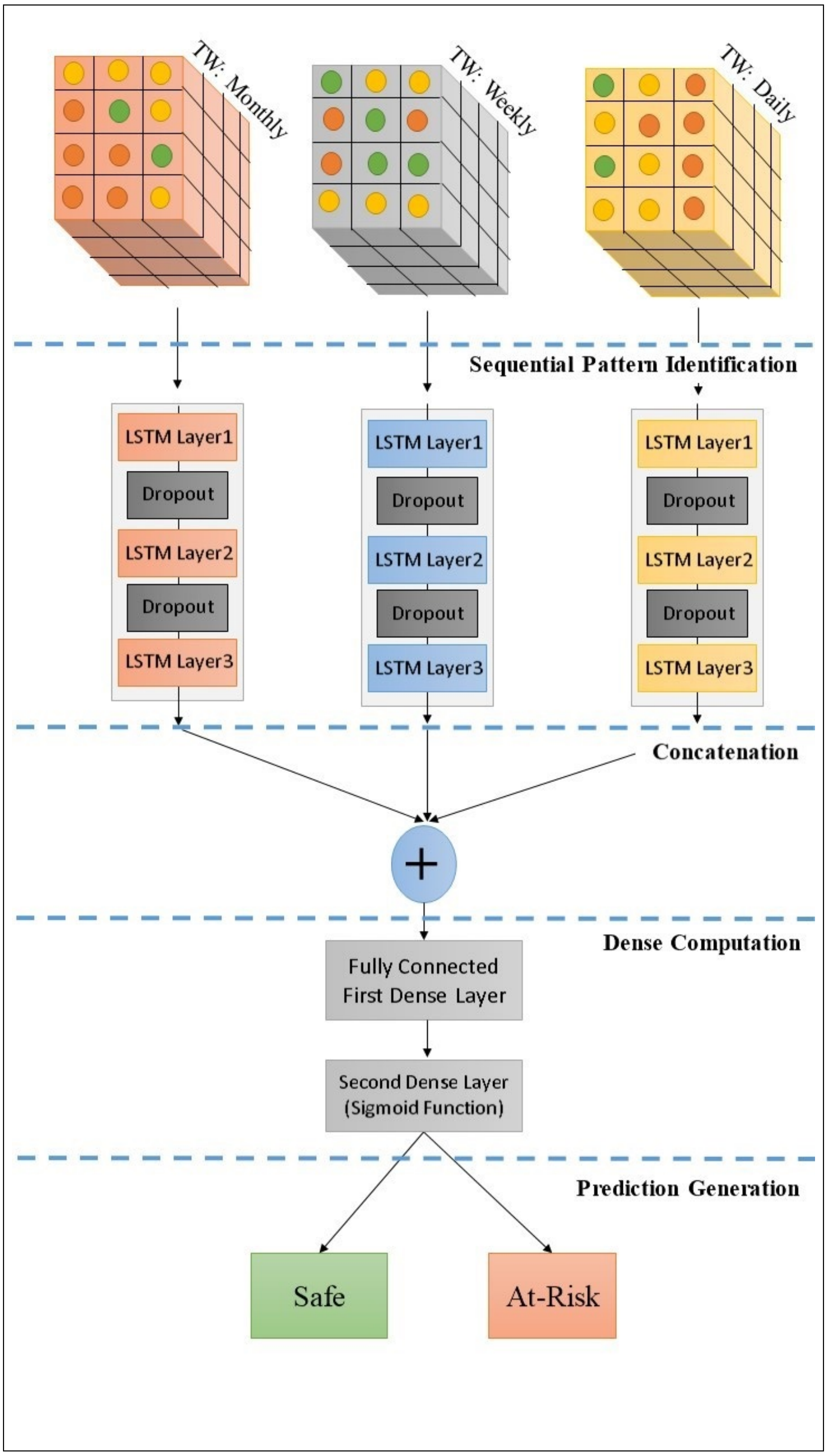


Figure 4.5: Proposed generalized deep learning architecture

It is widely used by educational researchers for MOOC dropout prediction. Out of the two datasets used for this study, it is one amongst them. It consists of two different training and testing files. Training files contain activity records of 120,542 distinct enrolment ids with 79,186 unique students. The unseen testing file contains activity records of 80,362 distinct enrolment ids with 58,364 unique students. These students are enrolled in 39 different courses, where each course spans 30 days. The clickstream logs contain information about the student's enrolment id, time of access, source (browser or server), seven events (navigate, access, page close, discussion, browsing the wiki, watching the video, and problem-solving), and object access. The truth files contain information regarding whether the student completed the course (marked as 0) or dropped out from the course (marked with 1).

- **OULAD:** Another public dataset OULAD is provided by the Open University, UK [241]. It is the second dataset that is used for the validation of this study. The dataset contains 22 module presentations of 4 STEM: Science, Technology, Engineering, and Mathematics courses and 3 Social Sciences courses with 32,593 students. The seven-course module presentations length approximates over 9 months. As each course carries at least two module presentations, the course data is divided into two parts: training dataset and testing dataset. In each course, one last or latest module unseen presentation is reserved for testing purposes, whereas all earlier presentations are used as the training dataset. By the end, all the seven courses' training and testing files are later combined into a single training and testing file, respectively. OULAD training file consists of 15-course representation, and testing file consists of 7-course representations. The anonymized dataset contains information about the courses, student demographics data, students course registration data, virtual learning environment components data along with student interaction logs and course assessment components data along with student assessment data. The virtual learning environment activity file has 21 unique course components comprising of access information of resources, quiz, questionnaire, homepage, subpage, *etc.* Further, student interaction logs consist of the information for code module and presentation, student id, date of access, and clicks. The final course result has been categorized into four classes: distinction, pass, fail, and withdrawn.

Table 4.1 describes the detailed dataset description for the two datasets used in this study.

Table 4.1: Dataset description of datasets used for this study

Ref. No.	Name	Year	Courses	Course Length	Training Set	Unseen Testing Set
[182]	KDDCUP15	2015	39	1 Month	120542	80362
[241]	OULAD	2017	22	9 Months	19085	10143

4.3.5.2 Dataset Curation: Considering the two datasets' availability logs and for streamlining the two datasets on common parameters, certain selections and changes have been made in the two datasets that are described below.

- **Feature Engineering:** With respect to the available logs, the datasets were found to be inconsistent on the following grounds: student demographics data, contextual data, within clickstream data: access source, timestamp versus date, object accessed, *etc.* The above inconsistencies are removed by not considering the respective parameters in the final two datasets. As a result, demographics and other contextual information are not leveraged upon in the present study. Out of the timestamp and date, only date is considered for both datasets, along with the number of clicks. However, as the access events per course can be different according to the course structural layout, so the major events are recognized and refined for each dataset, based on the correlation analysis. If the two parameters are found to be highly correlated, then they are considered under one event.

  For OULAD, the twenty-one components are reduced to six major events, namely discussion, course page access, navigate, problem, resources, and browsing the wiki. For example, quiz and questionnaire solving are clubbed under the problem-solving event based on higher correlation. Homepage and subpage access are clubbed under the course page access and so on. For KDDCUP15, each of the seven components contributed distinctly, so all the seven components are considered as input parameters. One additional feature, the total number of clicks for a particular day, week, or month, is also included for both datasets. So, KDDCUP15 has an overall 8 input features, and OULAD has overall 7 input features.

- **Binary Output:** KDDCUP15 already contained at-risk and safe student data in the form of binary classes. So, no changes are made to this dataset in this respect.

For the OULAD dataset, as per the objective of this study for the identification of at-risk students (dropout or failure), the final result categories are merged that results in binary classes. The fail and withdrawn classes are merged as at-risk, representing students either at-risk of failure or at-risk of dropout from the course. Pass and distinction classes are also merged and categorized as safe.

- **Dataset Partition:** For identification of optimum time period, the datasets are divided into quartiles. So, the two datasets are also divided across the quartiles, depending upon the complete course length. Here, Q1 represents the first quartile or first 25% of the time period of the course, and for this, the dataset contains the clickstream data for the initial 25% of the course. Q1-Q2 is the second quartile, and for this, the dataset contains the clickstream data for the initial 50% of the course time period. Q1-Q3 third quartile with initial 75% of the course clickstream data and Q1-Q4 as the fourth quartile with 100% of clickstream data.

4.3.5.3 Data Collection: As discussed, OULAD and KDDCUP15 datasets are considered for the study. Only clickstream data logs are explored. The enrolled students having entries in the clickstream logs are taken into consideration for this study. So, KDDCUP15 training set consisted of 120,542 enrolled students, whereas OULAD training set consisted of 19,085 enrolled students.

4.3.5.4 Data Modelling: The 3-D daily, weekly, and monthly clickstream data model is developed for both datasets. For example, for the KDDCUP15 training dataset, 120,542 students daily, *i.e.*, 30 days' data is modelled against 8 different features. So, the 3-D model cube has 120542 x 30 x 8 dimensions for daily training KDDCUP15 dataset. Similarly, for the OULAD training dataset, 19,085 students monthly, *i.e.*, 9 months' data, is modelled against 7 different features. So, the 3-D model cube has 19085 x 9 x 7 dimensions for the monthly training OULAD dataset.

The data is also created with respect to the quartiles. According to the complete course length of the datasets, 1 month in case of KDDCUP15 and 9 months in case of OULAD dataset, the courses data is divided into four quartiles. The first quartile contains data of the initial 25% of the course days. The second, third, and fourth quartiles contain data of initial 50%, 75%, and 100% of the course days, respectively. For KDDCUP15, for the first, second, and third quartile, there was no monthly data, whereas it was added in the fourth quartile. For OULAD dataset, all time periods data: daily, weekly, and monthly, contributed equally from the first quartile onwards.

4.3.5.5 Data Pre-processing: This includes refining the data through duplicate records removal and then data transformation. In the case of KDDCUP15 dataset after duplicate data removal, out of 120,542 enrolled students, only 79,662 unique student records have been identified and considered further for the training of the deep learning model. Whereas for OULAD dataset, no duplicate records were found, so 19,085 unique student records have been used for training the deep learning model. The sum of clicks across the 39 courses of KDDCUP15 training dataset and 15 courses of OULAD training dataset are shown in Figure 4.6. As Python language with tensorflow has been used for complete implementation of the code, Power Transformer of the scikit-learn library is used for 3-D data transformation of both datasets [15, 83, 277].

4.3.5.6 Model Generation: As per the proposed generalized architecture, the complete model is set up with three LSTM layers with dropout for sequential pattern identification. They are then concatenated for the different obtained vectors, performing dense computations and finally generating binary predictions. The hyper-parameters used in the development of the above model are discussed below. Hyper-parameter Tuning: The model takes three 3-D input time period based data. Within the sequential pattern identification module, three LSTM layers are used with units ranging from 128 to 512, depending upon the input pattern or dataset. The in-between dropout layer value has been set to 0.2. For LSTM layers, the activation function used is relu, and the recurrent activation function is hard sigmoid.

The output of the third LSTM layer for daily, weekly, and monthly is a vector of length ranging between 128 to 512 depending upon the third layer LSTM units. The concatenated vector length is between 3*128 to 3*512. The first fully connected layer has 512 units with relu activation function. The second dense layer has one unit with sigmoid activation function. Adam optimizer with 0.0001 learning rate is used. Early stopping with a patience level of 25 on minimum validation loss is used while training the deep learning architecture. The probabilistic output obtained is converted to 0-1 value using the 0.5 threshold. The final output of the model is a 0-1 value, where 0 indicates safe class, and 1 indicates at-risk class with optimal threshold value of 0.5 for binary classification. The results obtained after the comparison of different threshold values between 0.2, 0.4, 0.5, 0.6 and 0.8 are shown in Table 4.2.

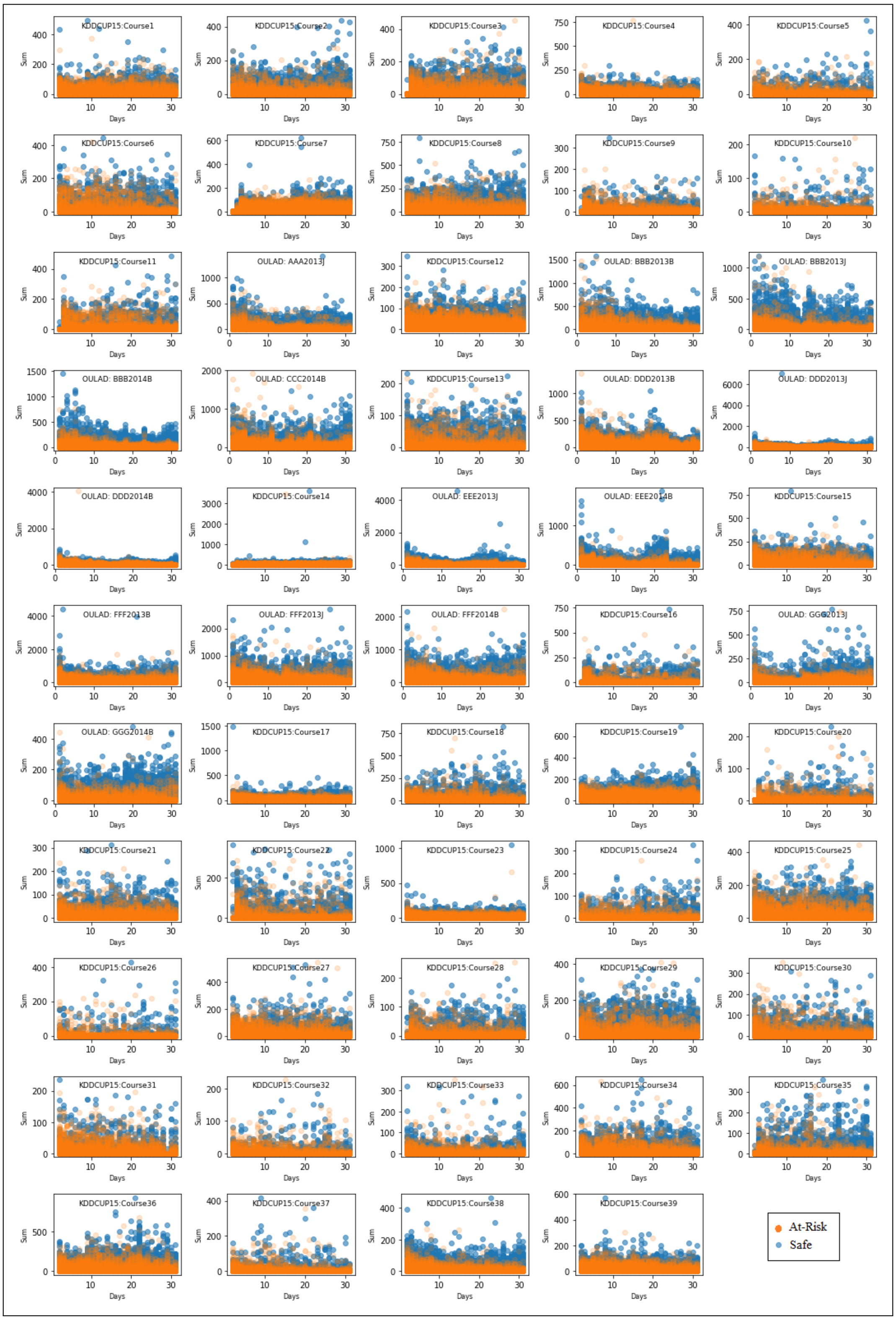


Figure 4.6: Sum of clicks across the days for 39 KDDCUP15 courses and 15 OULAD courses of training dataset

Table 4.2: Comparison of binary classification results with different threshold values

S. No.	Threshold Value	KDDCUP15					OULAD				
		Accuracy	Precision	Recall	F1	Kappa	Accuracy	Precision	Recall	F1	Kappa
1	0.2	0.851	0.847	0.992	0.914	0.408	0.887	0.851	0.915	0.882	0.774
2	0.4	0.875	0.882	0.972	0.925	0.558	0.916	0.936	0.878	0.906	0.830
3	0.5	0.876	0.893	0.959	0.925	0.585	0.919	0.952	0.868	0.908	0.836
4	0.6	0.875	0.894	0.942	0.923	0.569	0.917	0.959	0.858	0.906	0.833
5	0.8	0.836	0.932	0.855	0.892	0.554	0.915	0.974	0.838	0.901	0.827

As per the research questions, the study is carried over a two-fold analysis. One considers overall at-risk student prediction, whereas another one considers quartile based data. The data is classified into at-risk and safe categories. As the rate of classification of an at-risk student to the safe category is a costlier operation than vice-versa, along with accuracy, other parameters like precision, recall, ROC-AUC, *etc.*, are also taken into consideration. The analysis is performed using the following evaluation parameters: Accuracy, ROC-AUC, Precision, Recall, F1-score, and Cohen's kappa statistics.

4.3.6 Results

This section describes the results according to the posed research questions for this study.

RQ1: *Can the sequential nature of clickstream data assist in the early identification of at-risk students across the diversified educational environments?*

Through the proposed architecture, the sequential nature of clickstream data assists in the early identification of at-risk students. Table 4.3 and Figure 4.7 show the evaluation results for the two datasets for 100% course length. Here, the proposed model is compared with respect to the three-time periods: daily, weekly, and monthly independent outputs.

For KDDCUP15, out of the three independent models, daily sequential patterns contributed significantly towards the development of the proposed model. The decreasing order for contributions made by the independent outputs for sequential pattern identification is: daily, weekly, and monthly. The monthly identified patterns are the weakest amongst the three with only 85.5% accuracy, 0.844 AUC value with 0.497 kappa reliability coefficient. Weekly identified patterns with 87.3% accuracy, 0.873 AUC value, and 0.573 kappa value gave an average performance. Daily identified patterns reported an accuracy score of 87.5%, 0.876 as AUC value with 0.584 kappa value, which is highest amongst the three independent outputs. The proposed model, however, leveraged the three sequential identified patterns outputs and resulted in the highest AUC value of 0.881, accuracy as 87.6%, F1-score as 0.925 with 0.585 kappa reliability coefficient showing moderate agreement.

Table 4.3: Evaluation results of datasets for proposed model

S. No.	Model	Accuracy	Precision	Recall	F1 Score	Kappa
DATASET: KDDCUP15						
1	Daily	0.875	0.896	0.953	0.924	0.584
2	Weekly	0.873	0.892	0.955	0.923	0.573
3	Monthly	0.855	0.875	0.952	0.912	0.497
4	Proposed Model	0.876	0.893	0.959	0.925	0.585
DATASET: OULAD						
1	Daily	0.911	0.967	0.836	0.897	0.819
2	Weekly	0.916	0.960	0.854	0.904	0.829
3	Monthly	0.918	0.962	0.859	0.907	0.836
4	Proposed Model	0.920	0.952	0.868	0.908	0.836

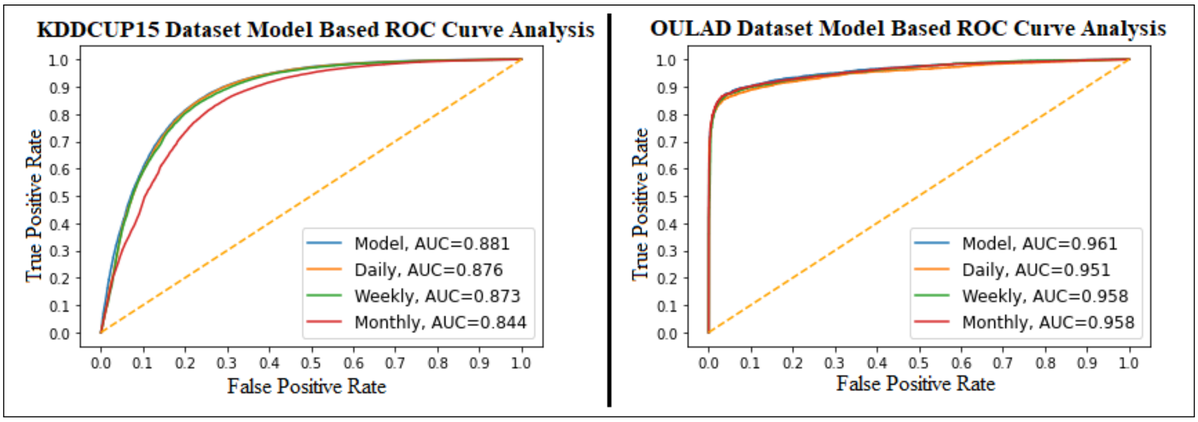


Figure 4.7: ROC curve analysis with AUC values for proposed model across KDDCUP15 and OULAD datasets

In case of OULAD dataset, the scenario is quite different. Here, the monthly model outnumbered the other independent outputs and contributed significantly towards the development of the model. The decreasing order for the contributions made by the independent outputs for sequential pattern identification is: monthly, weekly, and daily. Although with good evaluation scores, here daily identified patterns formed the weakest with 91.1% accuracy, 0.951 AUC value, and 0.819 kappa reliability coefficient. Weekly identified patterns were average with 91.6% accuracy, 0.958 AUC value, and 0.829 reliability coefficient. Monthly identified patterns contributed the highest, with 91.8% accuracy, 0.958 AUC value, and 0.836 kappa coefficient. The proposed model outnumbered all the independent outputs and produced the best results with an accuracy of 92%, 0.961 as AUC value, 0.908 as F1-score, and a significant reliability coefficient value of 0.836, representing perfect agreement. For both the diversified datasets, respective clickstream data with the help of the proposed model can contribute efficiently towards the early identification of at-risk students.

RQ2: *What is the optimum time for the prediction of at-risk students using sequential clickstream data?*

For identification of optimum time period, the datasets are divided into quartiles representing data from initial 25%, 50%, 75%, and 100% course lengths, as mentioned in earlier sections. For the analysis purpose, the comparisons are made between these quartiles' evaluation metrics as shown in Table 4.4, Figure 4.8, and Figure 4.9. The proposed model is used for making predictions across all the quartiles. The best results are obtained with data from 100% course length. However, earlier quartile predictions also contributed significantly to both datasets.

Table 4.4: Evaluation results of datasets across the quartiles

S. No.	Quartile	Accuracy	Precision	Recall	F1 Score	Kappa
DATASET: KDDCUP15						
1	Q1	0.816	0.834	0.959	0.892	0.294
2	Q1-Q2	0.834	0.854	0.954	0.901	0.412
3	Q1-Q3	0.852	0.871	0.954	0.911	0.481
4	Q1-Q4	0.876	0.893	0.959	0.925	0.585
DATASET: OULAD						
1	Q1	0.720	0.671	0.774	0.719	0.443
2	Q1-Q2	0.821	0.811	0.799	0.805	0.639
3	Q1-Q3	0.872	0.905	0.813	0.854	0.741
4	Q1-Q4	0.920	0.952	0.868	0.908	0.836

For KDDCUP15, the first quartile yielded an accuracy of 81.6% with a 0.720 AUC value and 0.294 kappa coefficient representing a fair agreement. However, the results improved for the second quartile with 83.4% accuracy, 0.774 AUC value, and moderate

0.412 kappa value. Similarly, the third quartile also added further relevant information to the results, with 85.2% accuracy, 0.810 AUC value, and 0.481 as reliability coefficient. 100% of the course data, *i.e.*, fourth quartile, produced the best results with 87.6% accuracy, 0.881 AUC value, and 0.585 as kappa value. For OULAD, the first quartile yielded an accuracy of 72%, F1-score of 0.719, AUC value of 0.819, and kappa value of 0.443 on unseen testing data. The second quartile added significantly to the results with 82.1% accuracy, 0.805 F1-score, 0.899 AUC value, and 0.639 kappa coefficient, indicating considerable agreement. In the third quartile, the evaluation metrics further improved with 87.2% accuracy, 0.854 F1-score, 0.936 AUC value, and 0.741, *i.e.*, considerable kappa value.

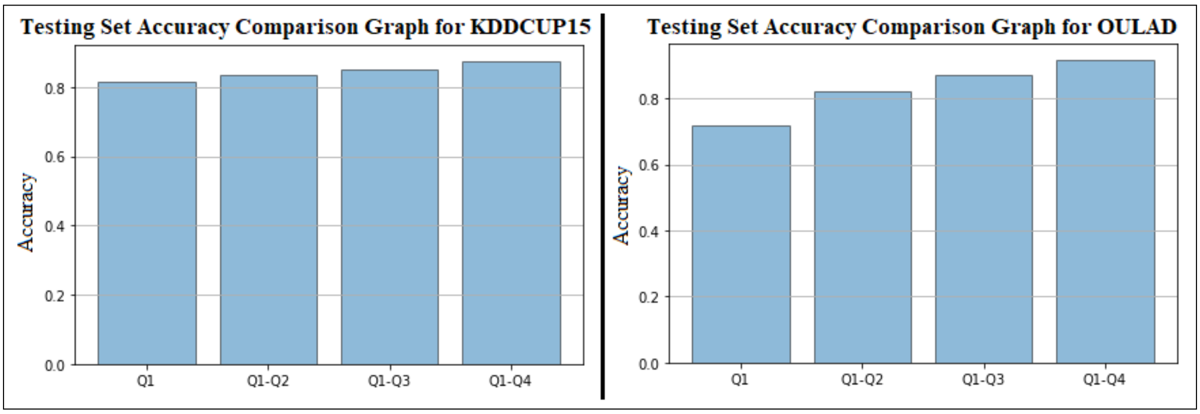


Figure 4.8: Unseen testing accuracy graph analysis across the quartiles for KDDCUP15 and OULAD datasets

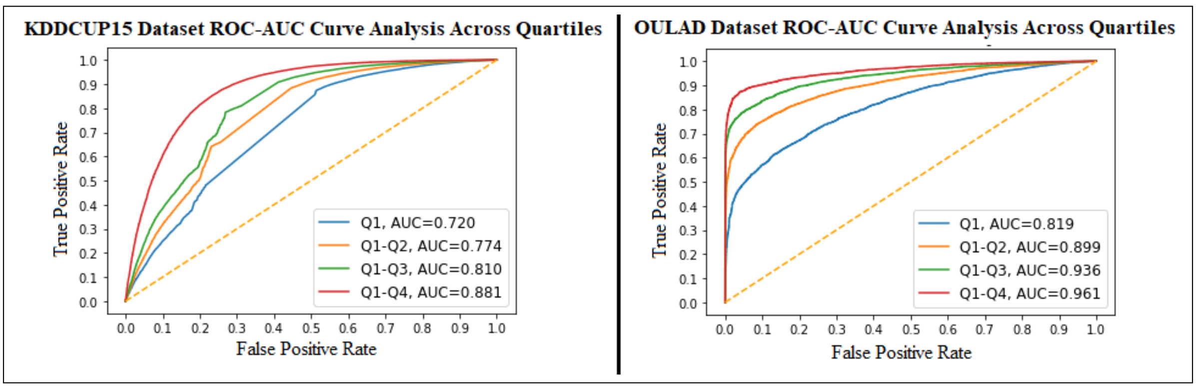


Figure 4.9: ROC curve analysis with AUC values across the quartiles for KDDCUP15 and OULAD datasets

The fourth quartile again yielded the best results with 92% accuracy, 0.908 F1-score, 0.961 AUC value, and 0.836 kappa value representing perfect agreement. For both the datasets from the first quartile, the results are significant and comparable with fair or moderate reliability agreement. This shows that the proposed model produces considerable results and has the capability of early identification of at-risk students since the first quartile. However, later quartiles add up to the accuracy, AUC scores, and produce refined results.

4.3.7 Comparative Analysis

This section compares the proposed generalized model results with that of the existing baseline machine learning and deep learning models, as mentioned in the literature survey section. Figure 4.10 and Table 4.5 show the evaluation results along with the ROC-AUC curve, respectively. The baseline machine models used for comparison are Random Forest (RF) ensemble classifier with 1000 estimator trees, Logistic Regression (LR) classifier, Support Vector Machine (SVM) with linear kernel, Naïve Bayes (NB) classifier, eXtra Gradient Boosting (XGB) ensemble classifier, k Nearest Neighbor (kNN) classifier with k value as five and Decision Tree (DT) classifier. The comparative analysis clearly represents the significant upper edge of the proposed model on the evaluation results. Amongst the machine learning models, XGB produced the highest accuracy of 85.5%, with 0.842 as AUC value and 0.913 F1-score for the KDDCUP15 dataset. Whereas for the OULAD dataset, considering all the parameters, RF produced the highest results with an accuracy of 80%, AUC value as 0.880, and 0.794 F1-score. However, for both cases, the proposed model evaluation metrics are much higher than the highest performing machine learning model.

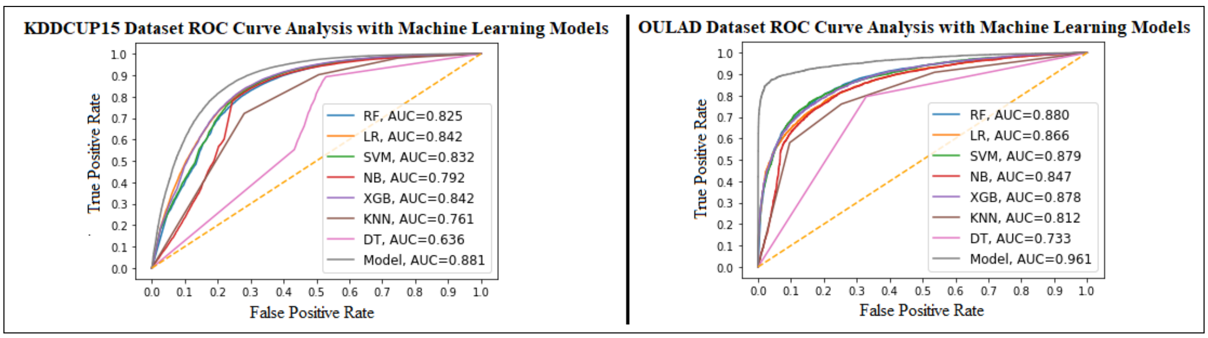


Figure 4.10: ROC curve comparative analysis with machine learning models for KDDCUP15 and OULAD datasets

The next part discusses the results of existing deep learning models with that of the proposed model results. This research aims to propose a generalized architecture that may be applicable across the institutional datasets irrespective of the various real-world contexts and diversities. So, the comparison is made on the following parameters: direct evaluation metrics values, generalizability testing with a focus on selective versus complete data usage and data specific models, and testing methodology adopted for checking real-world adaptiveness.

Table 4.5: Comparison of proposed model with baseline machine learning models

S. No.	Model	Accuracy	Precision	Recall	F1 Score
DATASET: KDDCUP15					
1	RF	0.850	0.879	0.940	0.909
2	LR	0.851	0.861	0.967	0.911
3	SVM	0.854	0.876	0.950	0.912
4	NB	0.844	0.856	0.966	0.908
5	XGB	0.855	0.876	0.953	0.913
6	kNN	0.817	0.871	0.902	0.887
7	DT	0.800	0.865	0.886	0.876
8	Proposed Model	0.876	0.893	0.959	0.925
DATASET: OULAD					
1	RF	0.800	0.759	0.832	0.794
2	LR	0.769	0.711	0.841	0.771
3	SVM	0.801	0.802	0.774	0.788
4	NB	0.672	0.592	0.936	0.725
5	XGB	0.789	0.744	0.830	0.785
6	kNN	0.753	0.721	0.760	0.740
7	DT	0.734	0.681	0.798	0.735
8	Proposed Model	0.920	0.952	0.868	0.908

Table 4.6 shows the comparison of the proposed model with the existing deep learning models. In terms of direct evaluation metrics values, the proposed model produced comparable results with respect to the models that produced higher evaluation metrics values for both datasets. For KDDCUP15 dataset, the proposed model performed better than most of the models, except one where contextual data along with clickstream data is also used [276] . Out of the considered research studies for OULAD dataset, since no other existing study considered complete data instances of withdrawn and fail classes collectively for making the at-risk predictions, the results are not directly comparable. But from the available research studies, the proposed model performs better than others in terms of AUC score as per the evaluation metrics. The accuracy parameter of the two studies seems to be higher, but partial dataset usage with ignorance of withdrawn or fail class instances may be the underlying reason [272, 303].

Table 4.6: Comparison of proposed model with existing deep learning models

Ref. No.	Model	Accuracy	Precision	Recall	F1 Score	AUC	Comments
DATASET: KDDCUP15							
[257]	CNN-RNN	0.874	0.886	0.965	0.924	0.874	Training: 120542; Testing: 4:1 split
[288]	DP-CNN	-	0.86	0.87	0.8627	0.86	Training: 120542; Testing: 4:1 split
[274]	DT-ELM	0.893	-	-	0.915	0.858	10 courses data only
[276]	CFIN	-	-	-	0.928	0.909	C with Cnx data
[304]	FWTS-CNN	0.871	0.863	0.865	0.864	-	60,000 random pieces of data
**	Proposed Model	0.876	0.893	0.959	0.925	0.881	Training: 120542; Unseen Testing: 80362; C data only
DATASET: OULAD							
[272]	LSTM	0.952	0.935	0.758	-	-	Withdrawal instances ignored
[281]	GLM	-	-	-	-	0.91	C-A-D
[294]	RNN-GRU	0.90	-	0.85	-	-	Withdrawal instances ignored; C-A-D
[303]	Deep ANN	0.886 (P-F); 0.932 (W-P)	0.93 (P-F); 0.96 (W-P)	0.69 (P-F); 0.86 (W-P)	-	-	Partial Datasets; C-D
[305]	RF	0.91 (P-F)	0.92 (P-F)	0.91 (P-F)	0.91 (P-F)	-	Partial Datasets; C-A-D
**	Proposed Model	0.920	0.952	0.868	0.908	0.961	All instances used; Unseen Testing: 10143; C only

**P-F: Pass-Fail Category; **W-P: Withdrawn-Pass Category; **C: Clickstream Data; **Cnx: Contextual Data; **A: Assessment Data; **D: Demographics Data.

When comparing based on generalizability testing, the proposed model utilizes only readily available activity logs as features with a generalized architecture across the datasets. It has taken care of all the available course and class instances (not partial or course or class-specific instances) for student pattern identification. Also, due to the inconsistency in the type of contextual data available across the datasets and avoiding specificity, this research has not included contextual data in the present study. Adding context-specific information above this generalized architecture may result in higher evaluation metrics values and may become a part of future research. While testing the real-world adaptiveness of the present study, the proposed model scores over other models across the datasets, as it uses unseen testing dataset. This makes the model more robust for handling the real-world unseen course instances. So, the results obtained for the proposed model are found to be more realistic and effective.

4.3.8 Discussion

The present study contributes largely to the growing body of literature for early identification of at-risk students through its proposed architecture. With the integration of the proposed generalized at-risk students' prediction model in different types of online, distance, and blended learning courses, this study validates the enhanced capabilities of the instructors for timely interventions. Instructors can fairly identify the at-risk students of their respective courses as early as the first quarter of their respective course lengths. Overall evaluation of the proposed model for both datasets yielded considerable results. The underlying fact for this may be due to the sequential pattern identification for daily, weekly, and monthly clickstream activities of the enrolled students. However, the patterns are not the same for both datasets. KDDCUP15 dataset is composed of courses with a course length spanning one month. In this daily activity, patterns yielded the highest results. Whereas in OULAD, the courses spanned over nine months. This is a very large time period as compared to KDDCUP15 datasets. In these, monthly activity patterns yielded the highest results. Irrespective of the evaluation metrics excellence irregularity for the independent models' pattern identification, the proposed generalized architecture produced better results for both cases. This may be since the model adjusts itself according to the identified patterns and concatenates optimal as well as sub-optimal model vectors for further dense computations. The dense computations identify the effective patterns as received through the concatenated vector input and thus help in generating efficient predictions for both datasets. So, the generalized nature tends to the adaptive-ness of the model towards the sequential identified patterns across different time periods.

The optimal time period for early identification of at-risk students for both datasets is the first quarter with a fair reliability coefficient. Here, for the KDDCUP15 dataset, the first quarter relates to the first week, *i.e.*, after the first week, the model starts giving reliable results. So, for courses spanning one month, the model has the capability of early identification of at-risk students to as early as seven days or one week. Later quartiles further add up to its evaluation metrics with moderate and perfect reliability results at later stages. For the OULAD dataset, where the course length is of nine months, the first quarter represents approximately ten weeks. After the first quartile, the model yielded results with moderate reliability. So, for the long courses spanning as long as nine months or 38-40 weeks, the predictions can be made as early as the tenth week. So, the proposed model has the capability of producing effective and efficient results at the early stages of the courses irrespective of the diversifications present within the courses, in terms of course lengths, course components, course data logs, *etc.*

This study contributes to the literature by proposing a sequential learning trajectory mining generalized architecture for the early identification of at-risk students. The use of sequential deep learning models for differential sequential trajectory mining has added to the efficiency of the system. This tracing across different time periods via three-dimensional temporal clickstream data modelling has been found to be very effective for the EWS. This may help in easy implementation for the instructors. For generalization, the results are validated on two big data educational datasets from diversified institutions, educational environments, number of courses, course lengths, course domains, *etc.* The effectiveness and generalization of the deep learning model may help the educator's community for the timely intervention of at-risk students. Through the timely interventions and aids provided to the at-risk students by the instructors in the online, distance, or blended learning courses, may lead to better student course understanding, satisfaction level, and student retention rates. Such data-driven studies can help the stakeholders in the decision-making process through early interventions. It help in improving the retention rate and quality of higher education, leading towards everlasting impact and continuous evolvement.

4.4 At-Risk Model with Assessment Data

This section discusses about the research study that uses assessment data for building the at-risk student model.

4.4.1 Overview

Considering the efficiency of the EWS, a large variety of input parameters are explored by the researchers. The data ranges from demographic and legacy data to clickstream and performance data. Out of the above, performance parameters are found to be highly influential in determining the at-risk students. But as these assessments are limited in number, so the time-span taken by these systems for early identification of at-risk students is more. Usually, it spans after mid-semester tests when fifty-sixty percent of the course is over. For blended learning environments, the educationists are experimenting with audience response systems like clickers or light-weight assessments (assessments that carry low weightage in final marks computation) (LWAs) as a replacement. The data generated by these is sent as input parameter for EWS and the results show a significant increase in the student performance along with shorter time-span prediction, discussed later in literature survey section. So, experimentation with LWAs data for online virtual learning environments, in early prediction of at-risk students seems to be promising.

Also, EWS use a variety of machine learning models for its predictions. The models can be divided into two categories. One that utilizes the cross-sectional data properties and other utilizes longitudinal data properties. The models that use longitudinal or sequential temporal data have illustrated high performance evaluation metrics as compared to other models, in recent literature. This observation may account to the fact that the considered educational data varies over time and carries within itself the sequential learning trajectory of each student. For example, a sequential activity pattern of diminishing numbers spanning over the weeks, may prove to be a better predictor, representing lower interest of the student within the course. So, explainable models exploring the sequential temporal nature of the data may also prove to be fruitful.

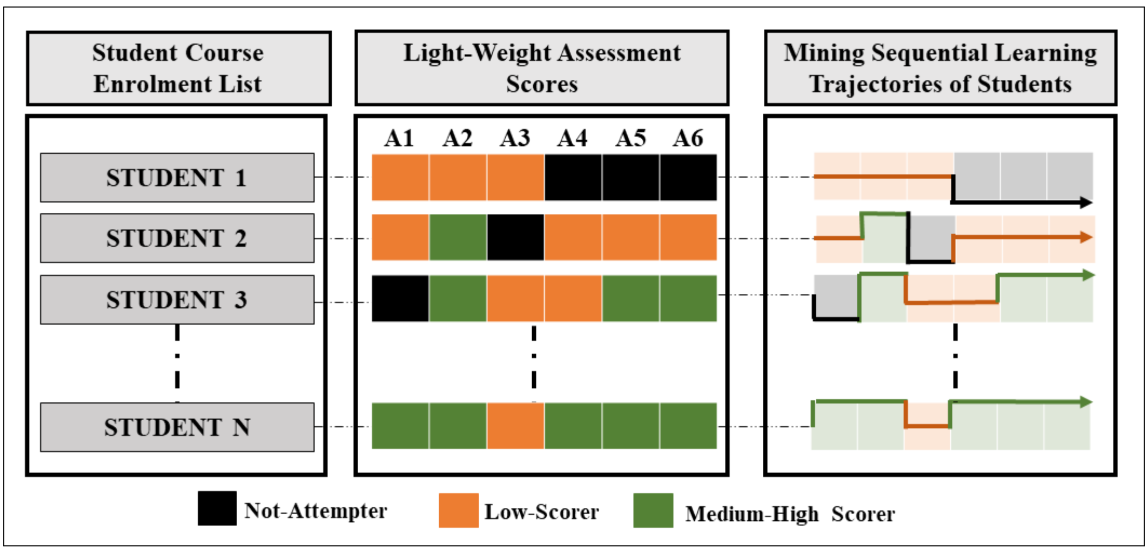


Figure 4.11: Conceptual framework for the proposed approach used in this study

This study proposes an EWS that utilizes the LWAs as input features and deploys Hidden Markov Model (HMM) for predicting the state of the student, across the course time-span. Figure 4.11 represents the conceptual design of the proposed approach. A simple, transparent and interpretable HMM, due to its remarkable property of temporal pattern recognition, was selected for student's sequential learning trajectory recognition on performance data. The predicted outcomes belong to two major classes: at-risk and safe. The study also analyses the periodic course data for identification of appropriate time period for its implementation. It identifies the relationship existing between the number of LWAs, time period and system accuracy. Further, post-model analysis of the obtained results is done for measuring the efficiency of the outcomes obtained and its associated inferences. Overall, this study contributes to literature by providing a generalized framework for the internet based pedagogy, that can be effectively embedded by the stakeholders for progressing on the path of sustainable education.

4.4.2 Contributions

This study contributes to the literature in following ways.

- Utilizes simple, transparent and interpretable HMM, due to its remarkable property of temporal pattern recognition, for student's sequential learning trajectory recognition on performance data.
- Analyses the periodic course data for identification of appropriate time period for its implementation. It identifies the relationship existing between the number of LWAs, time period and system accuracy.
- Does post-model analysis of the obtained results for measuring the efficiency of the outcomes obtained and its associated inferences.
- Providing a generalized framework for the internet based pedagogy, that can be effectively embedded by the stakeholders for progressing on the path of sustainable education.

4.4.3 Research Objectives

Research studies regarding the applicability of efficient sequential temporal models on performance data is limited. Also, the already applied models on activity-interaction data, lack interpretability of their predicted results. This redirects to a research gap where one can explore the dimension of interpretability for their successful implementation in practical educational environments. Another research gap pertains to the applicability of these models on unseen data. Usage of audience response systems like clickers have also been found to be restrictive. As it is not always possible for an instructor to have tools and technological support along with coordination for their classrooms.

For bridging the gap within the literature and experimenting with sequential nature of light-weight performance parameters through HMM and analyzing their role for early predictions in EWS, this research study poses the following research questions.

RQ1: Can light-weight assessments with sequential learning trajectory mining, assist in efficient identification of at-risk students?
RQ2: What is the optimum time for early prediction of at-risk students, using light-weight assessments?
RQ3: What is the optimum number of light-weight assessment, that can help in early identification?
RQ4: Does the proposed framework outperform other models?

4.4.4 Data Collection

The publically accessible BED OULAD was used for experimentation and validation of this study, as it had sufficient number of LWAs data embedded within in its course datasets [241]. The dataset contains 22 module presentations of 4 STEM: Science, Technology, Engineering, and Mathematics courses and 3 Social Sciences courses with 32,593 students. The seven course module presentations length approximate over 9 months. The courses have at least two module presentations each presented over different time period. The anonymized dataset contains information about the courses, enrolled students, interaction logs, assessment data *etc.* The final course result has been categorized into four classes: distinction, pass, fail and withdrawn.

Further each course has assessment data that comprises of Computer Marked Assessments (CMA), Tutor Marked Assessments (TMA) and Final Exam. The Final Exams (taken at the end of the course) data have been excluded from the public dataset, as they were scored and used for final marking purpose and course decision making. Whereas, the rest assessments (CMA and TMA) that were floated periodically within the course duration with deadlines, are included in the dataset as performance parameters. Each of these assessments carried low weightage individually and hence are termed as LWAs. The assessments that carried no weightage, were excluded considering the scope of this study. Out of seven, only six courses fulfilled the criterion and availability of LWAs data and hence, the data was extracted for each of the six course module presentations. Further details on OULAD dataset can be found in [241].

For analysis of the student performance prediction, the final result categories were merged that resulted into two-classes. There are two reasons behind this. First reason is the skewed proportion between the number of fail versus pass students. So, for elimination of class imbalance problem, similar classes were merged. Secondly, the learning assessment behaviour for fail and withdrawn as well as pass and distinction classes were found to be very much similar. This ranged in terms of attempted assessments, marks and sequential learning trajectory. Hence, the fail and withdrawn classes were merged as at-risk, representing students either at-risk of failure or at-risk of dropout from the course. Similarly, pass and distinction classes were also merged as Safe. Table 4.7 shows the course feature details with total number of students considered.

Table 4.7: Course details with number of students considered

Course	**Domain**	**Total LW Assessments**	**No. of Students**
AAA	Social Sciences	5	748
BBB	Social Sciences	11	5617
CCC	STEM	9	4434
DDD	STEM	7	4969
EEE	STEM	4	2934
FFF	STEM	5	7762

For the early prediction of the at-risk students, the dataset is also divided across the quartiles, depending upon the complete course length. Here, Q1 represents the first quartile or first 25% of the time period of the course, Q1-Q2 as the second quartile or 50% of the time period, Q2-Q3 as the third quartile and Q3-Q4 as the fourth quartile of the course. Figure 4.12 shows the frequency of LWAs being floated to the students as per their deadlines, across the quartiles.

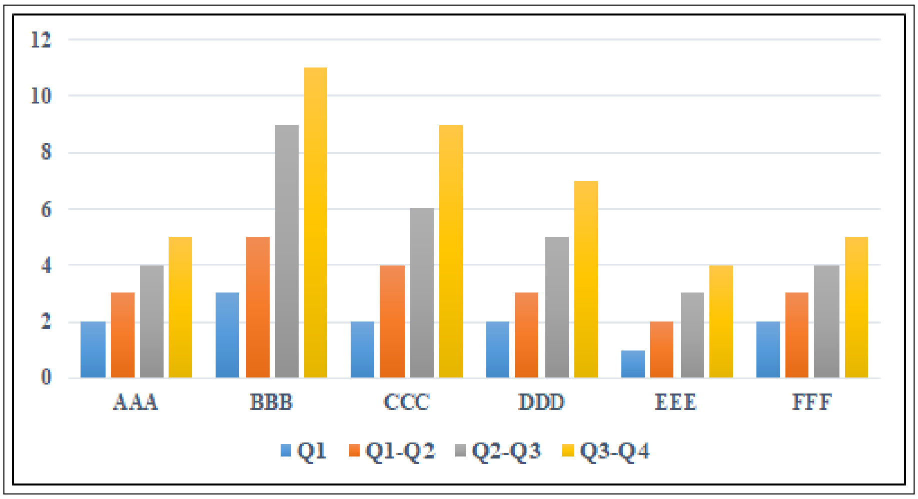


Figure 4.12: Timeline of course LWAs across quartiles

4.4.5 Methodology

This section presents the detailed discussion of the proposed system generalized architecture, dataset, data pre-processing, feature generation and HMM, employed for the execution of this research study. The proposed system architecture, as shown in Figure 4.13, comprises of three basic parts. Derived feature generation, HMM application on derived features and final predictions based on the probabilities.

4.4.5.1 Light-weight Assessment Scores: The mined temporal assessment data included LWAs as features. This dataset was further processed for obtaining the derived features as "states". These states were generated based on the following observations. An assessment contains collection of marks for the group of students who attempted it. The data when studied mathematically, mostly follows normal distribution $N(\mu, \sigma)$ [36]. The probability density function for the normal distribution is defined as:

$$g(x) = \frac{1}{\sigma\sqrt{2\pi}} exp(-\frac{1}{2}\frac{(x-\mu)^2}{\sigma^2})$$

Here μ is the mean and σ is the standard deviation. Normal distribution is symmetrical with narrow tail at both ends. Since the objective is to identify the at-risk students, so concerned area for this study is the lower tail of the normal distribution.

Considering the left-hand side fifty percent area of the normal distribution, it can be divided into two parts or quartiles. Lower quartile represents students who got lowest marks and form the lowest 25% of the student population. These students can be considered at high risk as they may opt out of the course if they continue to be in the same state. Next quartile (those between lower tail and average) are those students that are at lower risk. These can either remain in the same state or can waver their state to upper or lower, depending upon their mental or psychological perception about the assessment marks or progress within the course. The rest students lying on the right hand side of the distribution are considered as safe.

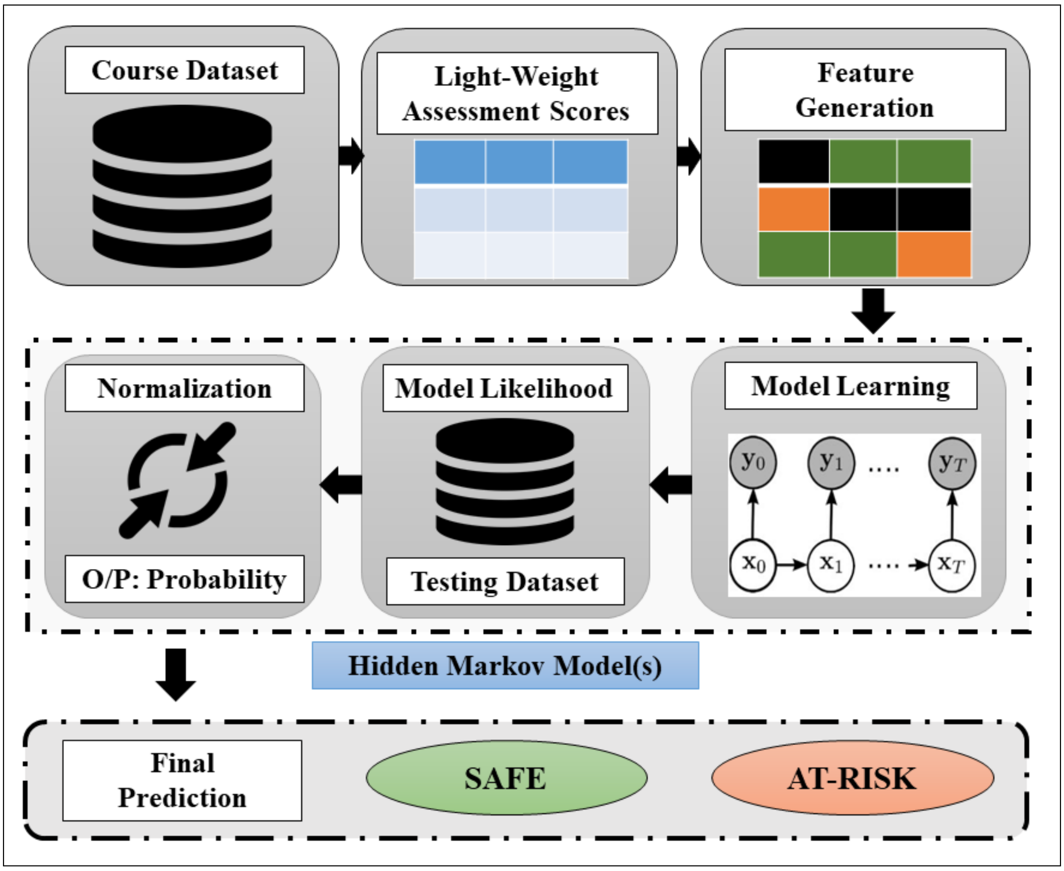


Figure 4.13: Proposed system architecture

For a medium level assessment, ideal normal curve is obtained. Ideal normal curve is symmetrical where mean is equal to the median. But for easy or difficult assessments, the distribution may be skewed. For such distributions, mean marks often mislead the data. Here median proves to be a good parameter for estimation, as it divides the complete data into two parts of fifty percent each. So, in this study median and quartiles were used for derived feature generation.

Figure 4.14 shows the sample histograms for 5 assessments in one module presentation of the course AAA for 383 students.

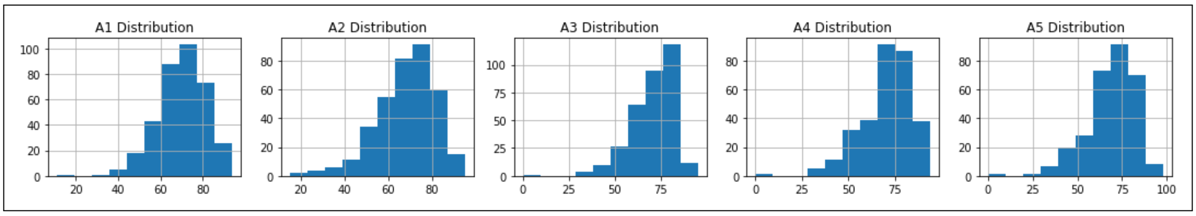


Figure 4.14: Five LWAs normal data distribution for course AAA

Considering the sorted list of N student Marks as Marks[1..N], the following formulae were used for the calculation of Median (MD) and lower quartile (LQ): If N is odd:

$$MD = Marks[\frac{N+1}{2}]$$

If N is even:

$$MD = \frac{Marks[\frac{N}{2}] + Marks[\frac{N}{2}+1]}{2}$$

If floor(N/2) is odd:

$$LQ = Marks[\frac{(floor(\frac{N}{2})+1)}{2}]$$

If floor(N/2) is even:

$$LQ = \frac{Marks[floor(\frac{N}{4})] + Marks[floor(\frac{N}{4})+1]}{2}$$

Thus, lower quartiles and median marks values of the single temporal assessment under consideration, were calculated.

4.4.5.2 Feature Generation: Once the lower quartile and median marks were obtained for an assessment, the data was encoded into observable states for each student. Mainly four states were identified.

- 'A' state for all non-attempters, *i.e.*, those students who have not-attempted the assessment.
- 'B' state for all those students, whose marks ranged between 0 to lower quartile marks.

- 'C' state for all those students, whose marks lie within the range of lower quartile to median.
- 'D' state for all those safe students, whose marks were greater than the median marks.

This procedure was repeated for all temporal assessments. Algorithm 4.3 shows the complete algorithm followed for the generation of derived features. As an output of this stage, the dataset consists of encoded student states for each assessment. These states were capable of generating learning trajectories for each student.

Algorithm 4.3: Feature generation algorithm

INPUT: 2-D Matrix of Student Scores across different light-weight assessments: score $[1..M, 1..N]$
OUTPUT: Encoded matrix of student scores $encoded\_scores[1..M, 1..N]$
ASSUMPTION: All scores are non-negative
Step 1: Initialize 2-D matrix: $encoded\_scores[1..M, 1..N]$ **Step 2:** for j in $score[, 1..N]$: **Step 3:** $lower\_quartile, median = Quartile\_Calculation(score[, j])$ **Step 4:** for i in $score[1..M, j]$: **Step 5:** if $score[i, j]$ == NA: **Step 6:** $encoded\_scores[i, j]$ = A // Encoded Observed State for Not-Attempted **Step 7:** else if $score[i, j] >= 0$ *and* $<= lower\_quartile$: **Step 8:** $encoded\_scores[i, j]$ = B // Encoded Observed State for Student at High-Risk **Step 9:** else if $score[i, j] > lower\_quartile$ *and* $<= median$: **Step 10:** $encoded\_scores[i, j]$ = C // Encoded Observed for Student at Low-Risk **Step 11:** else if $score[i, j] > median$: **Step 12:** $encoded\_scores[i, j]$ = D // Encoded Observed State for Safe Student **Step 13:** return $encoded\_scores[1..M, 1..N]$

4.4.5.3 Hidden Markov Model: According to Rabiner, HMM is a "doubly stochastic process with an underlying stochastic process that is not observable (it is hidden), but can only be observed through another set of stochastic processes that produce the sequence of observations" [11]. HMMs have the capability to represent time-varying processes under a probabilistic or statistical framework. That is why their applications range from natural language processing to bioinformatics [8, 13]. A very brief introduction to discrete HMMs along with its applications, relevant for this study is described below.

An HMM has the following components [240]: $HMM \in Q, O, A, B, \pi$ where $Q = q_1, q_2, .., q_N$ representing the set of N hidden states, here q_t represents state at time t; $O = o_1, o_2, .., o_T$ represents number of distinct observation symbols per state from vocabulary $V = v_1, v_2, ..v_V$; $A = a_{11}, a_{12}, ..a_{ij} \ldots, a_{nn}$ is transition probability matrix, each a_{ij} representing the probability of transition from state i to state j $a_{ij} = p(q_{t+1} = j|q_t = i)$ such that $\sum_{j=1}^{n} a_{ij} = 1 \; \forall \; i$; B represents the emission probability matrix and is represented as $b_i(o_t)$, which means the probability of an observation ot being generated from a state $ib_i(k) = p(o_t = k|q_t = i)$; and $\pi = \pi_1, \pi_2, \ldots \pi_N$ described as initial probability distribution over the states $\pi_i = p(q_1 = i)$ and $\sum_{i=1}^{n} \pi_i = 1$. A first-order HMM makes two basic assumptions: Markov Assumption, *i.e.*, the probability of a particular state depends only on the previous state and Output independence, *i.e.*, the probability of an output observation depends only on the state that produced that observation. A compact notation of HMM as $\lambda = (A, B, \pi)$ is used further for indicating a completely specified model. Out of the three fundamental problems solved by HMMs, only two are discussed here, as per the scope of this study.

- **Model Learning:** With the generated observable features (learning sequences) and training data, the next step involved training of two different HMMs (one for each class) for optimization of initial, transition and emission probabilities, respectively. This was done using the Learning problem for HMMs which states that, "given an observation sequence O and set of states in the HMM, learn the HMM parameters A, B and π." This uses iterative forward-backward algorithm as a solution. The iterative forward-backward algorithm starts with some initialized values for A, B and π.

  It then iteratively runs in two stages: E-step (Expectation) and M-step (Maximization) until the convergence criterion is met [240]. In E-step, expected state occupancy count γ and expected state transition count ξ are computed from earlier provided A and B probabilities:

$$\gamma_t\;(j) = \frac{\alpha_t(j)\;\beta_t(j)}{\alpha_T(q_F)}\;\forall\; t\; and\; j$$

$$\xi_t(i,j) = \frac{\alpha_t(i)\;a_{ij}\;b_j(o_{t+1})\;\beta_{t+1}(j)}{\alpha_T(q_F)}\;\forall\; t,\; i\; and\; j$$

Later in M-step, these are only used for re-computing the values of new A and B:

$$\hat{a}_{ij} = \frac{\sum_{t=1}^{T-1} \xi_t(i,j)}{\sum_{t=1}^{T-1} \sum_{k=1}^{N} \xi_t(i,k)}$$

$$\hat{b}_j(v_k) = \frac{\sum_{t=1 \ s.t. \ o_t=v_k}^{T} \gamma_t(j)}{\sum_{t=1}^{T} \gamma_t(j)}$$

When the algorithm converges, optimized HMM $\lambda = (A, B, \pi)$ is returned as output. In context of the present study, the generated learning sequences were mapped to the observable states O {A, B, C, D}. For Q, *i.e.*, number of hidden states, BIC (Bayesian Information Criterion) scores were used for finding the optimal number of hidden states for respective class model. The lower the BIC score, better is the model performance. Sample BIC scores obtained during the selection procedure of the optimal hidden states for the course AAA is shown in Table 4.8. Here 3 hidden states for Safe class HMM and 3 hidden states for At-Risk class HMM, were selected. A, B and π were initialized to equally distributed values, in order to avoid any biases at later stages. With these initializations, two HMM models with respect to two different classes were trained.

Table 4.8: BIC values for HMM hidden states in course AAA

S. No.	Number of Hidden States in HMM	BIC Value for Safe Class	BIC Value for At-Risk Class
1	2	2504.105	1007.800
2	3	2492.474	989.009
3	4	2554.539	1038.603
4	5	2626.865	1103.411

The optimized HMM models hidden states for each course is shown in Figure 4.15. It contains the detailed information regarding the number of hidden states and their transition probabilities for two different Safe and At-Risk models, for each course. These are accountable for model interpretability and behaviour identification of the two class students.

- **Model Likelihood:** For each course, two trained and optimized HMM models, one for each class (Safe and At-Risk), exist. Now, testing dataset observations were provided to these optimized HMMs. Corresponding likelihood probabilities of observed states were generated, for each model. These were calculated using the likelihood computation problem of HMMs which states "Given an HMM $\lambda = (A, B, \pi)$ and an observation sequence O, determine the likelihood $P(O|\lambda)$." It uses the forward algorithm. It sums over the probabilities of all possible hidden state paths that could result in the observation sequence as shown below [240]:

Initialization:

$$\alpha_t(j) = \pi_j \; b_j \; (o_1) \; 1 <= j <= N, \; t = 1$$

Recursion:

$$\alpha_t(j) = \sum_{i=1}^{N} \alpha_{t-1}(i) \; a_{ij} \; b_j(o_t); \; 1 <= j <= N, \; 1 < t <= T$$

Termination:

$$P(O|\lambda) = \sum_{i=1}^{N} \alpha_T(i)$$

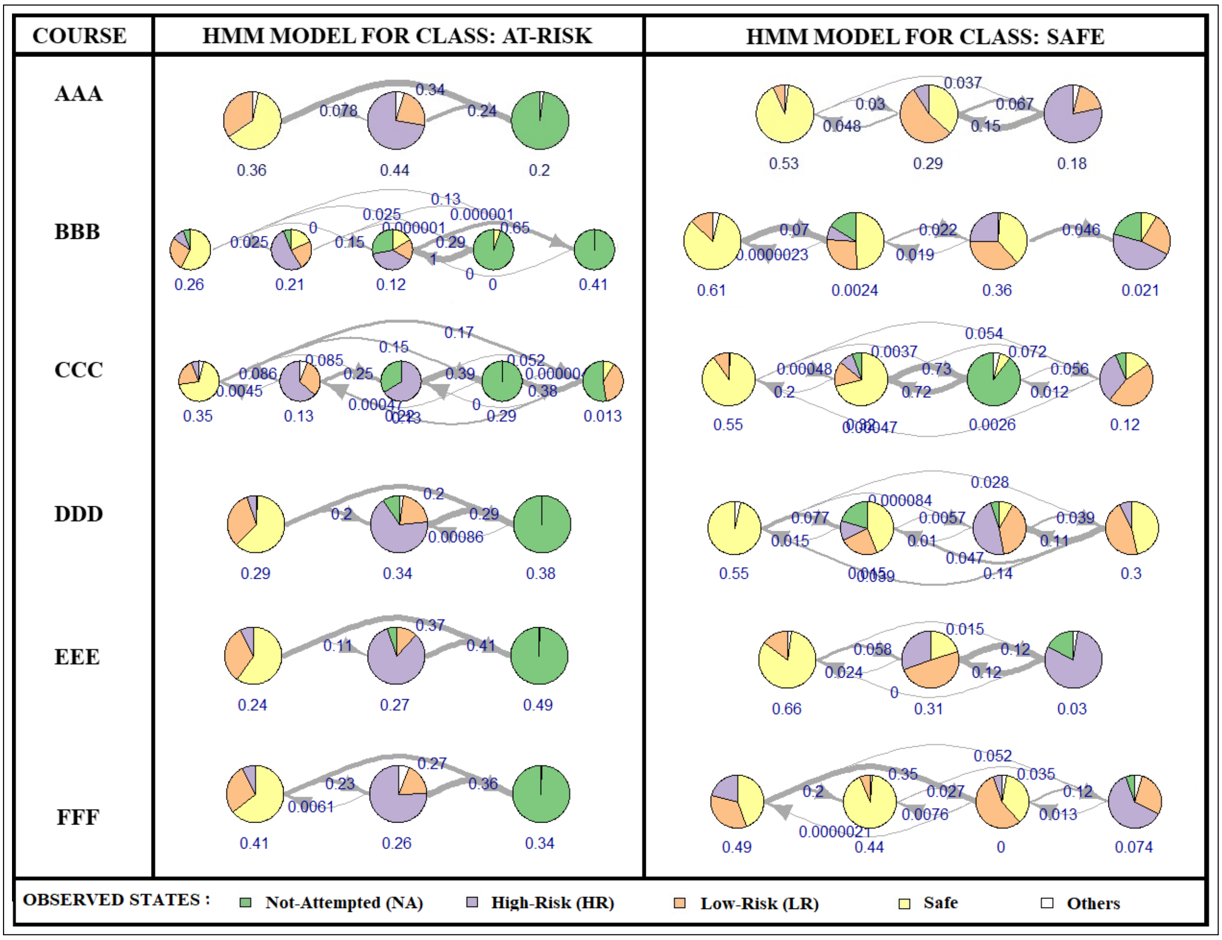


Figure 4.15: Two different class based optimized HMMs with hidden states for each course

As an output of this phase, likelihood probabilities for each model were obtained. Normalization Since the obtained likelihood probabilities varied and were not normalized, a normalization procedure was carried out in order to sum up the probabilities to 1. The following formulae were used for this purpose:

$$P_n(Safe|\lambda) = \frac{P(Safe|\lambda)}{(P(Safe|\lambda) + P(At - Risk|\lambda))}$$

$$P_n(At - Risk|\lambda) = \frac{P(At - Risk|\lambda)}{(P(Safe|\lambda) + P(At - Risk|\lambda))}$$

$$P(Safe|\lambda) + P(At - Risk|\lambda) = 1$$

The output contained final normalized predicted probabilities for each class, Safe and At-Risk. Final Prediction With a basic threshold of 0.5 (50% for binary class problem), the class having the probability greater than the threshold was predicted as the final class for the student. Thus, for each student the respective class, Safe or At-Risk, was predicted.

4.4.6 Data Analysis

The analysis of the proposed system was performed through OULA dataset. For this, six course datasets were separated into training and testing data. As each course carried at least two module presentations, so the course data was divided into two parts: training dataset and testing dataset. In each course, one last or latest module presentation was reserved for testing purpose whereas all earlier presentations were used as training dataset. However, if the module presentations were inconsistent about the number of assessments floated, then the inconsistent presentation data was skipped. The detailed course description of the training dataset and testing dataset size are shown in Table 4.9. As the datasets carried multiple observation sequences, seqHMM of R language with global optimization for EM algorithm, was used for its implementation [232].

As per the research questions, the study carried over two-fold analysis. One comprised of overall course student performance prediction whereas another one considered quarterly data. The analysis was performed on the following evaluation parameters: Accuracy, AUC, Precision, Recall, F1-Score and Cohen's kappa statistics.

Table 4.9: Course training and testing dataset details

Course	**Train Size**			**Test Size**
	Safe	**At-Risk**	**Total**	
AAA	278	105	383	365
BBB	1875	2129	4004	1613
CCC	1015	1483	2498	1936
DDD	1308	1858	3166	1803
EEE	966	780	1746	1188
FFF	2531	2866	5397	2365

4.4.7 Results

Further results are represented as per the research questions for this study:

RQ1: *Can light-weight assessments with sequential learning trajectory mining, assist in efficient identification of at-risk students?*

To answer this research question, the overall prediction results for safe and at-risk classes were calculated and considered. With the help of proposed architecture, end probabilities with threshold based predictions were calculated. The predicted results were compared with actual results and respective evaluation metrics were generated. Table 4.10 and Figure 4.16 show the overall analysis parameters of the courses over complete course time-span.

All the courses except AAA, are having an accuracy greater than 90%. Course CCC reported the highest accuracy of 94.83% and F1 score of 0.926. Correspondingly, kappa statistic also binned into the 0.81-1 slot, representing almost perfect reliability results. Only AAA course was an exception with considerable kappa statistic and 0.909 F1 score. For measuring the effectiveness of EWS (minimize false negative cases while not-increasing false positives), ROC-AUC curve is also used as a distinguishing parameter. Fig. 6 shows the ROC-AUC curve for all courses. The AUC values ranged from 0.927 for course AAA to 0.989 for course CCC. The comparatively lower metrics of course AAA, pertain to its lowest training data size, *i.e.*, 278 and 105. The basic requirement of training of HMM is that it works on sufficiently large data [8]. Due to sufficient number of training data for all courses except AAA, all course models yielded good results. However, course AAA with exceptionally small training data size resulted in comparatively lower accuracy (87.67%) with considerable Cohen's Kappa coefficient as 0.719.

Table 4.10: Performance parameters for 6 courses

Courses	Accuracy	Precision	Recall	F1 Score	Kappa
AAA	87.67	93.33	88.54	0.909	0.719
BBB	91.20	88.24	92.85	0.905	0.823
CCC	94.83	90.98	94.27	0.926	0.886
DDD	92.40	85.71	99.24	0.920	0.848
EEE	92.93	94.64	92.98	0.938	0.856
FFF	93.40	94.20	91.67	0.929	0.867

The thorough analysis of the evaluation metrics suggests that LWAs with sequential learning trajectory mining can assist the instructors. The sequential learning trajectory for LWAs has also proved to be the better choice as compared to other baseline models considering independent inputs as discussed in detail in RQ4. With the help of HMMs, sequential learning trajectories can easily and effectively identify the at-risk students of the course. The very high ROC-AUC values show that the model is capable enough of efficiently distinguishing between the two classes. And with the help of the proposed process, the lower accuracies specifically for at-risk classes can also be mitigated.

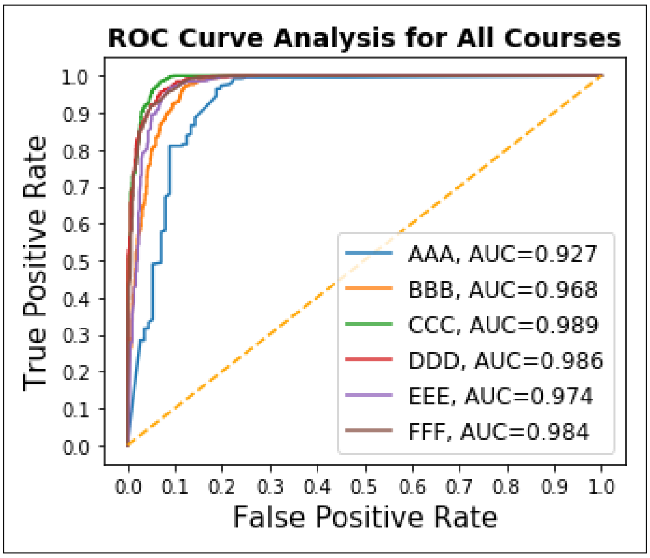


Figure 4.16: ROC curve with AUC values for 6 courses

RQ2: *What is the optimum time for early prediction of at-risk students, using light-weight assessments?*

To answer this research question, the course spans were divided into smaller time periods. Across these, the obtained prediction results were analyzed with the help of evaluation metrics. The "early" time period that had considerable reliability coefficient values across most of the courses, is identified as the "early" optimum time when the instructors can start relying on the obtained predictions.

Table 4.11: Quarterly performance parameters for 6 courses

Courses	Total No. of LWAs	Accuracy	Precision	Recall	F1 Score	Kappa
Q1						
AAA	2	76.44	86.15	78.66	0.822	0.475
BBB	3	77.93	72.00	83.49	0.773	0.561
CCC	2	77.69	61.54	92.91	0.740	0.559
DDD	2	78.09	69.56	89.14	0.781	0.568
EEE	1	-	-	-	-	-
FFF	2	83.55	79.84	87.20	0.833	0.672
Q1-Q2						
AAA	3	82.19	88.52	85.38	0.869	0.591
BBB	5	85.43	79.50	91.20	0.849	0.710
CCC	4	86.98	76.11	90.35	0.826	0.723
DDD	3	80.03	70.42	94.07	0.805	0.609
EEE	2	85.61	85.28	90.64	0.879	0.702
FFF	3	88.54	84.56	92.66	0.884	0.771
Q1-Q3						
AAA	4	83.84	92.17	83.79	0.878	0.641
BBB	9	89.71	85.02	93.67	0.891	0.794
CCC	6	92.15	85.34	93.06	0.890	0.829
DDD	5	86.30	77.72	96.46	0.861	0.729
EEE	3	90.32	90.13	93.42	0.917	0.801
FFF	4	91.46	88.80	93.73	0.912	0.829
Q1-Q4						
AAA	5	87.67	93.33	88.54	0.909	0.719
BBB	11	91.20	88.24	92.85	0.905	0.823
CCC	9	94.83	90.98	94.27	0.926	0.886
DDD	7	92.40	85.71	99.24	0.920	0.848
EEE	4	92.93	94.64	92.98	0.938	0.856
FFF	5	93.40	94.20	91.67	0.929	0.867

For determining the optimum time for early predictions, cumulative time-periods were used, to count the time from start of the course. So, Q1, Q1-Q2, Q1-Q3 and Q1-Q4 data was analyzed. Table 4.11 shows the detailed evaluation parameters along with number of LWA for different timespans. For Q1, course EEE parameters are blank, as for this course only 1 assessment was floated, during initial 25% of the course coverage. Whereas for the processing and application of HMM, a sequential transition between at least two states is required. Due to this, no predictions were made for this course during this time period. Also, for Q1, FFF course reported a highest accuracy of 83.55% with Cohen's kappa as 0.672. For courses BBB, CCC and DDD approximated over an accuracy of 78% with Cohen's kappa averaging over 0.56. Maximum number of assessments floated were 3 in course BBB.

For Q1-Q2, maximum number of assignments floated were 5 for course BBB. All the accuracies crossed 80% with highest being for course CCC (86.98%) with 0.723 Cohen's kappa. For Q1-Q3, for some courses the accuracy values were greater than 90%, with almost perfect kappa reliability value lying between 0.81-1. The maximum number of assessments floated in this period were 9 for the course BBB. Accuracy was reportedly highest for course CCC as 92.15% and Cohen's kappa as 0.829. Course AAA reported the lowest accuracy of 83.84% with lowest kappa statistic as 0.641.

For final Q1-Q4, all courses except AAA crossed an accuracy of 90% with almost perfect reliability of Cohen's kappa. Total number of assessments floated were highest for course BBB, *i.e.*, 11. A highest recall value of 99.24% is obtained for course DDD. Course EEE held the highest precision value as 94.64% and F1 score as 0.938. Accuracy: 94.83% was highest for the course CCC along with highest Cohen's kappa as 0.886. In Table 4.11, highlighted values represent the higher stability within the course results where models achieve higher accuracies along with almost perfect agreements with respect to kappa values.

Figure 4.17 shows the ROC Curve statistics across the quarters for all courses. For courses EEE Q1 curve is missing due to earlier stated reasons. The highest AUC values for all courses are achieved in Q1-Q4. However, for all courses the AUC values showed their highest deviation between Q1-Q2 and Q1-Q3 course spans. After that there was small incremental increase as compared to earlier ones due to their convergence.

Further incremental deviations across the courses for Q1-Q2 and Q1-Q3 also depended on the number of assessments floated for that time span. If the number of assessments floated were larger in Q1-Q2 than Q2-Q3, then there is larger incremental deviation between Q1 and Q1-Q2 than Q1-Q2 and Q1-Q3. Similarly, vice versa holds.

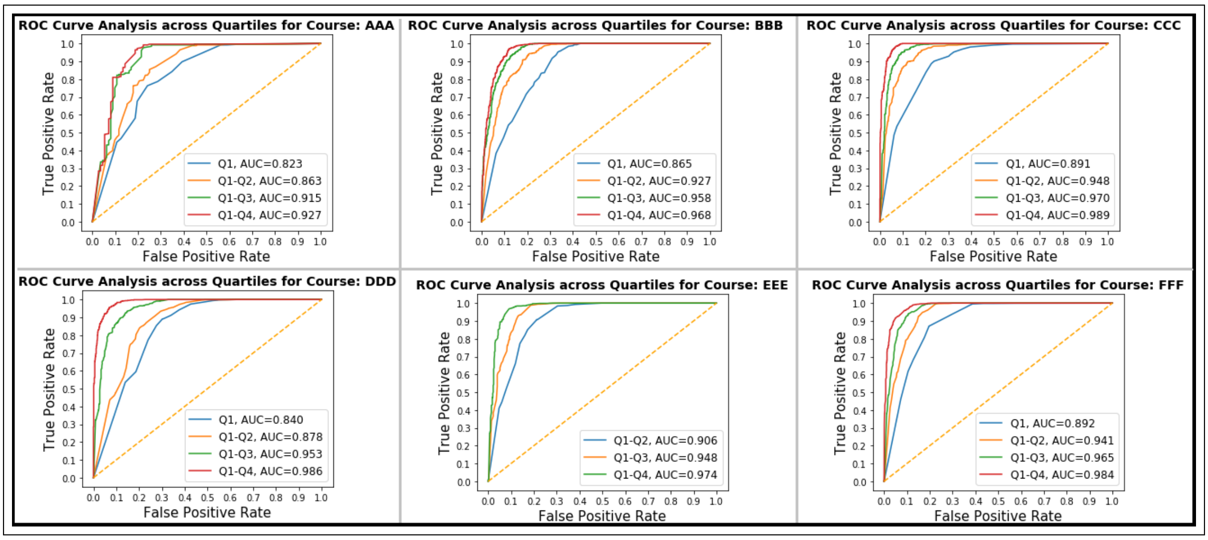


Figure 4.17: Quarterly ROC curves with AUC values for all 6 courses

The optimum time for prediction of at-risk students using LWAs, is suggested to be between Q1-Q2. With Q1-Q2, it means that if a course spans over 12 weeks, then optimum time for its implementation is between 3-6 weeks. Or else, if it has a duration of 32 weeks, then the optimum time for its implementation is between 8-16 weeks. A necessary condition for this is: it must also be accompanied with sufficient number of LWAs. Here, sufficient number of LWAs means enough LWAs (*i.e.* 2 at least) such that a learning trajectory can be made as per the model requirements. The above suggestion can be drawn as per the observations of the quarterly evaluation metrics parameters. Even predictions were not generated for some courses due to lack of sufficient assessments in this span. The initial Q1 values are not very reliable as stated by the Cohen's kappa. However, as the courses rolled ahead in Q1-Q2 span, the accuracies begin to elevate with all values above 80%. The reliability coefficients for this span also lie in considerable category. The AUC values were also higher for this phase and showed the model's significant distinguishing capability.

Although the metrics further were more accurate and gave stabilized results in subsequent quarters, but Q1-Q2 (25%-50% of the course coverage period) can be considered as the starting point for getting substantial results. These can further help in providing timely actionable data to the teaching fraternity. Through these timely stabilized predictions, the appropriate steps like counselling, providing timely and readily available gap-bridging additional resources and course contents, problem solving sessions *etc.* can be taken by the instructors for minimizing the loss of interest and at-risk student behaviour.

RQ3: *What is the optimum number of light-weight assessment, that can help in early identification?*

To answer this research question, three parameters namely accuracy, no. of assessments and time periods were considered. For finding the relationship between these parameters, linear and multiple regression analysis was performed. The objective was to identify whether number of assessments is directly proportional to the accuracy or there is involvement of some other factors as well. Evaluating output results with significant coefficient values, the recommendations regarding the optimum number of LWAs that can be floated by the instructors for obtaining reliable results, were made.

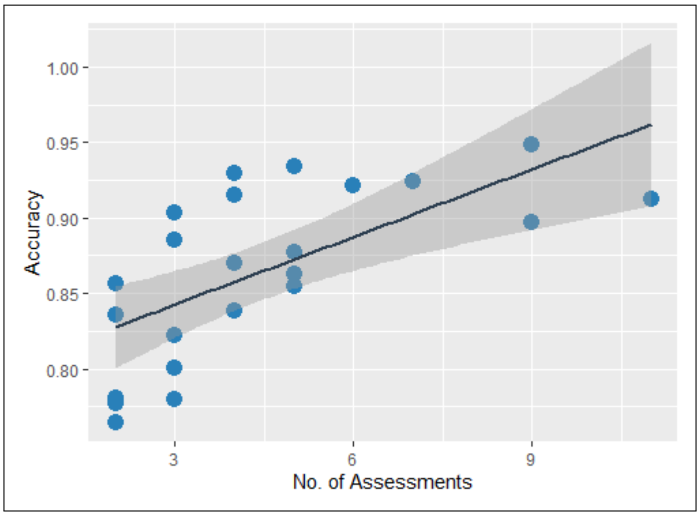


Figure 4.18: Relationship between accuracy and number of LWAs

For finding the optimum number of LWAs, a Pearson's correlation test along with simple linear regression was performed between the number of assessments floated (N) versus model accuracy. The statistics revealed a correlation value of 0.655 which was found to be significant at 0.001 level of significance (p-value: 0.0006893). It represented some positive correlation between number of assignments and accuracy. However linear regression yielded a linear relation as follows with R-squared (coverage) value of 0.4294:

$$Accuracy = 0.7978 + 0.0149 * N$$

Figure 4.18 shows the data with fitted linear regression line. As the R-squared test-statistic values were comparatively low, a multiple regression was performed between accuracy, quartiles (T) and number of floated assessments (N). This measured the effect of increasing number of assessments over a time span on the system accuracy. The regression line in 3-D plane is shown in Figure 4.19 and had the following relation:

$$Accuracy = 0.7518 + 0.0411 * T + 0.0017 * N$$

The R-squared test statistic value for multiple regression was: 0.7538. The F-Test statistic value also showed a value of 30.63 with 2 and 20 degrees of freedom and p-value as 0.0000000817. The above statistics reveal highly significant values at 0.001 significance level. The graph also displays that as the number of LWAs increase over time, the accuracy improves. For some courses, those having higher number of assessments in Q1-Q2 phase, the accuracy is also comparatively higher. In Q1-Q3 phase most of the courses achieved higher accuracy, except those having comparatively lower number of assessments. Similarly, for Q1-Q4 phase, the accuracy is highest as all courses have largest number of floated assessments.

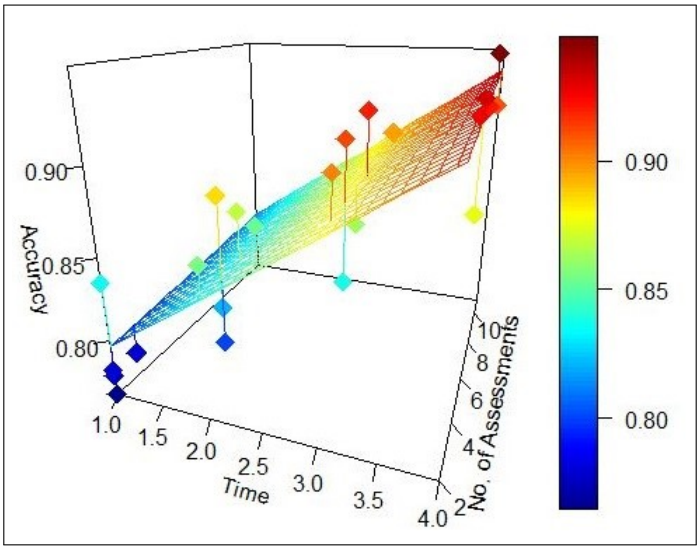


Figure 4.19: Relationship between accuracy, quartiles and number of LWAs

For determining the optimum number of LWAs above stated statistical tests were performed. The results suggested that if the LWAs are linearly increased over the time, then a higher accuracy is achieved. As per the analysis, increasing LWAs at the start of the course might not obtain fruitful results. The students are found to be better adapting and responding once they establish themselves within the course, over the time. This responding nature with time further helps the model in distinguishing between the behavioural traits of the safe and at-risk students. Based on the experimented dataset used in this study, the ideal LWAs that can be floated amongst the students can vary from 3-6 till Q1-Q2 and 7-11 from Q1-Q4, depends on the nature of the course under consideration.

A noticeable point here is that for every course, either having large number of LWAs or low number of LWAs, the results started to stabilize and converged when a transition from Q3 to Q4 was encountered. So, any further increase in the number of assessments at later stages is not expected to have any major impact on the evaluation parameters of the respective courses, for identification of the at-risk students.

Further, it is also observed that, amongst the courses, there is no clear demarcation in terms of evaluation parameters. For example, let us consider Q1-Q2, where for courses AAA, DDD and FFF, 3 LWAs were floated, but their accuracies varied from 82.19%, 80.03% and 88.54% respectively. This shows the dependency of results on other unseen factors too. The unseen factors may range from major, streams, involved instructors, their impact to implemented teaching pedagogy *etc.* Since they are not directly measurable through the given dataset, so they are out of scope for this study.

RQ4: *Does the proposed framework outperform other models?*

The comparison of HMM model's predictions with other existing baseline models, as per the literature survey, was performed on various evaluation parameters. The baseline models considered are: SVM: Support Vector Machine Classifier with kernel: rbf, degree 3, gamma: scale and decision function shape as one-vs-rest; RF: Random Forest Classifier with number of estimators: 100, criterion: gini, and minimum sample splits: 2; LR: Logistic Regression Classifier with solver: lbfgs, penalty: l2, tolerance: 0.0001, fit intercept: true and maximum iterations: 100; and DNN: Deep Neural Network with 3 hidden layers each comprising of 100 neurons, activations functions: relu and sigmoid, optimizer: rmsprop, loss: binary crossentropy, $batch_size$: 32 and epochs: 100 with convergence criterion.

The results of the comparison are shown in Table 4.12. As all the baseline models treat features as independent variables, so feature generation module binned outputs were not utilized for baseline models prediction. The HMM model outperformed all other models in all courses except one. As already stated, HMM made sub-optimal predictions and has underperformed in course AAA due to its extremely small sized training dataset. So, for course AAA, Logistic Regression is the best model with 91.51% accuracy and comparable 0.93 ROC-AUC value. For rest courses: BBB, CCC, DDD, EEE and FFF, HMM outperformed all baseline models and made the best optimal and reliable predictions across all parameters: Accuracy, F1 Score, Cohen's Kappa and ROC-AUC value. As per the comparative analysis of Table 4.12, the sequential learning trajectories as identified by sequential HMM model, have their relevance in effective identification of at-risk students.

4.4.8 Post-Model Analysis

For better HMM model interpretability, a post-model analysis was performed for determining the model behaviour, *i.e.*, exactly where it has gone wrong in determining the False Positive and False Negative cases. For this the baseline model was spanning hundred percent of the course time-span, *i.e.*, Q1-Q4. The hidden states along with associated probabilities of the HMM models generated for Safe and At-Risk classes helped in identification of the behaviour of the students for respective courses (Figure 4.15).

Table 4.12: Comparison with baseline models

		COURSE: AAA				**COURSE: BBB**				**COURSE: CCC**			
Sno	*Model*	*Accuracy*	*F1 Score*	*Kappa*	*ROC-AUC*	*Accuracy*	*F1 Score*	*Kappa*	*ROC-AUC*	*Accuracy*	*F1 Score*	*Kappa*	*ROC-AUC*
1	**SVM**	81.10	0.88	0.47	0.87	75.88	0.79	0.54	0.80	75.83	0.74	0.54	0.95
2	**RF**	89.04	0.92	0.74	0.90	84.62	0.84	0.69	0.92	92.41	0.89	0.83	0.98
3	**LR**	91.51	0.94	0.79	0.93	89.21	0.89	0.79	0.96	92.67	0.89	0.84	0.98
4	**DNN**	89.86	0.93	0.75	0.91	87.41	0.87	0.75	0.94	92.15	0.89	0.83	0.96
5	**HMM**	87.67	0.91	0.72	0.93	91.20	0.90	0.82	0.97	94.83	0.93	0.89	0.99
		COURSE: DDD				**COURSE: EEE**				**COURSE: FFF**			
Sno	*Model*	*Accuracy*	*F1 Score*	*Kappa*	*ROC-AUC*	*Accuracy*	*F1 Score*	*Kappa*	*ROC-AUC*	*Accuracy*	*F1 Score*	*Kappa*	*ROC-AUC*
1	**SVM**	73.04	0.77	0.49	0.92	86.03	0.89	0.71	0.88	87.10	0.88	0.74	0.95
2	**RF**	87.19	0.87	0.75	0.95	83.33	0.86	0.66	0.88	90.95	0.91	0.82	0.96
3	**LR**	88.57	0.88	0.77	0.97	86.45	0.89	0.71	0.92	92.09	0.92	0.84	0.97
4	**DNN**	87.52	0.87	0.75	0.96	85.44	0.88	0.70	0.91	91.75	0.92	0.84	0.97
5	**HMM**	92.40	0.92	0.85	0.99	92.93	0.94	0.86	0.97	93.40	0.93	0.87	0.98

From start of the course till course end, three generalized behaviours for at-risk students have been identified. Explorers: These may be the students who often dropout from the course. They register, explore but do not take part within the course activities.

Strugglers: These students persist in the course but due to consistent low performance loss interest within the course and dropout or fail. Sporadic Learners: Students who start with exceptional safe behaviour initially, but later with strong probability transit to high-risk states or become non attempters. For example, for course EEE, 49% at-risk students do not attempt the LWAs and remain within that state throughout that course. Whereas 27% at-risk students from the starting are at high-risk and later transit to not-attempted states with 0.41 probability. Rest 24% at-risk students are sporadic learners and later with 0.37 probability transit to non-attempted state. With the help of these states, sequential state transitions of students across all LWAs were plotted against the course time span on four confusion matrix categories: True-Positive (At-Risk), False-Positive (Predicted as At-Risk but belong to Safe class), False-Negative (Predicted as Safe but belong to At-Risk class) and True-Negative (Safe). The graphs obtained for 6 courses are shown in Figure 4.20. Here encoding used is as follows: True-Positive(At-Risk) as 0, False-Positive as 1, False-Negative as 2, True-Negative(Safe) as 3.

For all graphs, the state transitions as predicted by HMM model for all four categories is shown within the Fig. 10. After analysis of these graphs, the observations reveal that the students predicted as Safe (actual class: At-Risk) show a sequential transition history that is comparatively closely similar to the at-risk students, *i.e.*, they are comparatively low scorers or at later stages have become non-attempters or low-scorers. Similarly, for predicted at-risk students (actual class: Safe), they also show a sequential transition history that is comparatively similar to the Safe students, *i.e.*, they are comparatively high scorers.

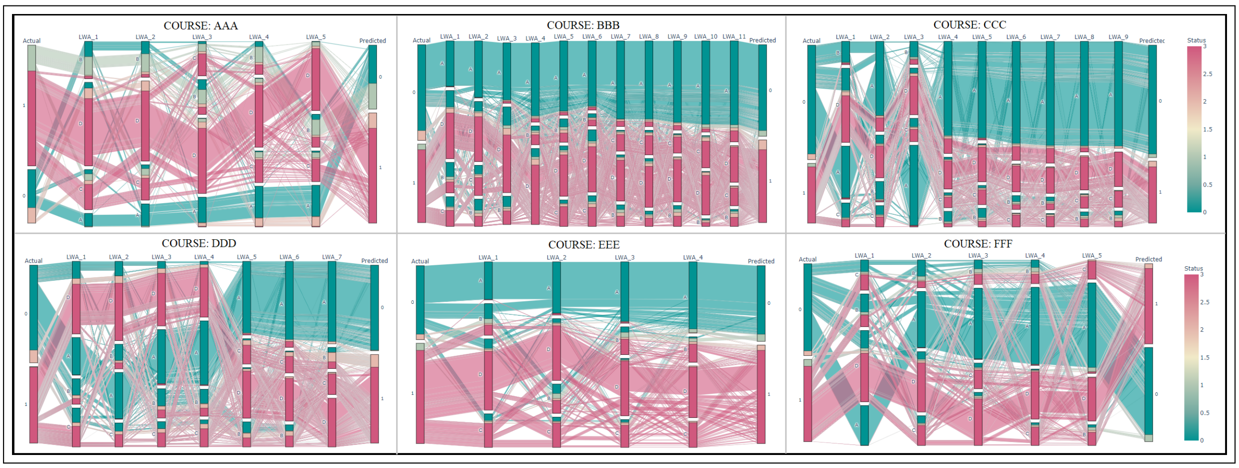


Figure 4.20: Post-Model analysis for safe and at-risk students' state transitions across the LWAs for 6 courses

Post analysis model results reveal the correctness of the misclassifications done by the model. The sequential learning trajectories for the false positive and false negative cases are actually matching to the classes in which they are predicted. The learning trajectory of the students misclassified as at-risk, matched more with the at-risk student's trajectories. So, the model classified them as at-risk. According to their learning behaviour, these students may be categorized as inconsistent and last-minute performers. With respect to the students under consideration for a particular course, these were not good scorers and have shown a lower learning path throughout the course. However, they must have peaked at the end of the course by scoring more than the minimum passing marks in Final Exam. This may account for the non-serious nature of students for LWAs. Similarly, the learning trajectory of the students misclassified as safe, matched more with the safe student's trajectories as compared to the at-risk students. Comparatively, these students can be categorized as consistent performers. But maybe, due to some end-time problems or other unseen reasons, they have either not appeared for final exams or did not score minimum passing marks.

4.4.9 Discussion

This study contributes to the literature by proposing a sequential learning trajectory mining framework for early identification of at-risk students. This tracing via light-weight assessments have been found to be very effective for the EWS. Use of HMM for sequential trajectory mining have added to the efficiency of the system. The effectiveness and interpretability of HMMs may help the educator's community for timely intervention of at-risk students. This may further help in improving the retention rates. As an outcome of this study, it is suggested for embedding light-weight assessments in-between the online courses for effective management. These may include small formative quiz or an automated assignment *etc.*, for periodic testing of the conceptual understanding. The instructors may find different ways for embedding these light-weight assessments in their online pedagogical design for effective results. The pedagogical experts can even formulate newer pedagogical designs and help the authorities for timely tracing of the digital patterns involved in students learning. This study used withdrawal and fail students' classes collectively. Future research may include independent study of these classes for detailed behavioural analysis of students. This study may further be combined with multiview learning across the institutions and environments, for generalized institutional level support and effective decision making.

4.5 Limitations

This section presents the limitations of the two case studies. For the first case study, as per the limited availability of different types of logs across the datasets, no other data logs are used for the development of the proposed model except the clickstream data logs. However, extending the proposed model with the availability and concatenation of demographics, assessment data, *etc.*, may add further to the evaluation metrics of the datasets. Further, the interrelated course and learner's information may help to identify the actual learning behaviour of the students across the courses. Concatenation of this learning behaviour for every student may help the model for effective and efficient binary classification and elevate the evaluation metrics. Also, for early identification of at-risk students, this study pre-divided the course length into quartiles representing 25%, 50%, 75%, and 100% of the course length. Time-period division with smaller course lengths like pentiles, deciles, or varying length percentiles may also be investigated further.

Considering the limitations of the second case study, it is performed on the dataset that belongs to single institution's virtual learning environment. Supporting multi-institutional studies across the various learning environments can further strengthen its generalizability. This study does not leverage upon the contextual information of the students like demographic, family background *etc.* As the proposed model rely on LWAs performance parameters only, the results may vary depending upon the notion and seriousness of involved students regarding LWAs. Also, as per the limitation of HMM, the predictions were not made for single assessment, due to lack of sequential transition states. Appropriate procedure or techniques can be implied for mitigating this cold-start problem.

4.6 Major Outcomes

Both the studies are found to be effective for early identification of at-risk students. However, when focussing on the evaluation statistics of both the studies, performance parameters outperform clickstream parameters. LWAs are found to be much more effective and efficient in early identification of at-risk students. So, usage of performance parameters for blended learning environment predictions, is highly supported for next phase research. The major outcomes for this chapter are as follows.

- Proposes a sequential learning trajectory mining generalized architecture for the early identification of at-risk students via three-dimensional temporal clickstream data modelling.
- Usage of sequential deep learning models for differential sequential trajectory mining has added to the efficiency of the system.
- For generalization, the results are validated on two big data educational datasets from diversified institutions, educational environments, number of courses, course lengths, course domains, *etc.*
- Proposes another sequential learning trajectory mining framework for early identification of at-risk students using light-weight assessments.
- Usage of HMM for sequential trajectory mining for effectiveness and better interpretability.
- Suggests for embedding light-weight assessments in-between the courses for effective management and efficient EWS implementation. These may include small formative quiz or an automated assignment *etc.*, for periodic testing of the conceptual understanding.

Chapter 5

BLENDED PEDAGOGY WITH AT-RISK MODEL

5.1 Overview

As an outcome from earlier research phases, behavioural analysis and at-risk model generation phase, the performance parameters are found to be the efficient in early at-risk predictions. The at-risk behavioural analysis suggests using active learning strategies within the classrooms with embedded short assessments. The at-risk model suggests using light-weight assessments as compared to clickstream data, for early identification of at-risk students. As, they are found to be more effective on publically available big educational datasets of online and distance educational environments. As per the above research findings, the performance parameters (LWAs) are considered for this research phase. The efforts have been put to try embedding these parameters across the different course runs of blended learning environments. A new pedagogy for embedding these assessments is proposed. Further, these assessments are used as input parameters for early identification of at-risk students of blended learning environments. Due to the limited and small course datasets and different educational environments, models from earlier phase were not used for validation. Instead, new machine learning models were tested and an effective ensemble model was built. The model was used for effective at-risk student identification across three courses of blended learning environments. This model based early warning system will lead to early identification of the at-risk students within the course. This early identification will help in timely interventions by the instructors. Timely support and counselling of such students can save them from the risk of failure or dropout. As an outcome to this, quality education and higher student success are expected irrespective of the class size, for blended learning environments.

Now-a-days educational researchers are experimenting with active learning strategies like the use of peer instructions pedagogy with clickers and variants to flipped classroom, for effective teaching in large classrooms [262, 71]. Extra data is being generated as a by-product of these pedagogies. The generated data is found to be positively related with the overall student's performance, attendance, interaction, and engagement level [216, 193, 217]. However, irrespective of the positive outcomes, each pedagogy involves its own overhead costs. It's up to the instructor to utilize these research aspects wisely and according to the availability of the necessary required resources and manpower [216, 126].

Secondly, the domain range for the applicability of such pedagogies is also found to be variable. These are found to be successful approximately across all Science, Technology, Engineering and Mathematics (STEM) domains [187]. Out of these domains, Computer Science and Engineering (CSE) is the focus domain of this research chapter. It is one of the top-notch computing research domains for educators, due to higher variability across its courses, complexity, and computational thinking paradigm. In CSE, the learner is expected to align his thought process in a stepwise and logical way, such that solution to real world problems can be obtained.

Usually, the learner is not acquainted with the logical and complex thinking paradigm since the initial years of the study and neither these are directly perceived through the natural environment. So, it needs special attention to redirect the learner's thought towards the computational thinking and stepwise solutions. As a result, educators are continuously trying to develop different methodologies for improving the student's ability to learn this computing subject, develop learning progressions and track the students' progress in various simplified ways [207]. The introductory programming based courses have attracted the attention of the educators and are often experimented with different pedagogies, due to their large classroom sizes and higher complexities [284, 217, 302]. However, generalized studies spanning the introductory as well as core subjects of the CSE domain are found to be very limited.

With the objective of exploring an effective pedagogy and its usage in early identification of at-risk students, the present research uses Short-lightweight Online Formative Assessments (SOFA) based pedagogy across different courses of CSE domain. SOFA helps to reduce the overhead cost as involved in clickers and can be easily embedded as well as adopted by the instructors. For better generalizability of results, three different CSE courses namely, Data Structures (DS), Advanced Data Structures & Algorithms (ADS) and Database Management Systems (DBMS) are utilized. These CSE courses contribute highly to outcome based learning, have high impact on the CSE programme outcomes, are varying in complexities and span across different under-graduation time periods. As an outcome of this research work, these lightweight assessments are found to be reliable. So, a generalized architecture for embedding them within the CSE courses, is also proposed.

5.2 Chapter Flow

After consideration of all the research aspects of this section in its totality, the following gaps have been identified.

- Alternative for clickers in large classrooms, that can overcome the frequent instructor's overhead cost and prove to be effective as clickers in early identification of at-risk students.
- Lack of a generalized strategy or pedagogical architecture for embedding of at-risk student identification parameters across the core courses of CSE domain.
- Lack of generalized machine learning model that can work across different courses for early identification of at-risk students within the courses.

These form the basis of the research objectives of the present research. Figure 5.1 describes the workflow carried out for bridging in these research gaps.

- Firstly, SOFA were defined and experimented as trustable parameters for blended learning environments.
- After the identification of reliable parameters, pedagogical space was explored for embedded these SOFA within the blended learning environments.

As an outcome, a generalized pedagogical architecture with reliable parameters SOFA embedded within it, was proposed. Further, a generalized machine learning ensemble model for early identification of at-risk students, across the diversified courses was built. It utilized SOFA as input parameters. The proposed generalized ensemble model was tested and validated across different courses of CSE.

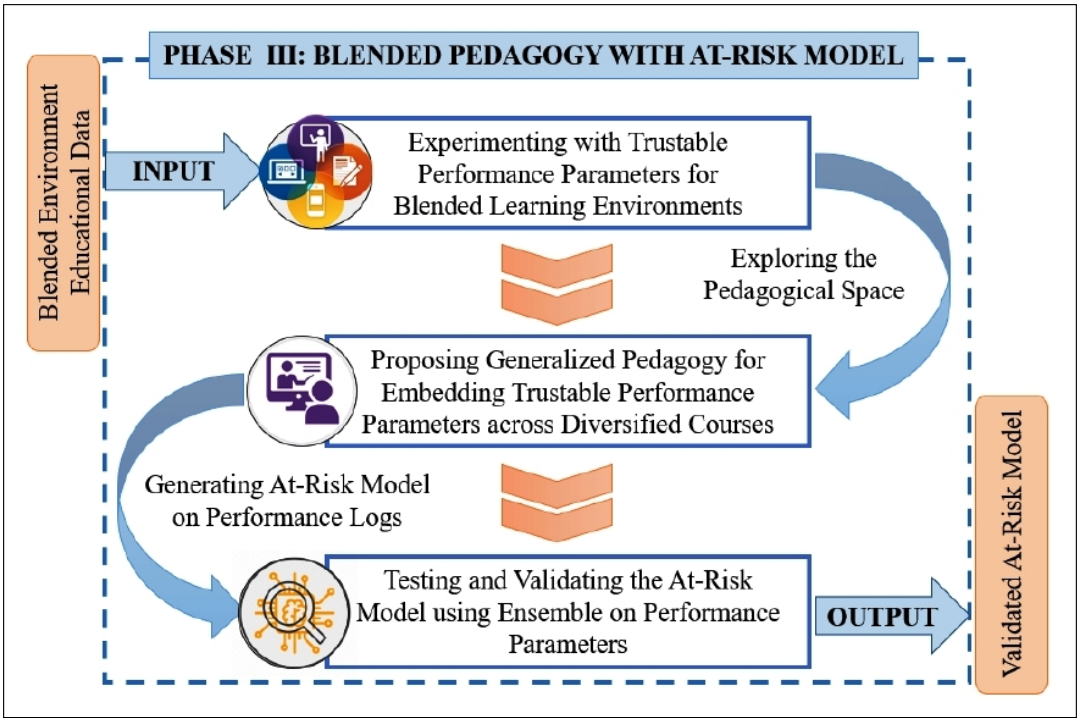


Figure 5.1: Adopted research workflow for proposal of blended pedagogy with at-risk model

5.3 Contributions

The contributions for this research work can summarized as follows.

- It proposes a generalized pedagogical architecture that helps in effective teaching across different types of courses of computer science major large classrooms.
- The proposed architecture helps to embed reliable light-weight parameters SOFA, that may further assist the instructors in early identification of at-risk students for their courses.
- It proposes an ensemble machine learning model that utilizes the embedded reliable parameters as inputs and help in prediction of at-risk students.
- It utilizes different training dataset and unseen testing dataset for model validation, that helps in providing realistic research results.
- The ensemble machine learning model produces optimal generalized results in terms of accuracy and other evaluation parameters, as compared to other existing studies.

- Through the proposed pedagogical architecture and ensemble machine learning model, it helps the instructors in tracing the learning behaviour of the students. This further helps in early identification of at-risk students and provide them necessary and timely assistance, so that their risk of failure or dropout from the course, is mitigated.

The remaining part of this chapter is organized as follows: Section 5.4 discusses about the research questions. In Section 5.5, context of the research section is explained. Section 5.6 contains the basic course information along with the implementation architecture. Section 5.7 discusses the proposed machine learning ensemble model. Results and discussion are presented in Section 5.8 and Section 5.9. Limitations and Major Outcomes for this research are discussed in Section 5.10 and 5.11, respectively.

5.4 Research Objectives

To bridge the gap existing within the literature, this research utilizes SOFA as input parameters and test them as potential parameters for at-risk student identification. It also tests their effectivity and outcomes across core CSE courses with different pedagogical aspects. With this holistic view, the following research questions are posed.

RQ1: Can Short-lightweight Online Formative Assessments assist in early identification of at-risk students?

RQ2: How to embed Short-lightweight Online Formative Assessments in core computer science courses with different pedagogical aspects?

5.5 Research Context

This section describes the context of integrating SOFA as pedagogical tool for core computing courses. It briefly describes the issues involved in programming and project based learning courses and how these can be overcome through the proposed assessment parameters. It further discusses the three core CSE course context and need analysis for embedding SOFA in the course pedagogy.

5.5.1 Programming Based Courses

Due to higher difficulty rate of the programming courses, these have generally higher dropout and failure rates. Educators have always been exploring the effective ways of teaching these subjects for better student retention. As per the literature, programming based courses learning and Problem Based Learning (PBL) involving problem solving skills are highly positively correlated [138]. Various pedagogical recommendations have been made for teaching programming based courses. According to the survey results, the recommended practices for teaching programming based subjects include well organization of learning material in sequential order of lecture and corresponding labs, implementing active learning strategies for more lecture awareness and engagement. Carrying out programming exercises in labs as students learn by doing, usage of learning management system for effective collaboration, timely and easy access of reading material provide better learning experience [219].

Another research study pedagogical suggestions include well organization of lecture and lab exercises for better problem understanding and solving, minimally guided environments, controlled group work, instant feedback support, well supervised exercise sessions and more formative assessments [138]. So, the common guidelines for teaching programming based courses include proper sequencing of lecture and lab topics, supervised labs with well-defined programming problems for students practice and feedback and easy tracing of student progress via formative assessments or other active learning strategies.

As per the recommendations a well-structured programming based course with properly arranged lecture and guided programming sessions accompanied with continuous formative assessments can act as a promising solution.

5.5.2 Project Based Learning (PjBL)

PjBL is found to inculcate in students the skills of adaptability via its co-operative learning experience and increases student satisfaction and efficacy according to the literature. However, the main challenges of PjBL include space availability, assessment difficulty, sustained scaffolding, and scalability in terms of student's headcount as well as integration within the university degree programs [179, 161]. Frank and Barzilai (2004), studied the implementation issues and processes in PjBL based higher education environment involving alternative assessments. The main challenges addressed included workload issues, teamwork conflicting situations and dealing with ill-structured learning material. However, continuous formative assessments were preferred as they helped in defining clear goals, progress evaluation, elaboration of confusion points and coping with conflicts amongst the team members [44].

For large classrooms, the above discussed implementation issues and challenges can further enhance. So, integrating PjBL with formative assessments for large classrooms can be a possible solution.

5.5.3 Short-lightweight Online Formative Assessments

Short and lightweight formative assessments in the form of Multiple-Choice Questions (MCQs) have often found to be very effective. These help in enhancing the student motivation and engagement level according to the existing literature [10, 30, 31, 40, 261, 122]. In lieu of the above-mentioned implementation issues of PBL and PjBL courses, if these courses are integrated with these SOFA, the problem of decreased motivation, satisfaction level and individual accountability can be minimized. So, considering the overall issues, this section investigates whether PBL and PjBL based courses integrated with SOFA has the effectiveness to handle the large classroom sophomores.

5.5.4 Course Context

This research is conducted in the computer science and engineering department of a reputed and highly rated Indian University. The three courses used are Data Structures (DS), Advanced Data Structures & Algorithms (ADS) and Database Management Systems (DBMS). These involve different types of learning: conceptual and programming based, problem based and project based learning. Along with the pedagogical variations, another reason for selecting these three core subjects is that they all play a very important role in future career aspects of a computer science student. These core courses collectively enable the students with the required skills of designing and providing optimized deployable solutions to the real-world problems. Further, they also contribute majorly and map significantly to the programme outcomes of computer science and engineering education for outcome based learning. Table 5.1 describes the basic introduction of such courses. The courses used for this research are spanning across various time of the undergraduate CSE domain. These are core courses of CSE domain and involve distinct course concepts as shown in Table 5.1. DS is taught during the third semester and is a core programming based course. It also forms the prerequisite for ADS, which is taught in fifth semester to the students and involves the development of problem-solving skills. During the fourth semester, DBMS is taught that involves PjBL. Databases concepts and SQL (Structured Query Language) and PL/SQL (Procedural Language/SQL) programming skills are taught to the students with the help of projects.

Table 5.1: Basic courses description

Code	Course Name	Description	Course Concept	Semester
DS	Data Structures	Learn Basic Data Structures along with sorting and searching algorithms	Programming Based Course	Third Semester
DBMS	Database Management Systems	Learn basics of Relational Databases along with SQL and PL/SQL Programming Language	Project Based Learning Course	Fourth Semester
ADS	Advanced Data Structures & Algorithms	Develop problem solving skills via efficient algorithmic approaches	Problem Based Learning Course	Fifth Semester

5.5.5 Need Analysis

The University student number intake for CSE department, largely varied from 241 in 2013 to 650 in 2017. As an after-effect of these large classrooms and large project or problem-solving student groups, the attendance levels of the students started dipping. The overall evaluation scores also declined. The decrease in quality of education was also confronted, as measured by the course learning outcomes achievement parameters obtained at the end of the course. The root causes when explored, revealed the following eye-opening facts.

- The projects or problems assigned to the students initially, did not motivate them as they lacked real-world implementation.
- The student teams suffered from Free-Rider and Sucker Effects [5, 14].
- Last night study and cramming became the norm of the students. The students were finding the concepts as well as programming hard due to overnight study issues [244].

Overall, the lack of individual accountability and motivation resulted in these issues. In quest of solving the above challenges, an opportunity arose to experiment with the proposed pedagogy in the three large undergraduate CSE courses. For fitting in the SOFA pedagogy, restructuring of the courses was done in the following major ways:

- Reframing and synchronization of the entire course content, evaluation scheme, and assessments.
- Reverse engineering where project or problems with peer discussion were used as a learning tool.
- MCQs in the form of SOFA for assessing general programming or project based skills.
- Online platform integration for periodic SOFA and automated reports.
- Increment in instructors' task force with teaching assistants for efficient scaffolding processes support.

In summary, the proposed section overcomes the problem of large classrooms in PBL and PjBL based core CSE classrooms, by embedding SOFA as a pedagogical tool. It further uses SOFA for early identification of at-risk students in these large classrooms of blended learning environments.

5.6 Proposed Pedagogical Architecture

The research design proposed can be divided into three broad perspectives namely instructor pedagogical perspective, student perspective and course assessments perspective. Instructor pedagogical perspective provides an overview of the main changes and integrations done in the pedagogical design on instructor's part. Student perspective focuses on the cooperative learning and individual accountability part, so student group formation and SOFA scheduling are discussed. Course assessments perspective includes introduction of new SOFA, online assessment platforms, modifications, and re-alignment of the weightage of various evaluation components of the course. Lastly, tools and technologies involved for easy facilitation of the proposed architecture are discussed.

5.6.1 Instructor Pedagogical Perspective

As per the suggested guidelines for PBL and PjBL courses, course content delivery composing of the theory, practical or project topics, was re-aligned. The whole syllabus was divided into five theoretical and four practical topics. The theoretical as well as practical topics were well-organized and complimenting each other. They were taught concurrently along with the project or problem solving. Programming topics including small real-world problem based assignments were aligned in a timely manner in labs. Since the project or problem solving was used as a learning tool for exposure to the different theoretical concepts, it was ensured that the project phases or problem-solving topics, mapped exactly to the theoretical topics delivered. For better understand-ability, well guided sessions with scaffolding were also in place. The complete generalized pedagogical design adopted for the three courses is shown in Figure 5.2. Here, three green blocks represent one week composing of three one-hour lectures as against one red block that represents one week.

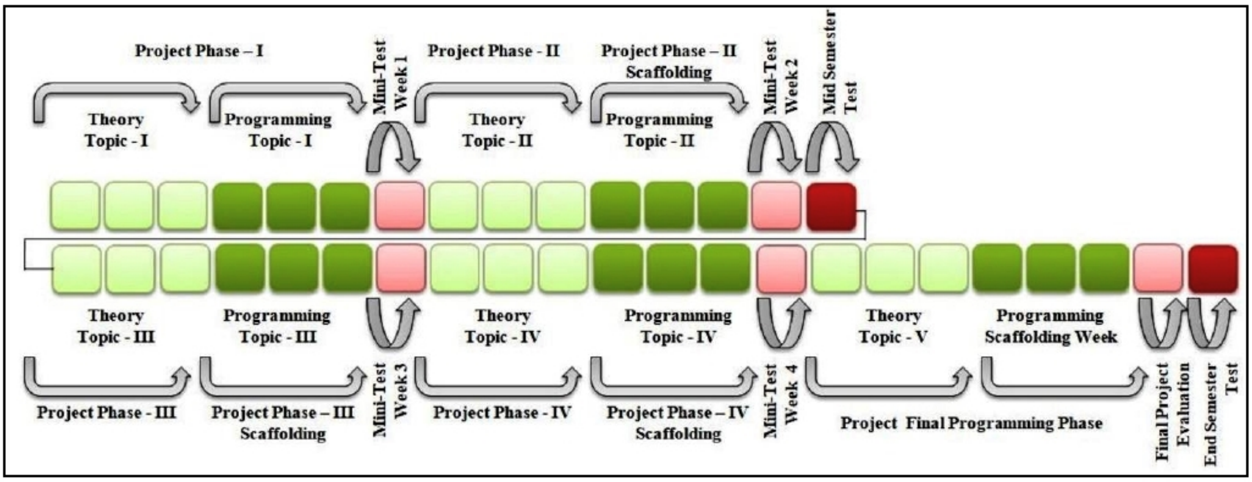


Figure 5.2: Proposed pedagogical architecture

5.6.2 Student Perspective

As project and problem solving were used as a learning tool, the class students were divided into groups. The lecture as well as lab were conducted in team based environments in order to promote peer and cooperative learning. Further, cooperative learning is all about students learning together as well as helping each other throughout the learning procedure [73, 24]. Learning Together and Alone method of cooperative learning was selected as it was best suited for the present scenario where individuals are expected to grow, in all the three dimensions: cooperatively, competitively as well as individualistic [34]. Learning together consists of three major components namely formal and informal cooperative learning and cooperative base groups. Cooperative base groups are those groups which provide support, encouragement, and assistance to the learners. They check as well as verify that the learners are progressing in the right direction in the respective field of study academically. For this research, teaching assistants were appointed and associated as base groups for the students. The student group size was strictly limited to 2-4 student members only.

The complete course span was divided into five phases. During the first week of every phase, students were taught theoretical topics with well supervised exercise in-class sessions. Second week of every phase focussed on the implementation part of theoretical topics, taught earlier in that field. Third week were specifically reserved for SOFA. In this week, during any one of the scheduled lecture and lab timings, the lightweight assessments were taken, independently. This structure helped them to prepare the topics through cooperative learning but were assessed individually that served as self-motivation amongst the students. These helped to overcome the group based issues and strengthened individual accountability.

5.6.3 Course Assessments Perspective

The assessments for this course were divided into three broad categories: Formative, Summative and Project or Problem based.

- *Formative Assessments*: Instead of embedding frequent weighted clickers in every class, the multiple SOFA with fixed time-periods were embedded throughout the course. The modified course evaluation plan along with marks weightage is shown in Table 5.2. The frequency of SOFA was fixed to five, for all three courses. The SOFA comprised of multiple-choice questions.

  The multiple-choice questions used were designed as per the CAD Guidelines [155]. Recommendations for writing an introductory programming test were also explored while designing of the formative assessments [26, 22].

- *Summative Assessments*: These consisted of MSE and ESE. Their weightage for all the three courses is shown in Table 5.2.

- *Project or Problem Based Assessments*: Rubrics were used for the evaluation of teamwork based parameters, as assessment rubrics have been an effective criterion for evaluating the quality of deliverables [129, 244].

Table 5.2: Evaluation components

Evaluation Elements	Total Weight	Component	Theory	Lab
Quizzes	15	SOFA 1	3	4
		SOFA 2	4	4
Lab Evaluations or Project	20	SOFA 3	4	3
		SOFA 4	4	3
		Project/ Problem Based	6	
Mid Semester Examination	25	25	25	
End Semester Examination	40	40	40	

5.6.4 Tools and Technology

The following e-learning ICT tools were used for facilitating the requirements of the proposed pedagogical design and decreasing the instructor's workload.

- *Google Sites:* An official course site was created as a common platform for all type of course related resource and information distribution.
- *Intranet iSQL Link:* For DBMS course, the iSQL environment, deployed on the University server, was provided to students for practicing SQL and PL/SQL as well as project development.
- *Hackerrank Assessment Platform:* Hackerrank was preferred and used over other available online assessment platforms, because of its user-friendly interface, easy creation and uploading of multiple-choice questions as well as case-study or problem-solving environment based questions, automatic assessment report generation, response saver feature *etc.*
- *Piazza Platform:* The students were given access to the piazza platform for posting of any type of course related doubts and queries, faced by the students during the various project development phases. Through this peer-to-peer discussion was promoted.

5.7 Methodology

In order to find the answer for whether these lightweight assessments can help in early identification of at-risk students, a machine learning model was developed. The first step involved data collection. In this phase the required data was collected for all the three courses using the proposed pedagogical design. Next phase involved data pre-processing. In this phase, the data was transformed into the required format for building the machine learning model. It involved data transformation, with defining the course based at-risk students and data balancing. After this, in the third phase the required machine learning model was built. For this, considering the consistency of results across the courses, the ensemble model is proposed. The final phase involved the model evaluation. Different model evaluation parameters were considered for validating the consistency of results across all the courses: Data Structures, Advanced Data Structures & Algorithms and Database Management Systems. The various stages of developing and evaluation of the machine learning model are discussed below.

5.7.1 Data Collection

The implementation was done across three courses within the CSE department of a renowned Indian University. According to the proposed pedagogical architecture, the SOFA was embedded in all the three courses, irrespective of the pedagogical differences. The strategy applied was same across all the courses, but instructors were different except one, who was involved in all the three courses. This assured the consistent application of the pedagogical architecture. As per the tools and technologies for the facilitation of the proposed pedagogy, these simplified the data collection process. The platform helped in generating automated performance reports which were downloaded in excel format from administrative panel.

Further two consecutive terms of each course were used in this process. The earlier term was used for training the model and is known as training set. Whereas the next consecutive term data was used for testing purpose and is known as testing set. The testing data was unseen for the trained model.

The details of the courses with number of training and testing data samples involved are shown in Table 5.3.

Table 5.3: Detailed course dataset description

S. No.	Course Name	Year	Ins truc tors	Total No. of Features Varying across 5 time-periods	Unbalanced		SMOTE Balanced	
					Training Set (N)	Testing Set (N)	Training Set (N)	Testing Set (N)
1	Database Management System	II	5	Checkpoint: 1 LWA-1; Checkpoint: 2 LWA-1,2; Checkpoint: 3 LWA-1,2,3; Checkpoint: 4 LWA-1,2,3,4; Checkpoint: 5 LWA1,2,3,4,5	644	647	1162	1260
2	Data Structures	II	3		391	411	684	748
3	Advanced Data Structures & Algorithms	III	3		258	304	424	486

5.7.2 Data Pre-processing

The following pre-processing steps have been taken.

- *SOFA data format:* As there were five continuous online lightweight assessments, there were five input parameters. However, as the effectivity of the parameters were checked across the time period, so five different phased time periods were selected. The first considered time period was on the third week of the courses and it consisted of first lightweight assessment data or LWA1. Next checkout point was on sixth week and consisted of two parameters, first and second lightweight assessments *i.e.*, LWA1 and LWA2 and so on. The last checkpoint consisted of all the five lightweight assessments data *i.e.*, LWA1, LWA2, LWA3, LWA4 and LWA5. The details of these features utilized for this research are shown in Table 5.3. The actual scores obtained in these assessments were considered as continuous input parameters without any changes. The absentee's data was marked as zero. No rows were discarded during the data pre-processing phase.

- *Defining At-risk and Safe students:* Considering this to be a binary classification problem, identification of at-risk and safe students categorizes the students into two main categories. Out of these, at-risk students are the ones who are either at-risk of failure or at-risk of dropout. However, there is a cut-off identified by the instructors below which the students are at-risk. According to the literature, these are taken to be either 50 % of the total marks or 40% depending upon the respective criterion [284]. For present research 40% cut-off score, usually close to failure category for blended learning environments, was selected *i.e.*, students obtaining below 40% of the total marks were considered as at-risk and others belonged to safe category.

- *Unbalanced to Balanced Dataset:* The dataset when analysed for at-risk and student category, was highly unbalanced. As number of failures in classroom environments are usually low as compared to the number of pass students. The distribution for at-risk and safe categories can be across the five lightweight assessments is shown in Figure 5.3. Here, the initial row represents the unbalanced data with distribution. For such unbalanced datasets, majority class dominates, and the results are usually biased due to model overfitting. To convert the data into balanced dataset, Synthetic Minority Over-sampling Technique (SMOTE) technique was used on the dataset. SMOTE is an oversampling technique that generates synthetic minority class samples with the help of k-nearest neighbours (k-NN) approach [32, 264]. Here the k was set to the value of 5. After the application of SMOTE, the unbalanced data was converted to balanced dataset through the oversampling of minority class. The second row of Figure 5.3 represents the balanced data with distribution for ADS course.

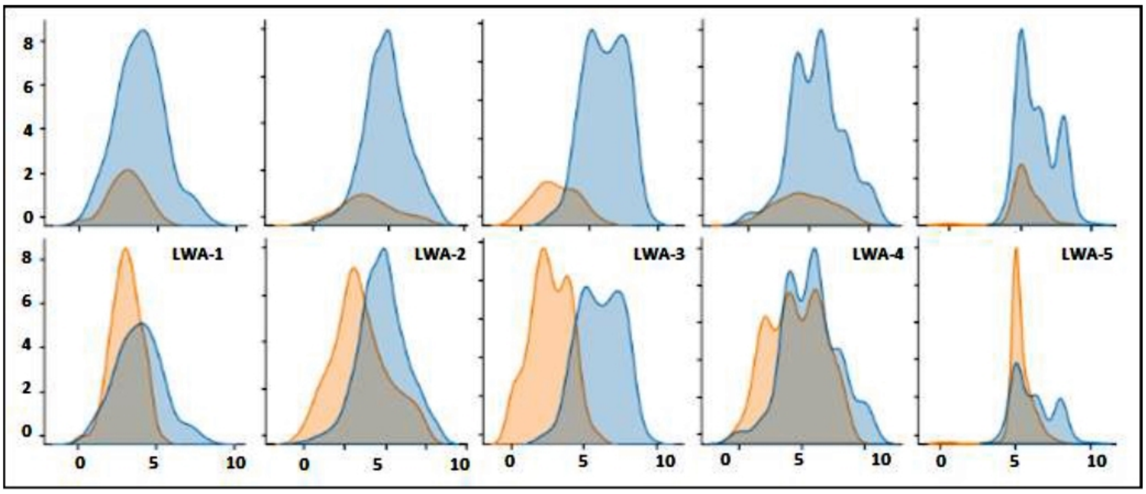


Figure 5.3 : Using SMOTE: Unbalanced dataset to balanced dataset for ADS course

5.7.3 Model Generation

As per the Chapter 2: Literature Survey, on the usage of machine learning models, some baseline models were experimented within this section. The balanced training dataset was fed into the following machine learning models and their evaluation results were compared.

- *Support Vector Machine (SVM):* This is the classification model that learns by dividing the data into hyperplanes, equal to the number of features, and thus help in distinctly classifying the data. For this research, linear kernel of SVM was used.

- *Logistic Regression (LR):* It takes the set of independent variables as input and helps to binary classification of the data with the use of logistic function.

- *Naïve Bayes (NB):* A probabilistic model that works on the principle of Bayes Theorem for assigning probabilities to the data. It assumes that the data features are purely independent.

- *Random Forest (RF):* A machine learning ensemble model used for binary classification. It builds multiple decision trees and then relies on the mode value for predicting the final class. As a hyper-parameter, number of trees were taken to be 100, for the present research.

- *eXtreme Gradient Boosting (XGB):* A machine learning ensemble model that works on gradient boosting decision trees, with higher efficiency in speed and gives better performance.

- *k-Nearest Neighbour (kNN):* This classification algorithm identifies the classes of the data points, with the help of its neighbours. For present research k was taken as five.

- *Decision Tree (DT):* A decision support classifier that uses tree model with internal and external nodes for classification. The external nodes represent decision rules which helps in binary classification of the data.

- *Artificial Neural Network (ANN):* A self-learning classifier, that tries to simulate human brain. It utilizes input, hidden and output layers with activation function for classification. For the present research, the ANN consisted of three hidden layers with hundred neurons each.

For periodic analysis of the results, LWA 1, LWA 1-2, LWA 1-3, LWA 1-4, LWA 1-5, these five data were considered, for all the three courses. These five periodic data were fed into the above models independently and their results were analysed. Numerically, for three courses, five different types of data were experimented with eight models, resulting in one hundred and twenty overall comparisons. The results lacked the consistency as different models outnumbered different phases. However, top five models that outperformed others across the phases were RF, SVM, LR, NB and XGB. Hence only these five models were selected for further analysis. Figure 5.4 represents the result analysis of ROC-AUC curve (discussed later in this section) for LWA 1 and LWA 1-5, for all the three courses. Here, performance differentiability amongst the models across the courses and phases can be easily noticed. For example, for LWA 1 in DBMS course, NB has outnumbered other models whereas for same course, during last LWA 1-5 phase, SVM and LR performed better.

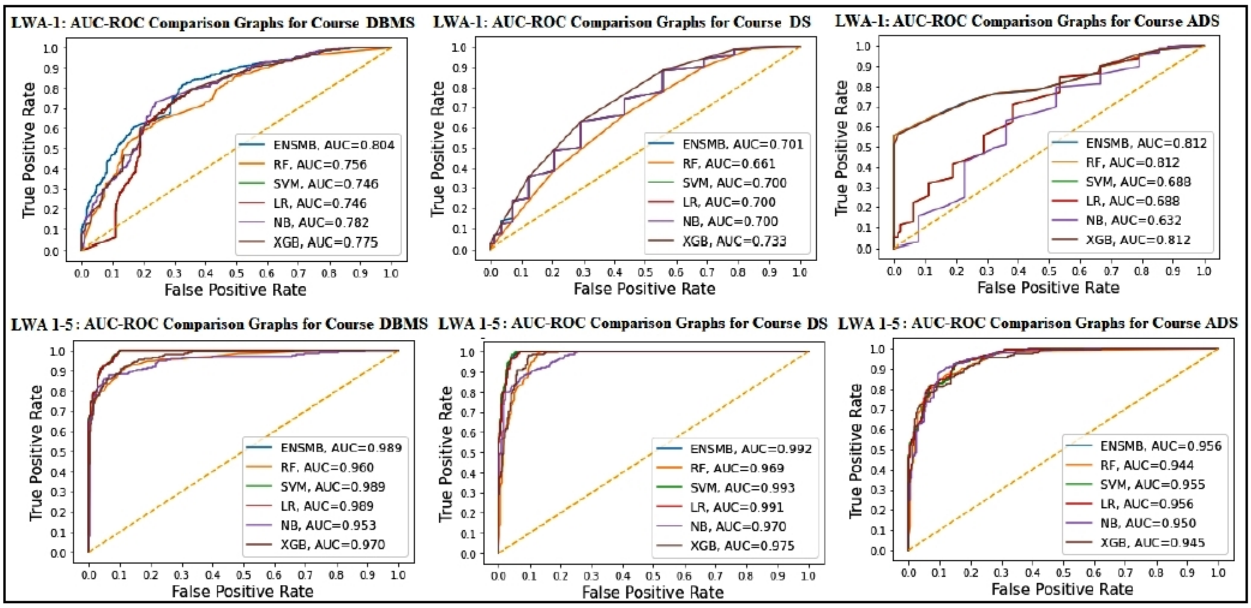


Figure 5.4: Comparison of ROC-AUC scores of models at two different time periods for three courses

So, for maintaining the consistency across the courses and in need of search for most efficient and effective model for all the phases, ensemble model was proposed. Voting ensemble classifier consisted of all the five models: RF, SVM, LR, NB and XGB with soft voting. With the help of ensemble classifier, comparable results were obtained as that of the best model of that phase. Figure 5.4 also shows these comparable results of ensemble classifier as opposed to other models. Across all the phases as well as courses, voting ensemble classifier produced comparable results as that of the best classifier.

So, the balanced training data has been fed into the voting ensemble classifier. The classifier has been trained on the training dataset. After the training, unseen balanced testing data has been used for making the final predictions. The complete machine model architecture is shown in Figure 5.5. The complete model has been implemented in Python language.

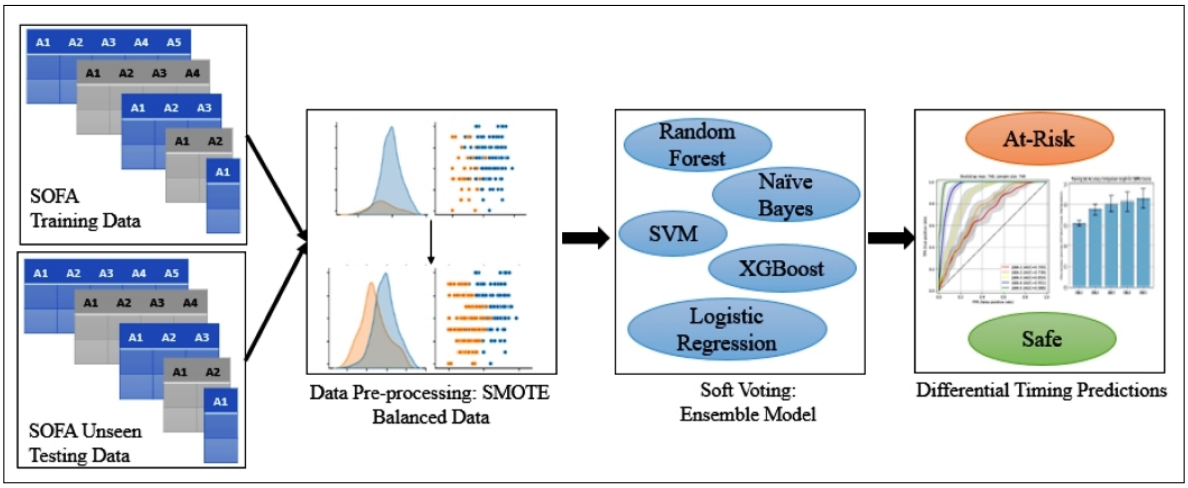


Figure 5.5: Proposed machine learning model

5.7.4 Model Evaluation

As per the research questions, the research was carried over two-fold analysis. One comprised of overall course student performance prediction whereas another one considered five phased data. The data was classified into At-Risk and Safe Category. The rate of classification of an at-risk student to the safe category is a costlier operation than vice-versa. So, along with accuracy, other parameters like Precision, Recall and ROC-AUC were also taken into consideration.

The analysis was performed using the following evaluation parameters: Accuracy, ROC-AUC, Precision, Recall, F1-Score and Cohen's kappa statistics. The detailed description for each of these is described in Chapter 2.

5.8 Results

Further results are represented as per the two research questions.

RQ1: *Can Short-lightweight Online Formative Assessments assist in early identification of at-risk students?*

As discussed earlier, for early identification the data was divided into five phases inline with the five assessments. For each course, five different voting ensemble classifier model were trained on the training dataset of the respective course. The training set validation accuracies were calculated for each of the course across the time periods. The training set validation accuracies along with five percent confidence interval are shown in Figure 5.6. After this, the trained model was tested for unseen testing data and the corresponding obtained accuracies are shown in Figure 5.6. Accuracies along with other evaluation metrics parameters are shown in Table 5.4.

- *Accuracy:* For the course DBMS and ADS, comparative accuracies of 74.3% and 73.3% were obtained with kappa value as 0.486 and 0.465 respectively. Good accuracies with moderate agreement represented reliable results after the first LWA 1 held during the third week of the courses. For DS course, comparatively a lower accuracy of 62.2% was obtained with kappa value representing fair agreement (0.243).

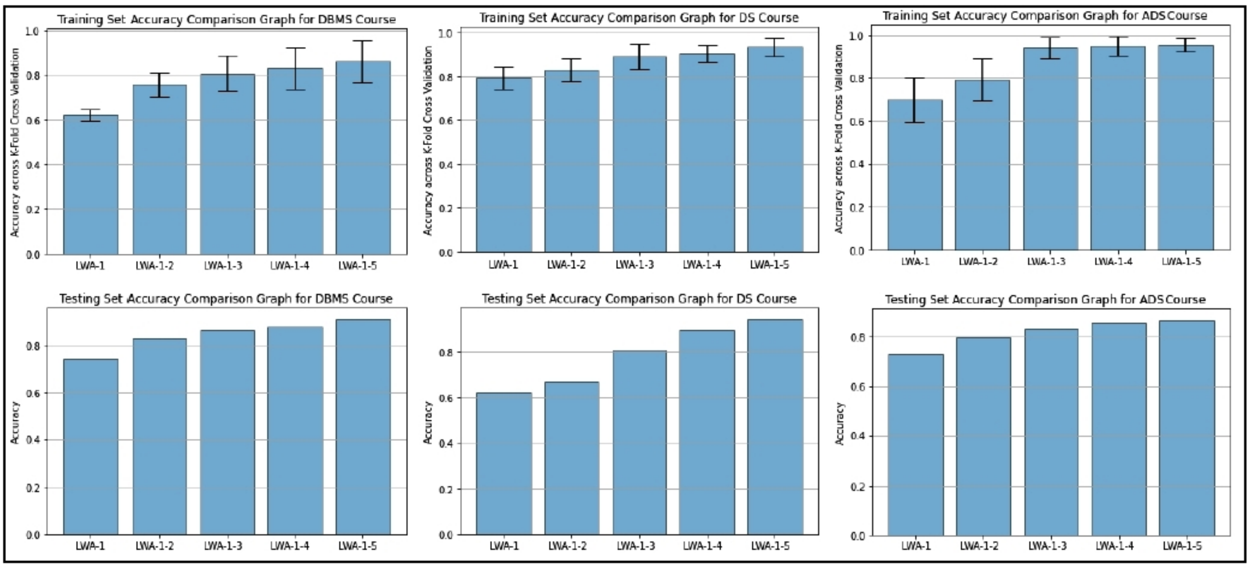


Figure 5.6: Comparison of training and testing dataset accuracies across different time periods for three courses

On analysis of the evaluation metrics for testing data, across the time period, showed positive results. The accuracy along with the reliability quotient of the model increased with time, for every course. However, the pace of increment is different for every course.

For DBMS, the accuracy increased consistently with maximum of 91.4% after fifth pace with nearly perfect agreement. Whereas for DS course, the accuracies increased at lower pace till second phase (LWA 1-2). But in third phase it increased with a jerk with a value of 80.6% and reached its maximum to 94.7% after the fifth phase. The reliability quotient was also high representing the perfect agreement. For ADS course, the accuracy increased consistently but at lower pace as compared to others. After the fifth phase it has a maximum value of 87% with considerable agreement.

Table 5.4: Evaluation metrics for all three across 5 phases

Course: Database Management System (DBMS)					
Phases	**Accuracy**	**Precision**	**Recall**	**F1 Score**	**Kappa**
LWA1	0.743	0.711	0.819	0.761	0.486
LWA1-2	0.829	0.817	0.846	0.832	0.657
LWA1-3	0.869	0.878	0.857	0.867	0.738
LWA1-4	0.878	0.921	0.827	0.871	0.756
LWA1-5	0.914	0.966	0.859	0.909	0.829
Course: Data Structures (DS)					
Phases	**Accuracy**	**Precision**	**Recall**	**F1 Score**	**Kappa**
LWA1	0.622	0.590	0.799	0.679	0.243
LWA1-2	0.666	0.621	0.850	0.718	0.332
LWA1-3	0.806	0.766	0.882	0.820	0.612
LWA1-4	0.900	0.837	0.966	0.908	0.799
LWA1-5	0.947	0.903	0.982	0.949	0.893
Course: Advanced Data Structures & Algorithms (ADS)					
Phases	**Accuracy**	**Precision**	**Recall**	**F1 Score**	**Kappa**
LWA1	0.733	0.790	0.634	0.703	0.465
LWA1-2	0.798	0.872	0.700	0.776	0.597
LWA1-3	0.831	0.917	0.729	0.812	0.663
LWA1-4	0.858	0.926	0.778	0.846	0.716
LWA1-5	0.870	0.933	0.798	0.860	0.741

- *ROC-AUC Value:* The ROC-AUC plots along with the value for the three courses across the five phases are shown in Figure 5.7. The ROC-AUC values after LWA 1 were lying in the range of 0.700 to 0.815. These values are obtained during the third week of the courses. For sixth week with LWA 1-2, this range lied between 0.739 to 0.923 and so on. For LWA 1-5, the final range was between 0.957 to 0.988. This represented highly accurate predictions.

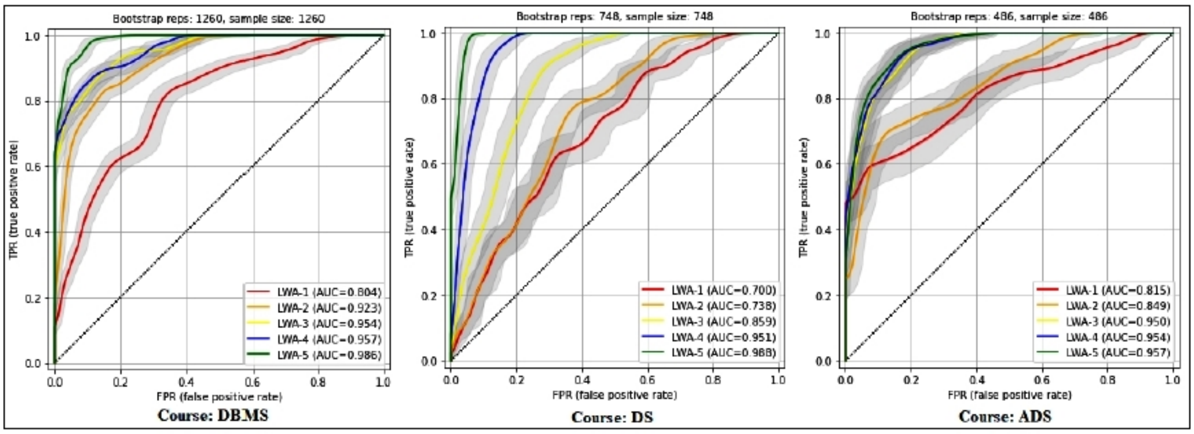


Figure 5.7: Comparison of ROC-AUC curves on testing dataset across different time periods for three courses

Table 5.5: Comparative analysis table for ROC-AUC scores

S. No.	**Research Study**	**Model**	**Time of Predic tion**	**Courses**	**ROC-AUC Score on Testing Data**	**ROC-AUC Range**
1	Veerasamy *et al.* (2020)	RF	Third Week of 18 week course	Introduction to Programming	0.58	0.58
2	Liao *et al.* (2019)	SVM	Third Week of 10-12 week courses	CS1-Python; CS1-Java; CS2-Java; Adv. Data Structures; Architecture	0.79; 0.67; 0.66; 0.65; 0.71	0.65-0.79
3	Proposed Study (2020)	Voting Ensemble Classifier	Third Week of 18 week courses	DBMS; DS; ADS	0.804; 0.700; 0.815	0.70-0.815

Even after LWA 1 the ROC-AUC values were high for DBMS and ADS courses with 0.804 and 0.815 values respectively. These courses results are significantly better than the course DS. It is comparatively lower with 0.700 as its ROC-AUC score. For comparative analysis, although the results cannot be directly compared as the pedagogical approaches, as well as courses used in this research, are different. However, while comparing on broader terms, Table 5.5 represents the ROC-AUC values for comparative two studies along with the proposed research. On generalized terms, the results obtained in the proposed research are comparable to research study based on Peer Instructions (PI), as illustrated by the ROC-AUC range [284].

This supports that proposed pedagogical architecture with SOFA are as effective as PI based clicker usage within the classrooms, during the third week of the courses.

RQ2: *How to embed Short-lightweight Online Formative Assessments in core computer science courses with different pedagogical aspects?*

Section 5.6 proposes the architecture of how to embed this pedagogy across the pedagogically different courses of CSE. For simple theoretical courses, each phase can be simply divided into theoretical and guided problem-solving sessions instead of implementation phases. Whereas for PBL or PjBL, the proposed architecture can be easily followed and implemented.

Table 5.6: Course experience questionnaire based on Ramsden

Scale	Defining Item
Good Teaching	The instructors motivated me to do my best work. The instructors and teaching assistants gave me helpful and timely feedback on how I was doing. The instructors were good at explaining the concepts
Clear Goals and Standards	From the start of the course, instructors made clear their expectations from the students. The standard of work expected from me was priorly known. The idea of what to do and what was expected during different project phases, was clear.
Appropriate Workload	I was able to manage this course well along with other courses. There was enough time to understand and implement the concepts. Project/ Problems and its implementation was well aligned throughout the course.
Appropriate Assessment	The formative assessments were well structured and fair. The assessment questions were more focused on judging my acquired course problem solving skills. The timings of delivery of course content, implementation and assessments were perfectly apt.
Generic Skills	The course developed my problem solving skills. Course inculcated in me the ability to work as a team member. As an outcome of this course I feel confident about handling and simulating real world problems.

For validation of the proposed model a reliability study was conducted. A direct survey from the students, about the implemented design was done at the end of the courses. The questions were designed according to the Ramsden five parameter scale and are given in Table 5.6 [157, 16]. However, this questionnaire was not compulsory for all the students and depended on their free will. It consisted of 15 questions as shown in Table 5.6.

Total of 292 students took part in the survey and responded variedly on the given questionnaire. After analysis of the received feedback on the five parameters and performing reliability test for the responses, Cronbach's alpha coefficient was calculated as shown in Table 5.7. Cronbach's alpha is the coefficient used for measuring the internal consistency or reliability of the item groups. It is used to calculate the scale reliability.

The formula for calculating Cronbach's alpha is:

$$\alpha = \frac{N * \bar{C}}{\bar{V} * (N-1) * \bar{C}}$$

where N is the total number of items, $\bar{C}$ is the average covariance between item-pairs and $\bar{V}$is the average variance. Cronbach's alpha value ranges between 0 and 1. The coefficient's value is as close to 1, greater is the internal consistency of the items in the scale. The interpretation of values is: " > 0.9–Excellent, > 0.8–Good, > 0.7–Acceptable, > 0.6-Questionable, > 0.5–Poor, and > 0.5–Unacceptable" [28, 38].

The implemented SOFA technique was found to be effective and showed satisfactory responses for Good Teaching Scale, Clear Goals and Standard Scale, Appropriate Assessment Scale and Generic Skills Scale except for the Appropriate Workload Scale. The pedagogy was found to be successful independent of the courses pedagogical structures as the students supported the facts that these courses represented good teaching with appropriate support at the backend.

Table 5.7: Qualitative assessment results directly measured from feedback responses of N=262 students

S. No.	**Scale**	**Mean**	**Standard Deviation**	**Cronbach's Alpha**
1	Good Teaching	3.751	1.383	0.886
2	Clear Goals and Standards	3.802	1.579	0.852
3	Appropriate Workload	4.190	0.820	0.621
4	Appropriate Assessment	3.590	1.542	0.923
5	Generic Skills	2.167	0.610	0.739

They were very clear about the course learning outcomes and the goals they needed to achieve. This also supported the fact of that the course helped them to develop general problem-solving skills supporting life-long learning. The assessments' structure and their relevance were highly supported and liked by the students as it had a Cronbach's alpha value above 0.9 *i.e.*, near to perfect.

The Cronbach's alpha coefficient value of 0.621 for this scale revealed that the implemented pedagogy proved to be time-consuming for the students, as it demanded consistent efforts from their side throughout the semester, for the respective courses. This revealed that students somewhat lacked behind in efficient time management skills.

5.9 Discussion

The proposed research study and analysis contribute largely to the growing body of literature for new educational pedagogies that aim to equip the learners with the required 21^{st} century skills. With the integration of SOFA in pedagogically different courses, this research validates the enhanced capabilities of the learners across different evaluation parameters considered. Instructors were able to fairly identify at-risk students of their respective courses as early as third week for eighteen-week courses. The MSE for these were scheduled during the seventh week. So, considering this, the proposed pedagogical architecture has the capability and efficiency of early identification of at-risk students.

However, out of the three courses DS has comparatively lower accuracy as well as ROC-AUC values initially. But later it produced comparable results. DS is a core CSE course that requires sufficient programming skills. These logic building and initial level programming skills depend on the prerequisite introductory programming courses knowledge. But if the students lack in the initial programming and logic building capability, then it takes time for the students to pace up and get on track. This may account for the reason that for DS course the evaluation metrics were initially lower but paced up as the course progressed ahead.

Accuracies for the ADS course even at the end are not very high as compared to the rest of the courses. ADS is the course that involves advanced concepts and algorithmic building. The topics at later stages are quite lengthy and even require more than one lecture for completion

Due to the increased complexity at later stages, the students may not be able to achieve good scores in the assessments that resulted in comparatively lower accuracies and ROC-AUC values for ADS course. This is also clearly reflected in the pedagogical validation part where students in their direct feedback ascertained that they lacked the time management skills because of which they felt quite overloaded. Except this, students were found to be affirmative and confident enough regarding the teaching methodology, pedagogical structure, assessments nature, and generalized problem-solving skills that they acquired during the study of these courses. They also desired that this pedagogy should be carried further and implemented for other computer science subjects too.

This research provides an alternative for Peer Instructions pedagogy with clickers [284]. It supports the use of lightweight assessments as an alternative by reducing the overhead costs involved during daily usage of clickers within the lectures. Here students can learn in teams via PjBL as well as PBL as learning tools within the classrooms. However, considering the drawbacks of group work, the learning and individual accountability of each student is measured and traced with the help of proposed pedagogical architecture with embedded SOFA.

5.10 Limitations

Some major issues and lessons learnt during the execution of the above methodology were regarding the efforts required on instructor's part. Development of question bank within a span of every fifteen days, uploading the questions on the required platform in the desired format, required pre-planning, greater attentiveness, and teamwork. Other issue faced by few students was due to the objectiveness of the assessments. For example, consider DBMS course. In online platform, no stepwise marking procedure was there. Although it was not a major problem in the case of MCQs, but during labs open-ended SQL queries raised some concerns for the instructors. The online assessment platform used in the research, executed only those queries which were completely correct. Even a small syntax error of not applying a semicolon resulted in rejection and awarded zero marks to the student. However, this was taken care of by checking such syntax errors manually.

This research work is conducted on CSE department courses of a single

University. Analogous studies from other institutions and even more pedagogically different courses for comparison purposes can also be conducted for better generalization and authentication of the results. The results obtained in this research work considered students and instructors as two different components. Variations within the components were not considered. It is possible that the unobserved factors like the instructors teaching style, student's differential learning capabilities, possessed skill-set and student's group compositions, that may have accounted and affected the overall performance and outcomes of the course.

5.11 Major Outcomes

Currently, due to the increased volume of students in higher education system, the efforts have also been laid upon the delivery of quality education within the educational community. This is done to equip learners with skill-set like critical thinking, real-world problem-solving. This research chapter has the following major outcomes.

- It proposes a generalized pedagogical architecture that assists in effective teaching across different courses of computer science major for blended learning environments.
- It relies upon embedding the light-weight parameters within the course runs. With these reliable parameters, an ensemble machine learning model is proposed that further support the instructors in early identification of at-risk students.
- It suggests the effective usage and incorporation of integrated proposed pedagogy within the course curriculum, may equip the learners with the desired skill-set.
- The students showing a lower learning curve can be easily traced and provided with necessary and timely assistance, for mitigating the overall risk of failure or dropout.
- On student's part, this modified pedagogy helps to increase the individual accountability and the motivation level of the students of large classrooms leaving an ever-lasting impact on the students with great learning experience.
- On the instructor's part, they can classify the at-risk students early within their courses. So, timely interventions and aids can be provided to the at-risk students, leading to better course understanding, satisfaction level and student retention.

Chapter 6

ADAPTIVE LEARNING SYSTEM

6.1 Overview

During the process of carrying out the present research study for the developement of an effective Adaptive Learning System (ALS) with EDM and LA, previous chapters discuss about the behavioural analysis for probable parameters search. Next research work focussed on at-risk model generation for finding the workable parameters for online environments and generating pedagogy and validated model that works effectively for blended learning environments. This chapter focus on describing the proposed ALS with EDM and LA, that has been developed as an output of this research. The underlying topic based learning management system supports the system, in mapping the concepts or knowledge components. In this, topic represents the basic units known as knowledge components. The proposed system is named as EduWeb and is available at the following link: `http://adaptivelms.in`.

ALSs or personalized learning systems are those educational systems that provide personalized recommendations to the students according to their skills level. The skills level is determined by the student's mastery level in particular knowledge component. Here the rule based ALS, forming the base of this research is discussed. The knowledge component is the coarse grain unit of the course. Multiple knowledge components in hierarchical order form the course. These are conceptually linked according to their complexity level. The course generally begins with simpler knowledge components, builds upon these, and proceed towards the complex ones as the course progresses. For assessing the skill level of the students on different knowledge components in ALSs, the self-assessment quizzes are usually designed. These self-assessment quizzes are designed for knowledge testing of the students. The students attempt the questions involved, based on single or multiple knowledge components. The questions are answered as correct or incorrect by the student. According to the answers given by the student, the knowledge level for associated knowledge component(s) are updated. This skills matrix associated with the knowledge components help in determining the knowledge level of the student. The associated values range between 0 to 1, where zero means no mastery and one means complete mastery of the associated knowledge component.

Once the skills level is obtained the associated rule based or decision tree based algorithms come into play. According to the mastery range and defined rule, the educational content is designed. The educational content is associated with knowledge component(s). This educational content may further belong to different categories based on the complexity level of the content. Generally, it may be of easy, medium or difficult level. According to the mastery range and defined rule, the corresponding educational content is mapped. For example, for lower mastery level, easy content may be displayed for making them aware of the basic concepts of the associated knowledge component. Similarly for higher mastery level, high level educational content may be helpful that may help them to skill up further and even redirect them towards the future research areas *etc.* Once the skills level is determined, and associated rule is explored the targeted personalized educational content is displayed to the student.

6.2 Chapter Flow

With the objective of creating an ALS with EDM and LA embedded, the following workflow has been followed in given order.

- Development of the basic topic based LMS for posting the required educational content with proper interfacing, for students as well as instructors.
- Extending the support through weighted topic based ALS for personalized learning support.
- Integration of the machine learning at-risk module interface to the above adaptive learning system, for effective teaching of the blended learning environments.

Figure 6.1 presents the workflow adopted for creation of the ALS with EDM and LA. The next sections of this chapter are arranged as follows: Section 6.3 discusses about the tools and technology used to develop the proposed online system. Section 6.4 describes the basic functionalities of the underlying topic based learning management system. Section 6.5 extends it further, by providing adaptive interface for the students. Section 6.6

integrates the at-risk module developed with the help of EDM and LA. It provides the glimpse of the complete machine learning interface developed for assisting the instructors of blended learning environments for effective teaching.

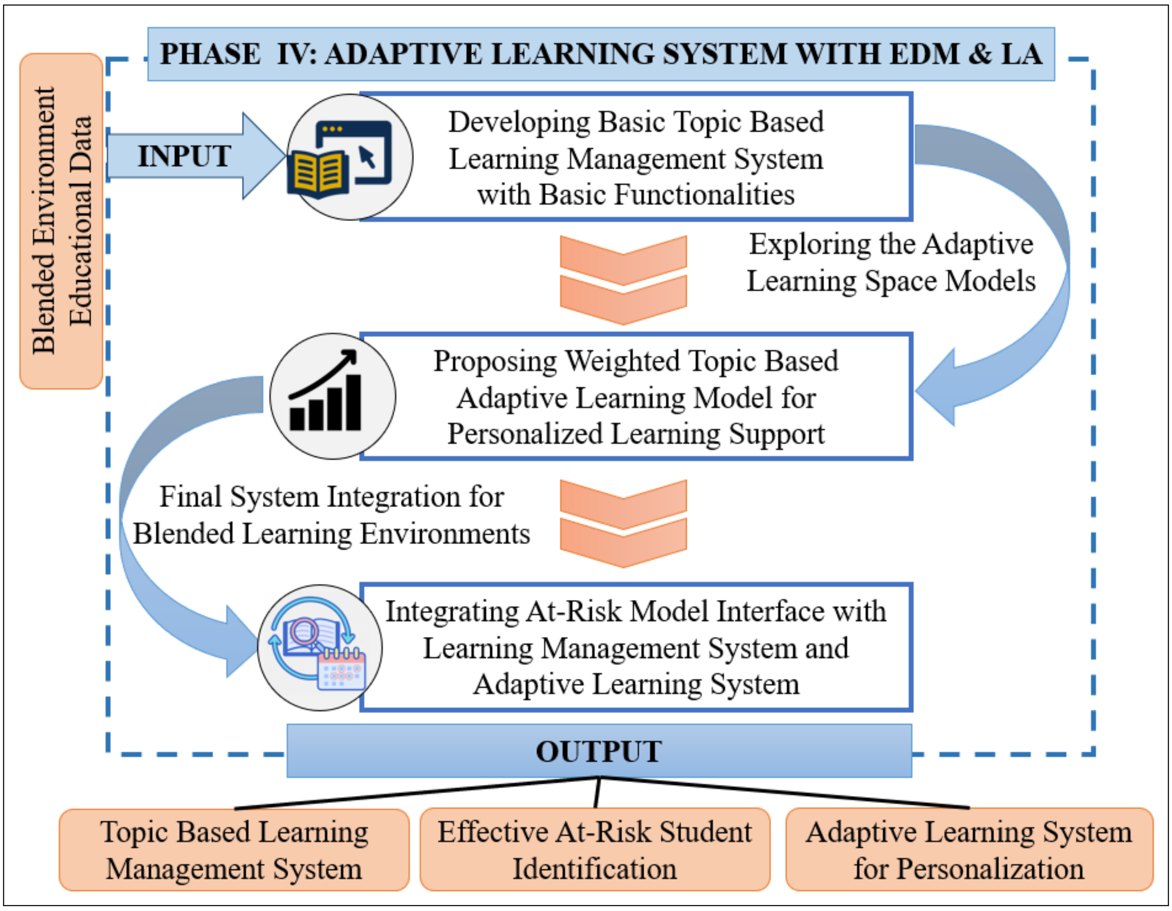


Figure 6.1: Adopted workflow for creation of adaptive learning system

6.3 Tools and Technology

The following is the technology stack, used to build the proposed system.

- *Python:* The underlying programming language used to develop the website is Python. Apart from the basic programming language constructs, it has support for machine learning libraries, that helped to implement the dynamic machine learning interface [15, 83].

- *Django:* The web interface uses Django web framework for back-end development. It is a high-level python based open-source web framework that helps to build in quick web applications. It is highly secured as well as scalable [52].

- *Apache Web Server:* This is the involved web server used for displaying the website content. This is implicit and is available in the default technological django web framework.

- *MySQL:* The complete database is designed using MySQL as backend database. This is also implicit and is available in the default technological django web framework.

6.4 Learning Management System

This section introduces to the proposed topic based learning management system. The basic functionalities of the proposed topic based learning management system are as follows. These are discussed in detail in present and sub-sequent sections.

- Session management
- Course details management
- Course student management
- Topic (knowledge components) management
- Announcements management
- Multi-instructor course management
- Educational content management
- Assignments management
- Questionnaire (Scored, Practice, External) integration and management
- Questionnaire attempt analysis
- Tagging of educational content/assignments/questions with topics
- Adaptive content management
- Analytical dashboard for students
- Adaptive learning Interface for students

- Analytical machine learning interface for instructors

- At-Risk prediction interface for instructors

Figure 6.2 and 6.3 show the basic snapshots of the proposed system along with the proposed functionalities. The system facilitates two separate modules for instructors and students, through session management. The new student can register into the system through *Register* Interface. The student and instructors can login to their portals through *Student Login* and *Teacher Login*, respectively.

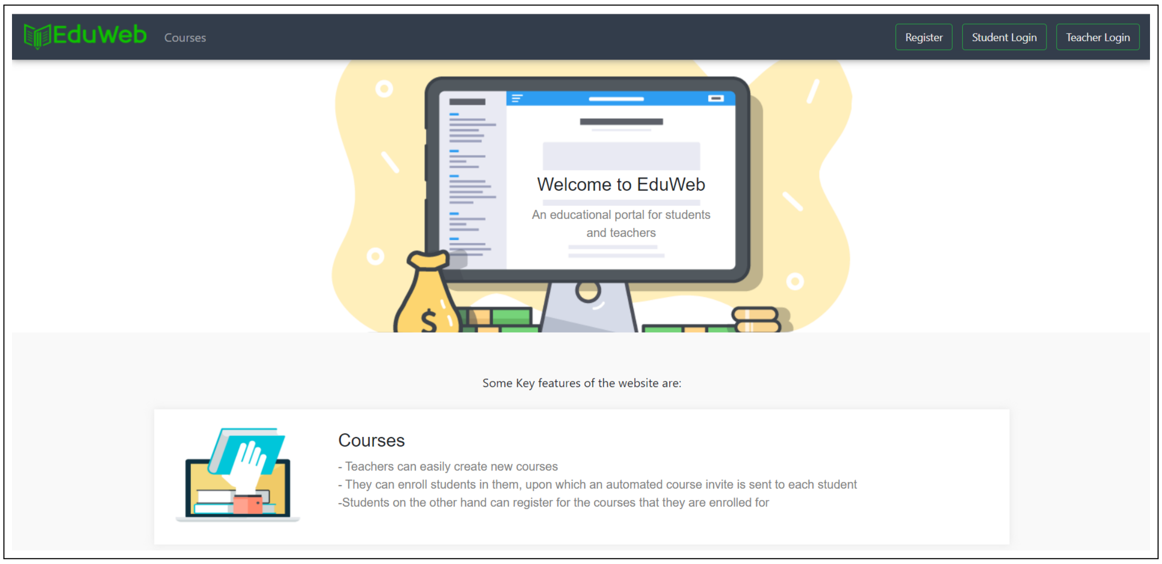


Figure 6.2: Main webpage of the proposed adaptive learning system

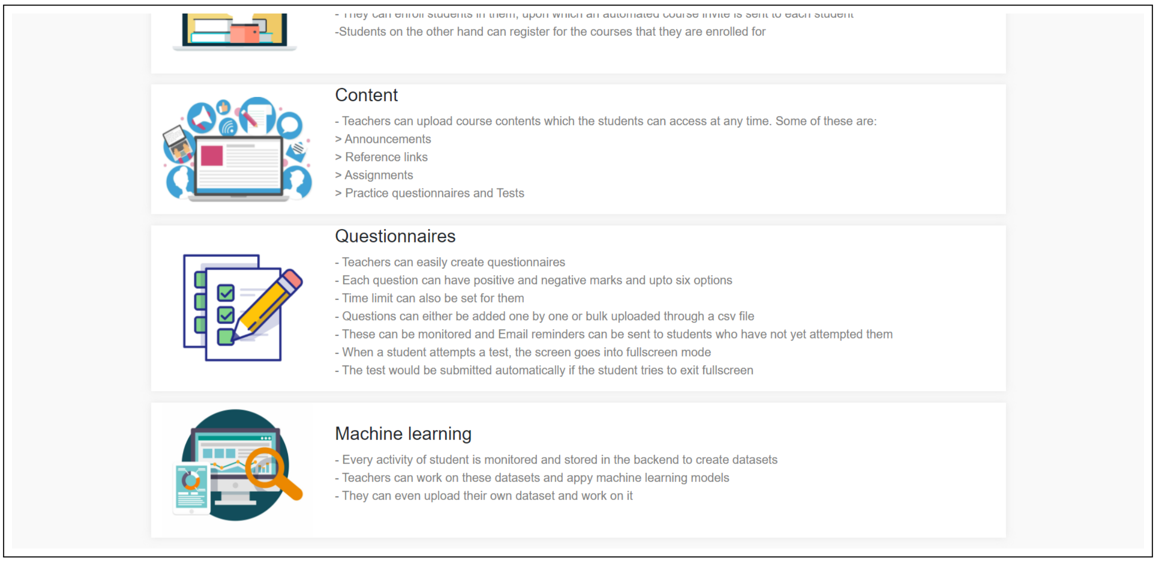


Figure 6.3: Functionalities provided by the proposed system

For representing the basic functionalities of the topic based learning management, the sample interface for instructor login is shown in Figure 6.4.

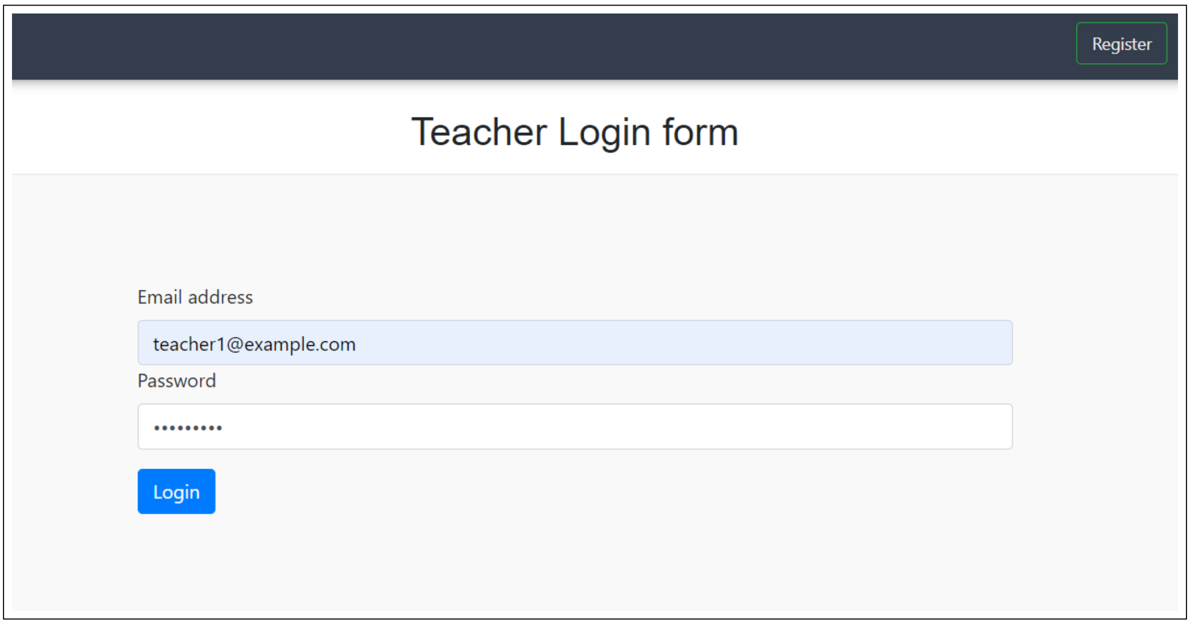


Figure 6.4: Sample instructor login interface

After logging into the system the instructor can see the already created courses, can add new course to the list or delete a particular course from the given list. Each course can be associated with multiple students and instructors. The data related to the respective courses can be kept as *Embedded Files* separately. The learning management system has also the provision of downloading different associated course logs. The respective instructor main interface is shown in Figure 6.5.

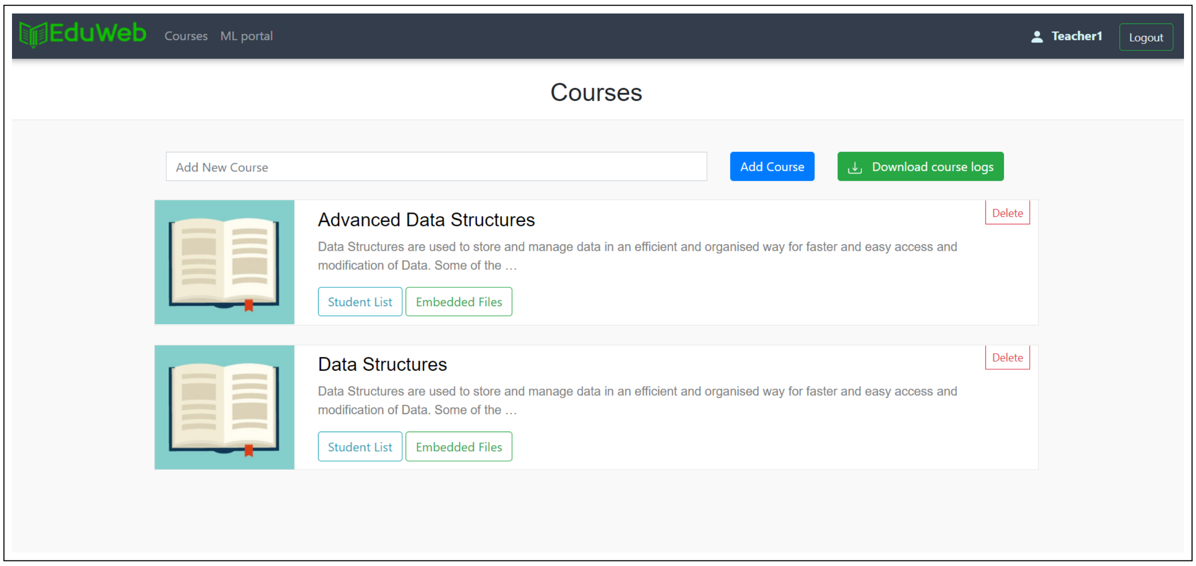


Figure 6.5: Instructor's main homepage

For each course, the students can be invited by the instructor through their associated emailIDs. The multiple student emailIDs can be entered by new line as separator and multiple invites can be sent through one click. After the invite is sent the status of the students can be seen below in the form of a list. The status represents the current state *invite sent*, *registered* of the student within the respective course. The students can also be removed from the course (if required). The snapshot for the same is shown in Figure 6.6.

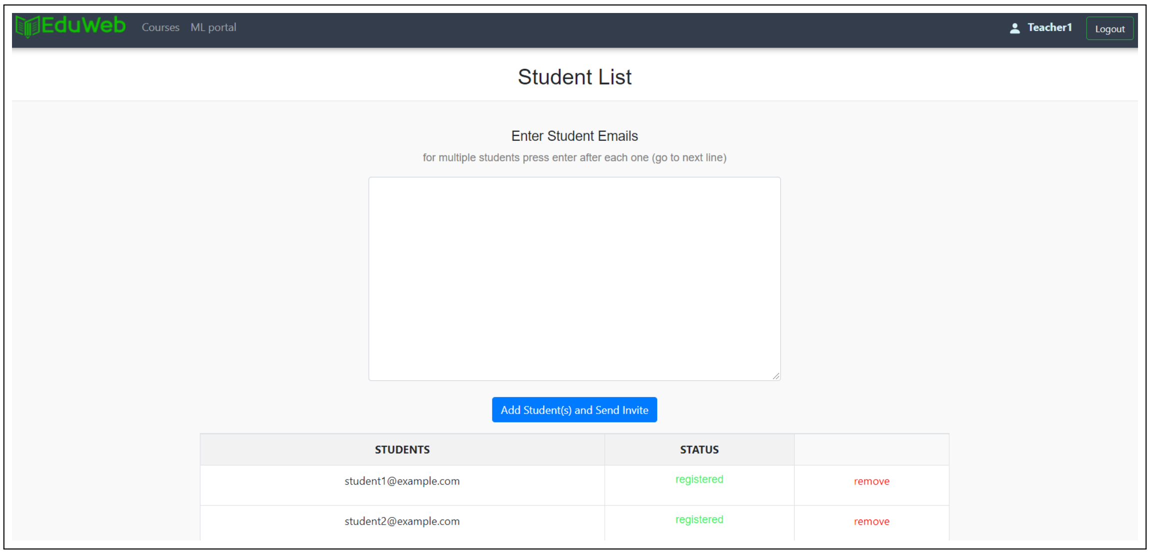


Figure 6.6: Course student managing interface

The intructors have also the provision of editing the course name, description, updating the course credits and syllabus as per the requirement. The respective snapshots are shown in Figure 6.7 and 6.8.

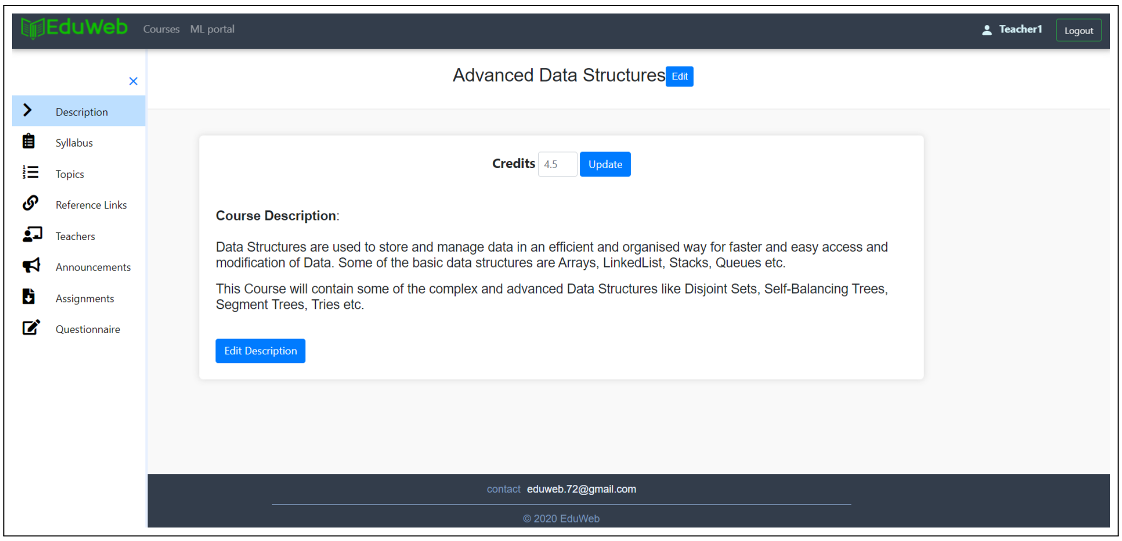


Figure 6.7: Course description editing interface

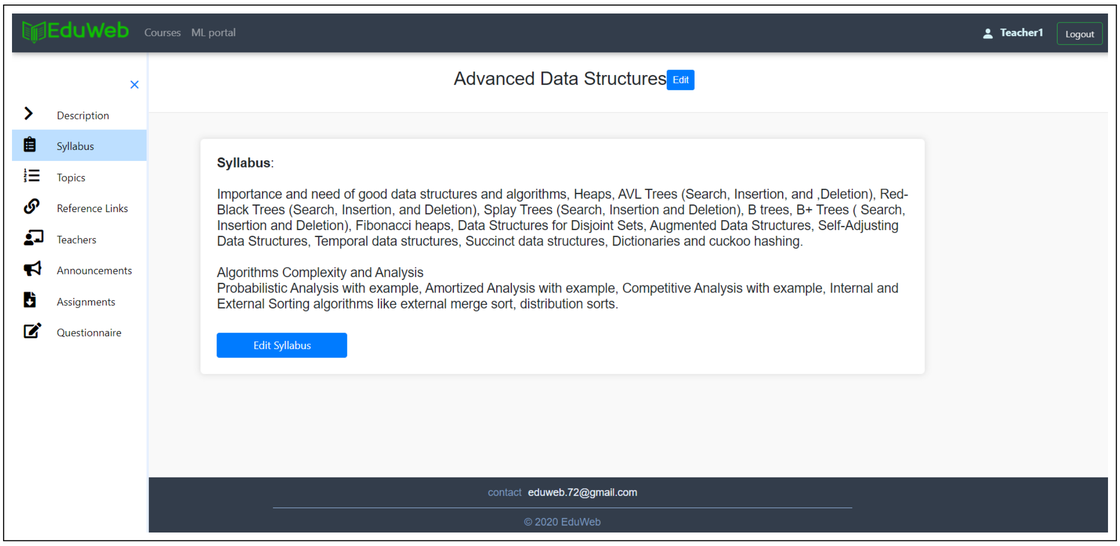


Figure 6.8: Course syllabus editing interface

Topics form the basis of this learning management system. They are similar to knowledge components described earlier. The course is built upon these topics. The topics can be simple initially, during the start of the course. Later they can be complex and may further depend on other topics as pre-requisites. This complete conceptual dependency in the form of concept maps needs to be designed and maintained by the instructor and uploaded accordingly within the portal.

On the portal, the topics are assumed to be independent. They will carry their own practice based questionnaire, that will be described later. The topics can be added and deleted as per the convenience of the instructor. Figure 6.9 shows the topic editing interface for the respective course.

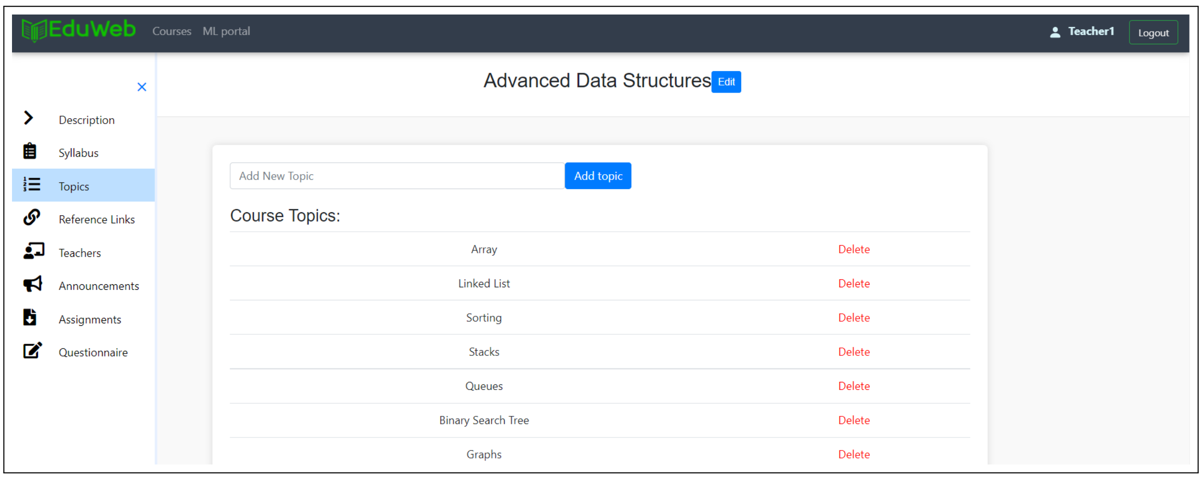


Figure 6.9: Course topic editing interface

The content management is an important aspect of the proposed system. The content is uploaded in the form of links, for keeping the system lightweight. The instructors are free to manage the data on their personal repositories and just share the link with the students as required educational content. Each educational content is associated with a topic. Another important parameter associated with the educational content is the difficulty level and these may be categorized in three categories *easy, medium and difficult*. The easy educational content is most basic and visible to all the students. The medium and difficult are associated with complex level concepts and hence are reserved for students who have crossed basic level. These are not visible to all students until they have achieved certain mastery level. However, links can be anytime enabled or disabled according to the course requirement as shown in Figure 6.10.

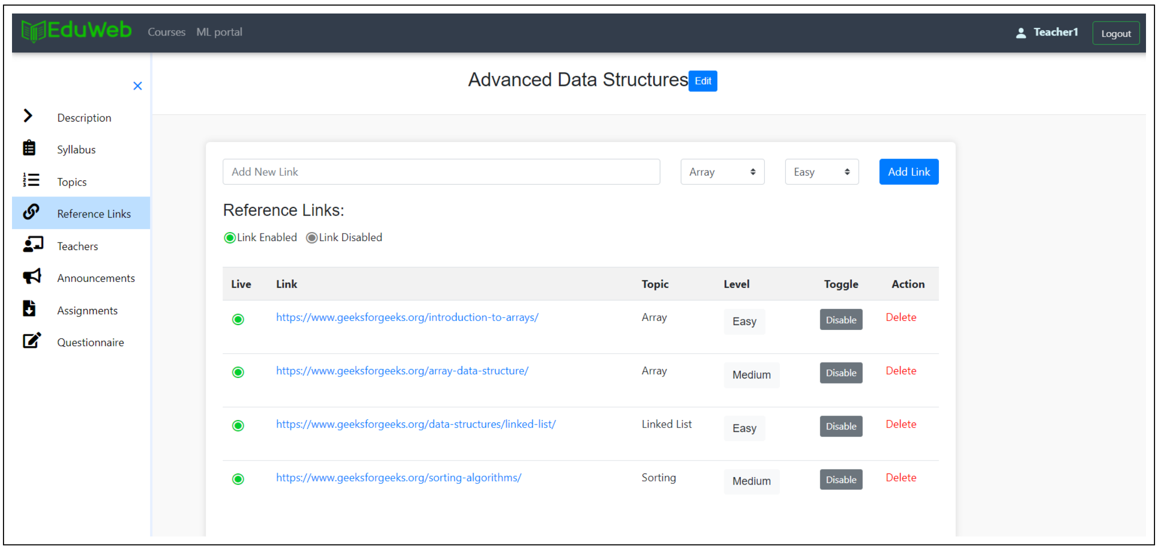


Figure 6.10: Course educational content editing interface

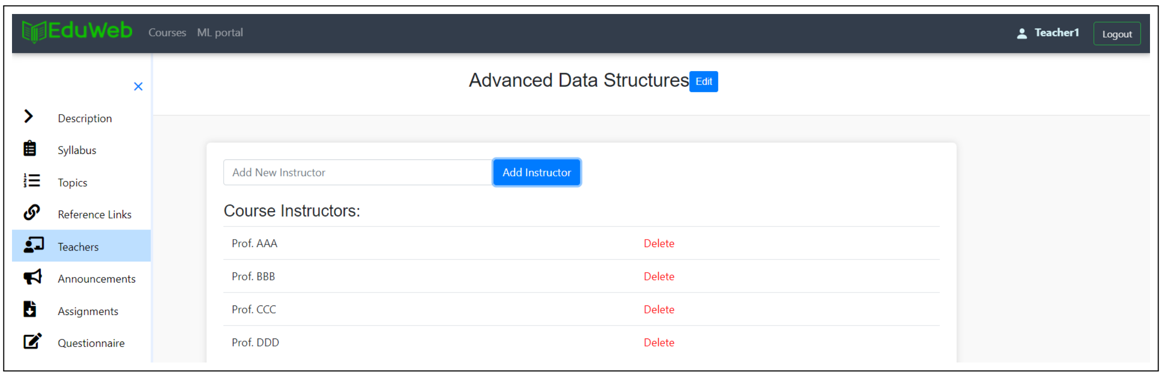


Figure 6.11: Course associated instructors editing interface

The main instructor can keep track of associated course instructors and can associate them with the course, depending upon the requirement. Figure 6.11 shows the respective interface for managing the associated course instructors.

The proposed system has also the provision of announcements. the instructor can post multiple announcements throughout the course. Figure 6.12 shows the interface for managing course related announcements.

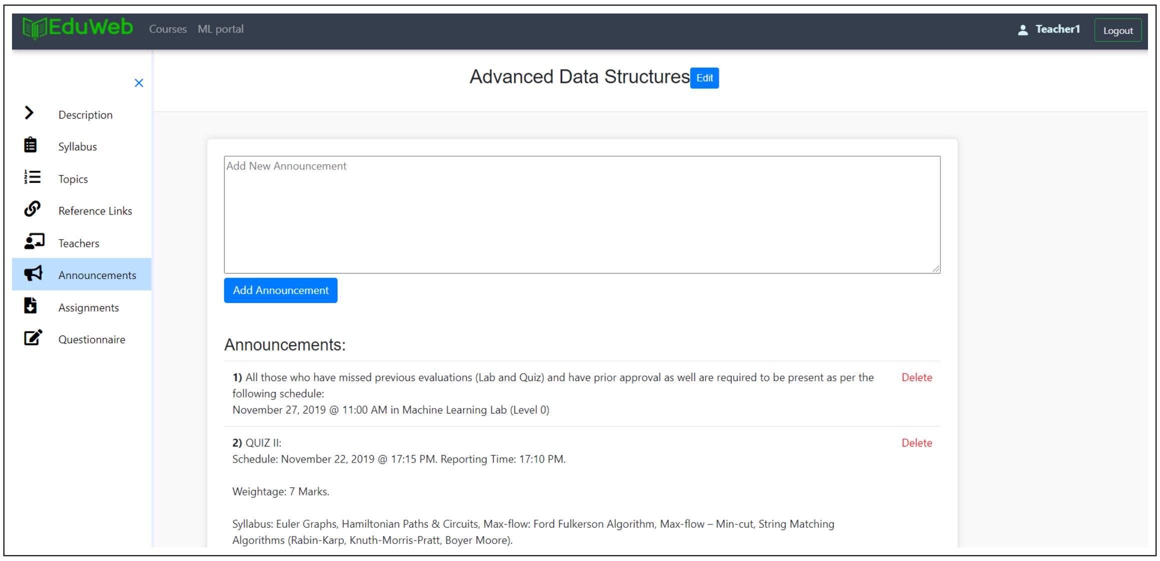


Figure 6.12: Course announcements editing interface

Similar to educational content assignments are also associated with the adaptive nature. They are also associated with topic and have level. Easy level assignments are visible to all students, but complex ones are adaptive and shown to student who have reached higher levels and depends on student's skill level. Figure 6.13 shows the interface for managing the course assignments.

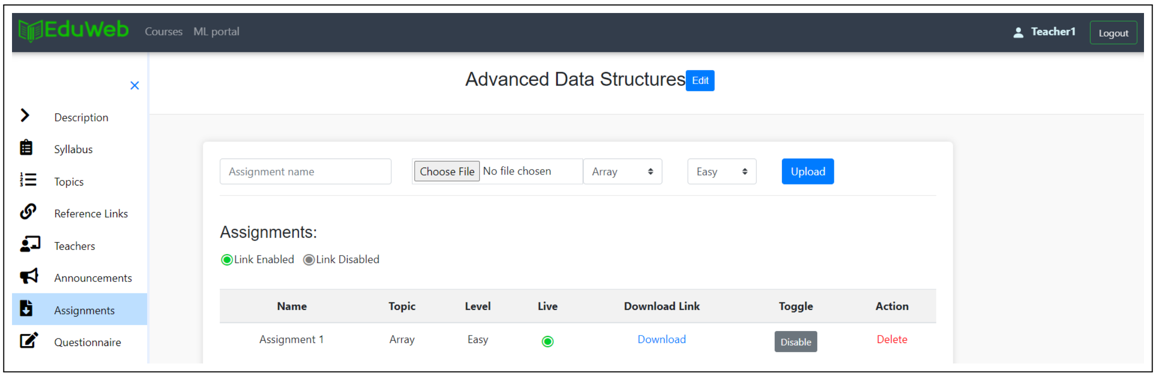


Figure 6.13: Course assignments editing interface

Questionnaire are the most important part of this learning management system. They are further of three types. All three-questionnaire interface is shown in figure 6.14.

- **Tests**: Normal timed course related tests and are usually associated with course evaluations.
- **Practice Tests**: Practice tests for student self-assessments. Carry no-weightage in course evaluation but form the basis of mastery based learning. Help in determining the topic based skill level of the students for adaptive learning.
- **External Tests**: External weighted tests (taken on some other platform) can also be integrated to the present system.

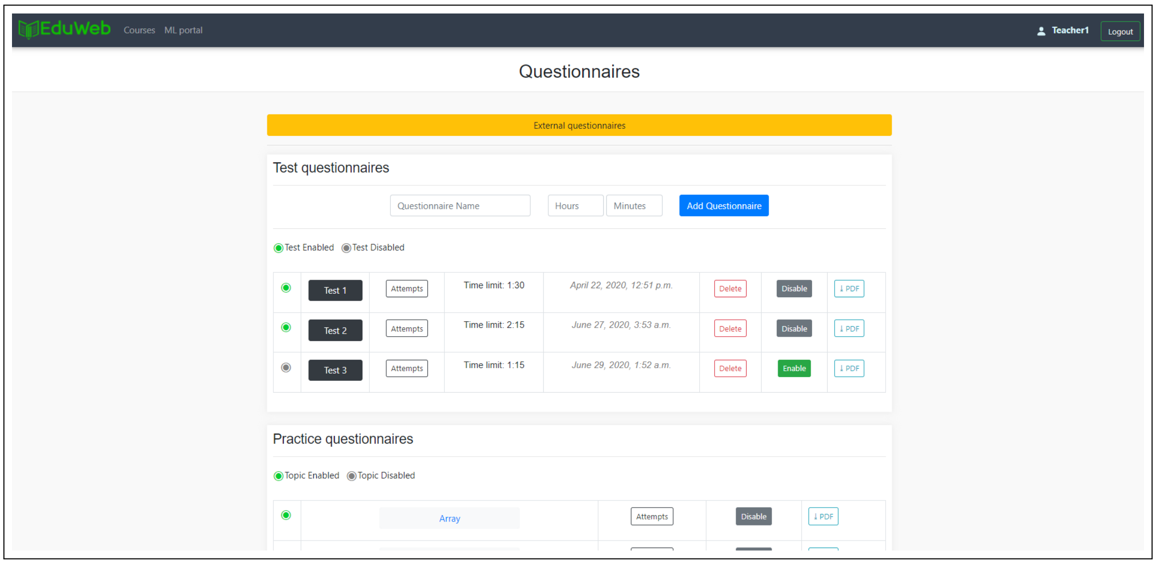


Figure 6.14: Course questionnaire editing interface

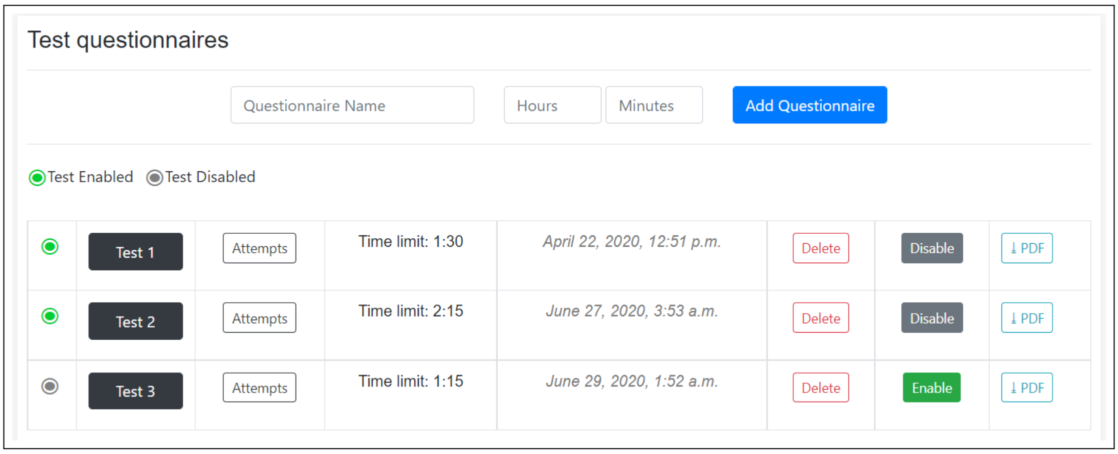


Figure 6.15: Course text editing interface

Normal weighted tests are timed can be created through interface. Each test can contain multiple questions. Once created these test associated questions can be downloaded in the form of PDF for record keeping and validation purpose. The test editing interface with associated parameters is shown in Figure 6.15.

Each test is attempted by multiple course students. So, by clicking on the respective *attempts* button the complete analysis of the associated students with respect to the test is shown. Figure 6.16 shows the test analysis for one such test.

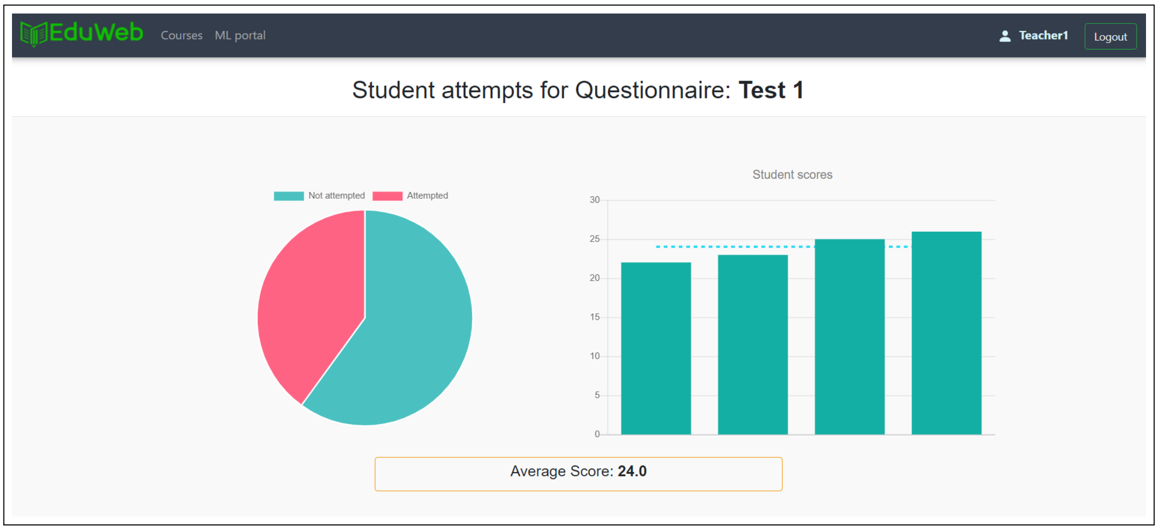


Figure 6.16: Course text based analysis

The students who have not attempted the test are also displayed. Those students can be sent automated reminder emails from the portal. Figure 6.17 represents the non-attempters list for one such test.

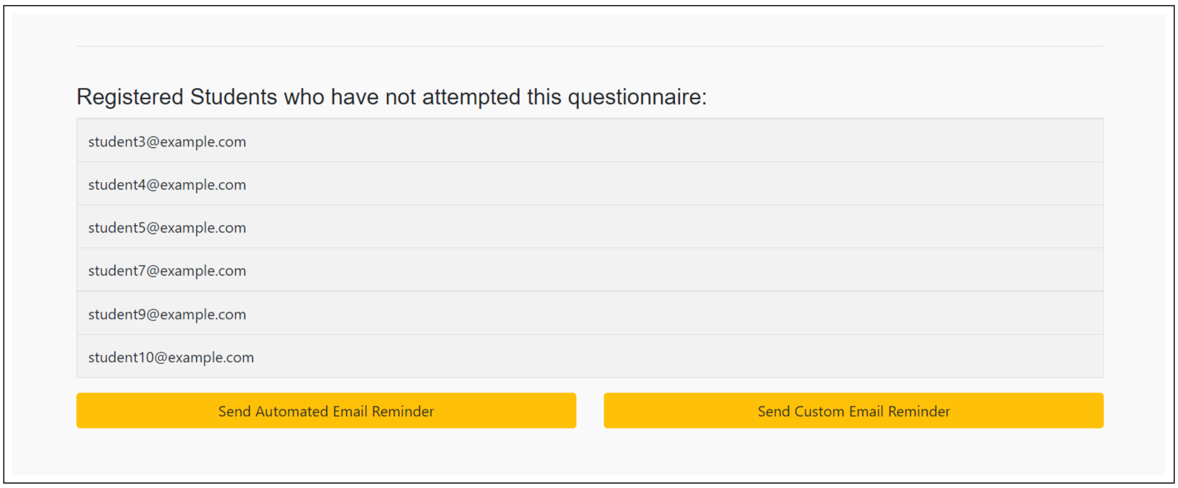
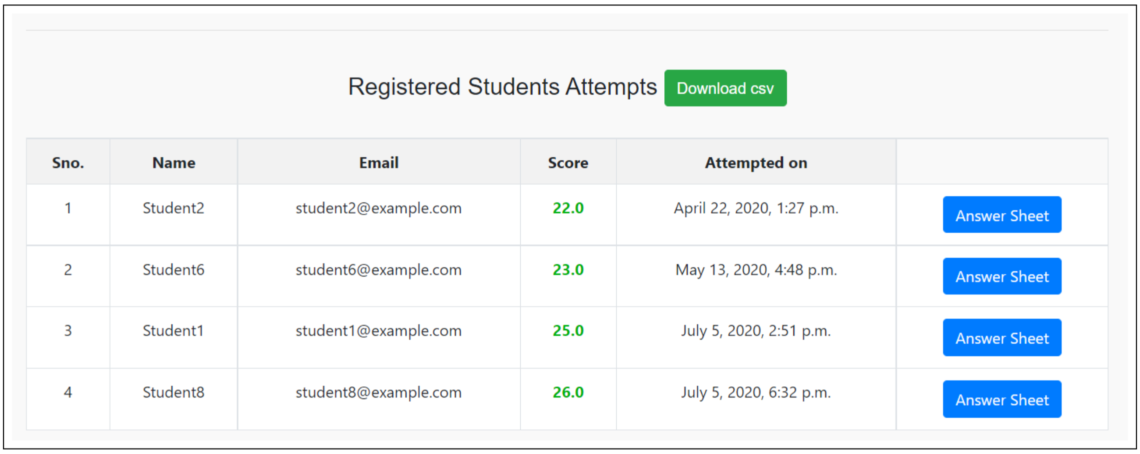


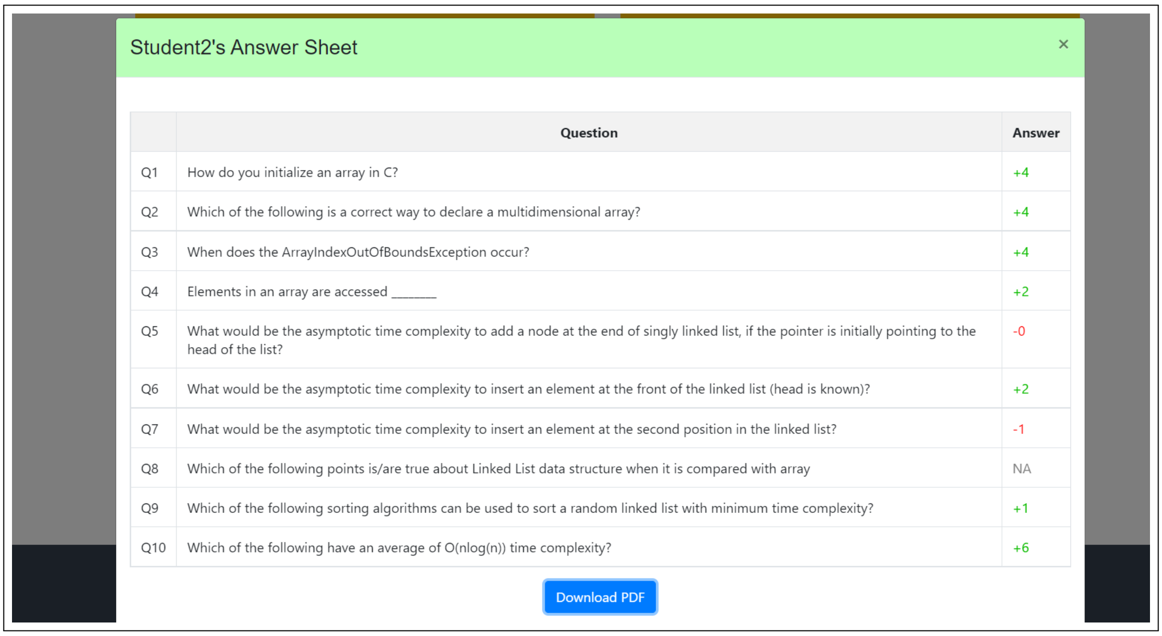
Figure 6.17: Course test based non-attempters

However, for those students who have attempted the test, their answer-sheets can be seen within the portal or can be downloaded in PDF format for records. Figure 6.18 displays the list of test-attempters. Figure 6.19 shows the answer sheet of a specific student when clicked on view *Answer Sheet*.


Registered Students Attempts Download csv

Sno.	Name	Email	Score	Attempted on	
1	Student2	student2@example.com	22.0	April 22, 2020, 1:27 p.m.	Answer Sheet
2	Student6	student6@example.com	23.0	May 13, 2020, 4:48 p.m.	Answer Sheet
3	Student1	student1@example.com	25.0	July 5, 2020, 2:51 p.m.	Answer Sheet
4	Student8	student8@example.com	26.0	July 5, 2020, 6:32 p.m.	Answer Sheet

Figure 6.18: Course test based list of test-attempters


Student2's Answer Sheet ×

	Question	Answer
Q1	How do you initialize an array in C?	+4
Q2	Which of the following is a correct way to declare a multidimensional array?	+4
Q3	When does the ArrayIndexOutOfBoundsException occur?	+4
Q4	Elements in an array are accessed _______	+2
Q5	What would be the asymptotic time complexity to add a node at the end of singly linked list, if the pointer is initially pointing to the head of the list?	-0
Q6	What would be the asymptotic time complexity to insert an element at the front of the linked list (head is known)?	+2
Q7	What would be the asymptotic time complexity to insert an element at the second position in the linked list?	-1
Q8	Which of the following points is/are true about Linked List data structure when it is compared with array	NA
Q9	Which of the following sorting algorithms can be used to sort a random linked list with minimum time complexity?	+1
Q10	Which of the following have an average of O(nlog(n)) time complexity?	+6

Download PDF

Figure 6.19: Course test based answer sheet view

The second type of tests are the practice tests that didn't carry any weightage but are used for self based assessment of the student. These support the concept of mastery based learning. These are associated with topics of the course. Each topic may contain multiple practice questions based on difficulty level. Multiple attempts are allowed for these questions, as the student may not be able to get the concept within the first attempt. But multiple attempts carry penalty with them. As the number of attempts for same question increases the penalty is levied and as per the penalty the marks are deducted for the respective question. Figure 6.20 represents the practice questionnaire interface. Here, each practice test is associated with multiple student attempts. These can be further downloaded as PDF for validation and record maintenance. As per the requirement, these can also be enabled or disabled timely.

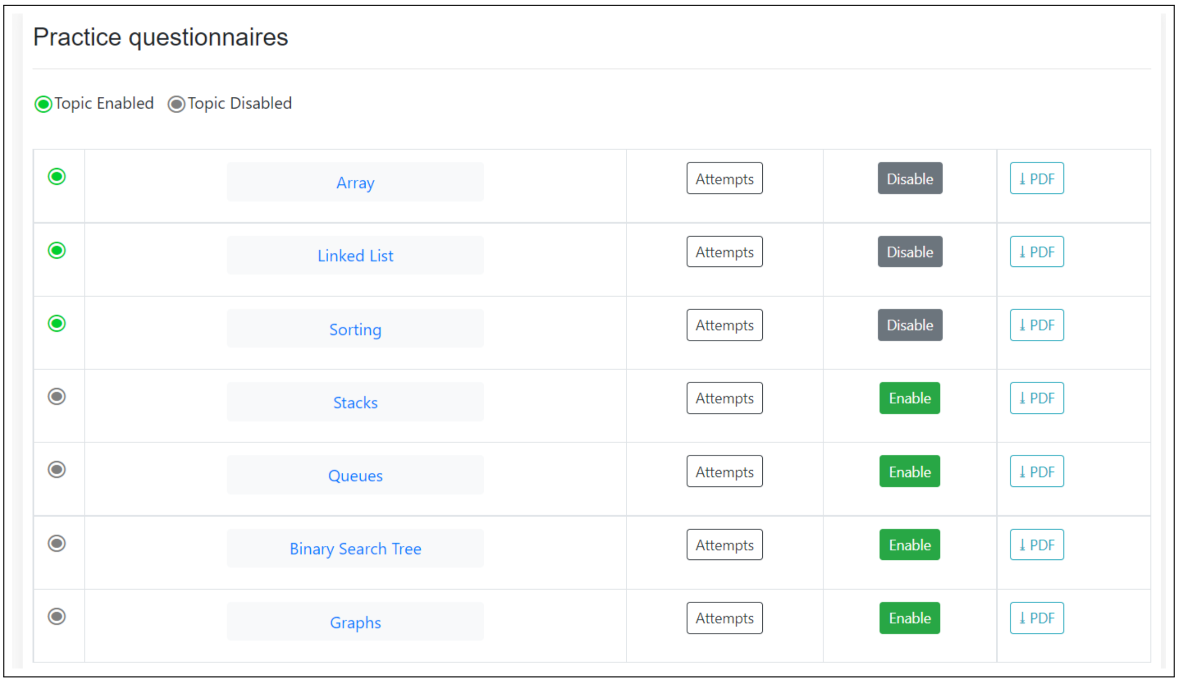


Figure 6.20: Course practice test interface

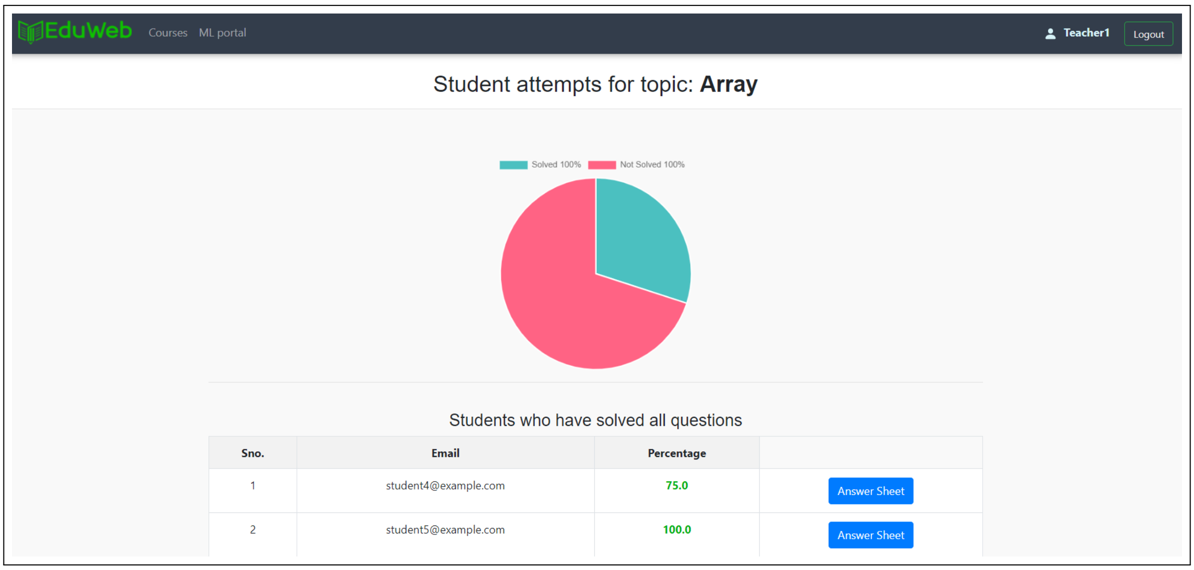


Figure 6.21: Practice test analysis interface

Since, each practice test is associated with multiple student attempts, the detailed analysis can be seen by clicking on *Attempts*. Figure 6.21 represents the practice test analysis interface. For accommodation of mastery based learning, each practice question is associated with multiple parameters as shown in Figure 6.22.

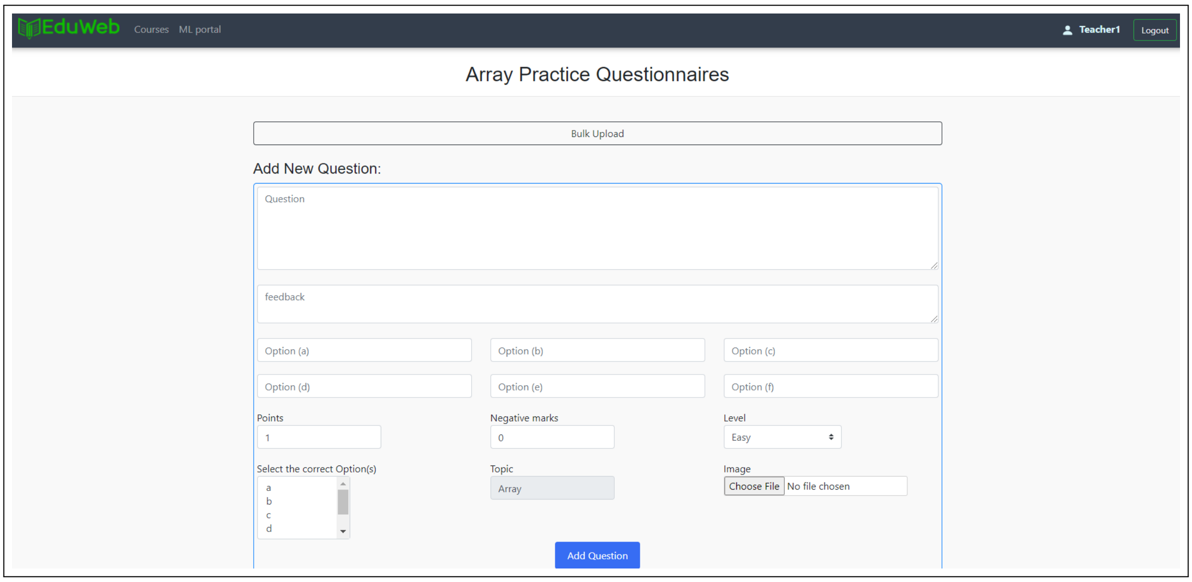


Figure 6.22: Course practice question associated parameters

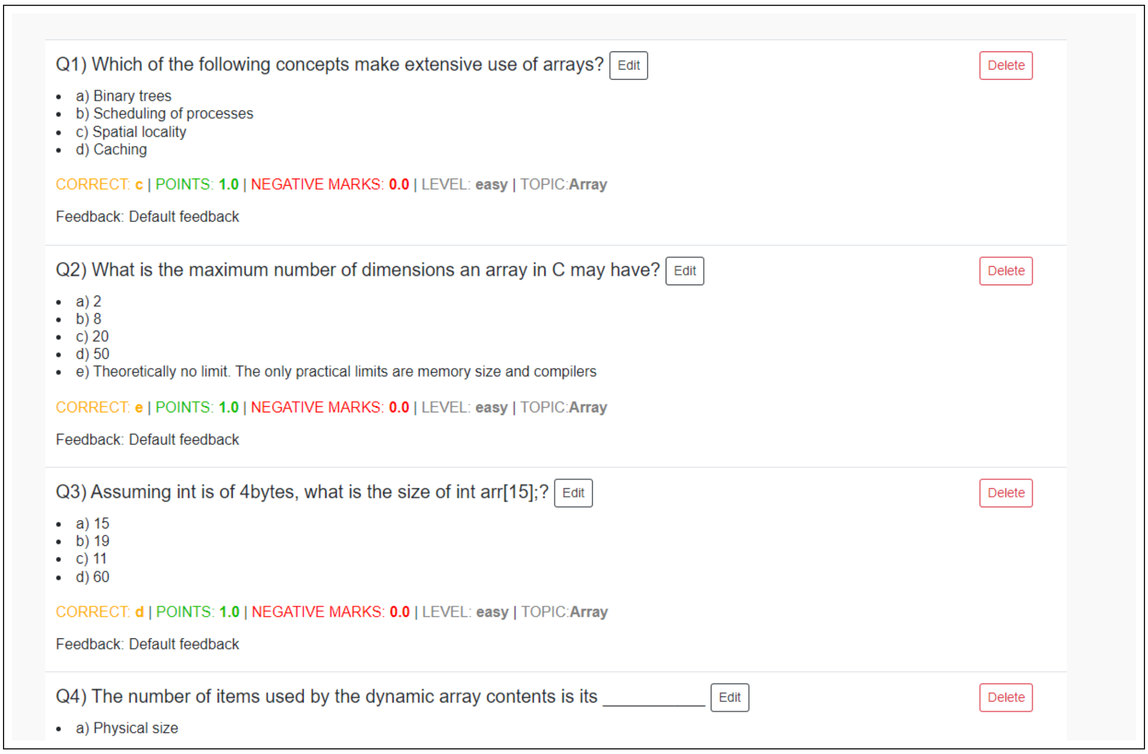


Figure 6.23: Course practice questions details list view interface

Each question is designed to be of multiple choice question with multiple options. Each question can carry marks, feedback and has level. Negative marking can also be associated if desired at later stages for experimentation. It need to be associated with a topic. Here a limitation is there, where each question is associated with single topic. The association of one question with multiple topics are not present in current version. Once uploaded the list of existing questions along with other parameters can be viewed on the portal for validation and corresponding editing as shown in Figure 6.23.

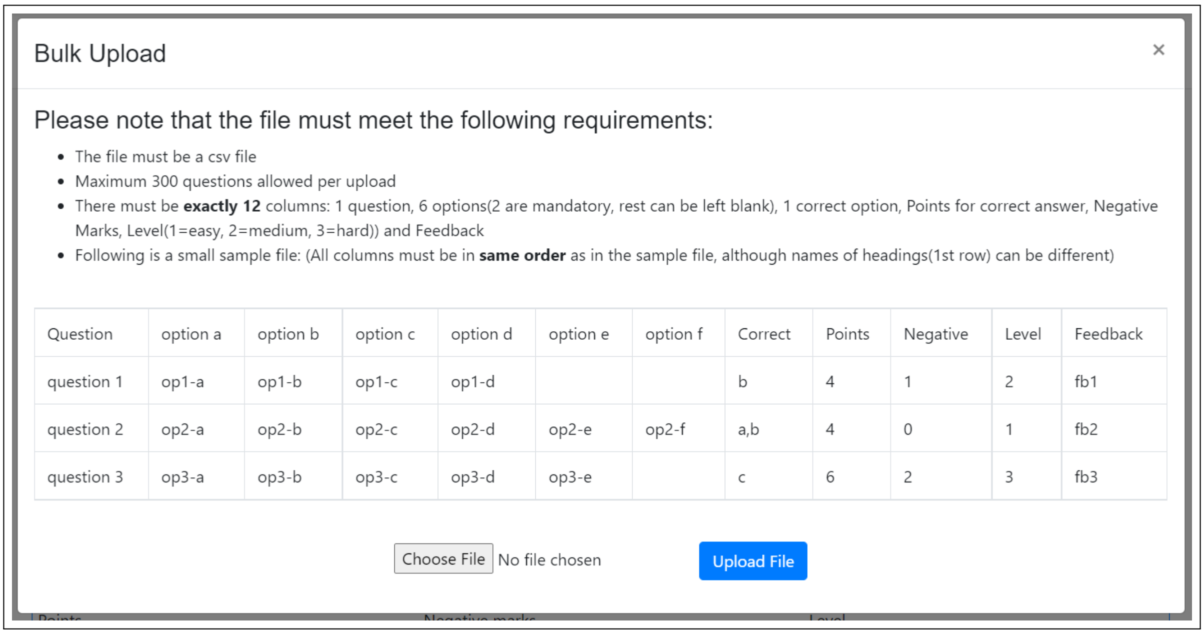


Figure 6.24: Course practice questions bulk upload support

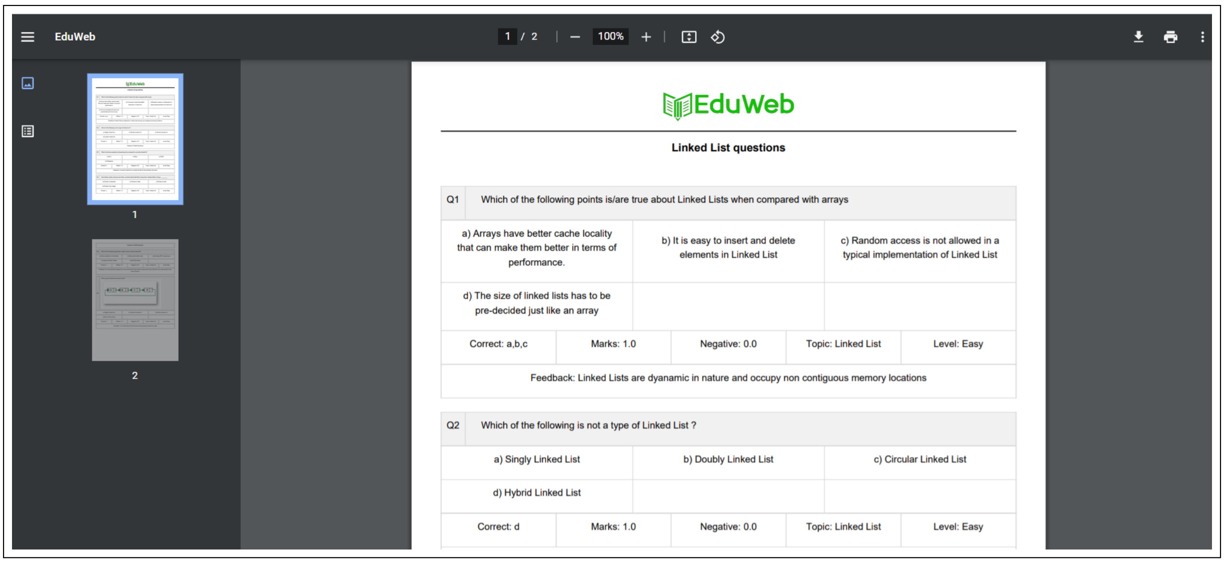


Figure 6.25: Course practice test PDF view

Bulk upload of practice questions is also supported through the interface. The sample of how to align the CSV file for bulk upload is shown in Figure 6.24. Figure 6.25 shows the PDF view of a specific practice test. These contain list of all the questions associated with the respective topic. Associated questions further contain all the details for validation and record maintenance.

The third type of test are external tests. These tests can be taken on other platforms and later their marks can be integrated within the system for evaluation purpose. The concept behind this is the fact that each course can have multiple features and aspects associated with it apart from the ones provided through the proposed system. For example, the course can have coding related evaluation, that is not supported by the proposed platform at present. So, for dealing with such situations, the platform has been provisioned for accommodating external questionnaire marks. The sample interface for external questionnaire integration is shown in Figure 2.26.

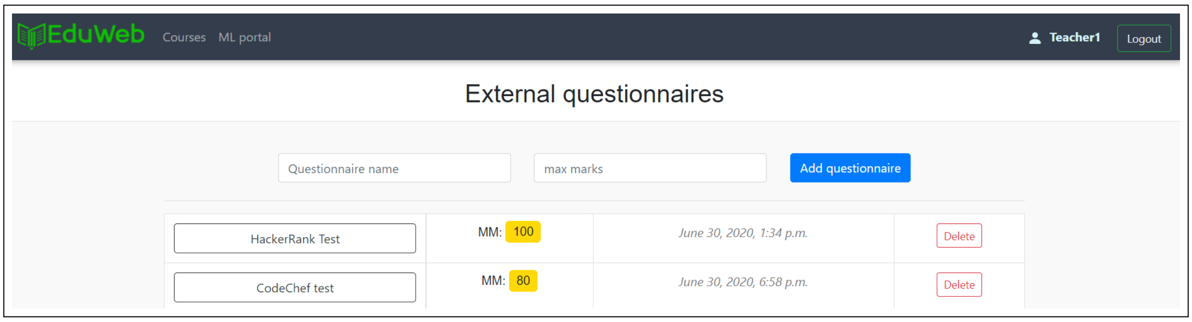


Figure 6.26: Course external questionnaire interface

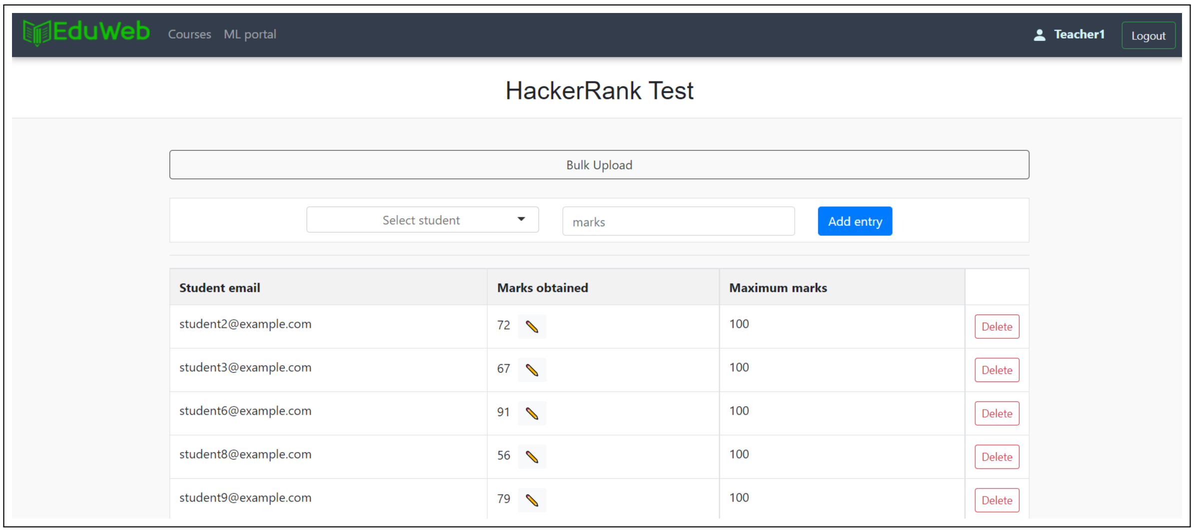


Figure 6.27: Course external test marks upload detailed view

The external test can be created through the interface initially name of the test and maximum marks need to be entered. After this each student marks can be entered individually or bulk upload through CSV file for integration. Figure 6.27 represents the detailed view of the external test marks upload.

The complete functionalities of the proposed topic based learning management system have been represented in this section. Along with the basic the future extendible associated parameters for adaptive learning and at-risk analysis support have also been discussed. The in-detail view of the ALS is represented in next section.

6.5 Adaptive Interface

In this section, detailed view of ALS interface is discussed. The emphasized part of the ALSs are the student topic wise knowledge estimation. Based on this, the further recommendations are done using appropriate recommendation algorithm. Here rule based adaptive learning is proposed.

For the proposed system, the topic wise student knowledge computation is done by a relatively *"Average of sums of averages"* modelling formula as follows:

$$K_i = \frac{\sum_{j=1}^{N_i} l_{ij} * (x_{ij}/z_{ij})}{\sum_{j=1}^{N_i} l_{ij}}$$

K_i is current level of knowledge for i-th topic,
N_i is number of questions participating in i-th topic,
l_{ij} is level (contribution) of j-th question in ith topic,
x_{ij} is number of correct attempts for the j-th question in ith topic,
z_{ij} is total number of attempts for the k-th question in i-th topic.

Here the knowledge estimation is done based on the number of missed correct question attempts along with the question level. It is differentiated from [194] as here level of each question is also taken into consideration. This can be further similarly extended for multiple item questions across multiple quizzes.

Once the knowledge estimation is done for i-th topic, the following rules have been used for making the recommendations.

if($student\_knowldege <= easyLevel\_threshold$) :

Recommend *EASY LEVEL* educational content and assignment to the learner

else if ($student\_knowldege > easyLevel\_threshold$ && $<= mediumLevel\_threshold$) :

Recommend *MEDIUM LEVEL* educational content and assignment to the learner

else if($student\_knowldege > mediumLevel\_threshold$) :

Recommend *DIFFICULT LEVEL* educational content and assignment to the learner

With the help of above rules the i-th topic coursewise recommendations were made for the students.

Further the flow-wise control of ALS is shown. The student logs into the system and lands in student homepage where different courses in which he is enrolled are displayed. Figure 6.28 represents the homepage view for specific student.

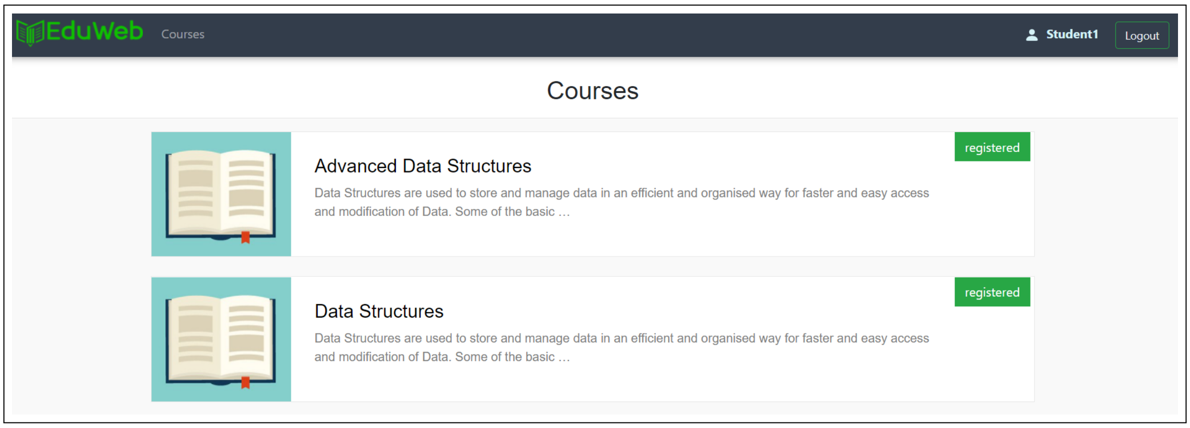


Figure 6.28: Student home page view

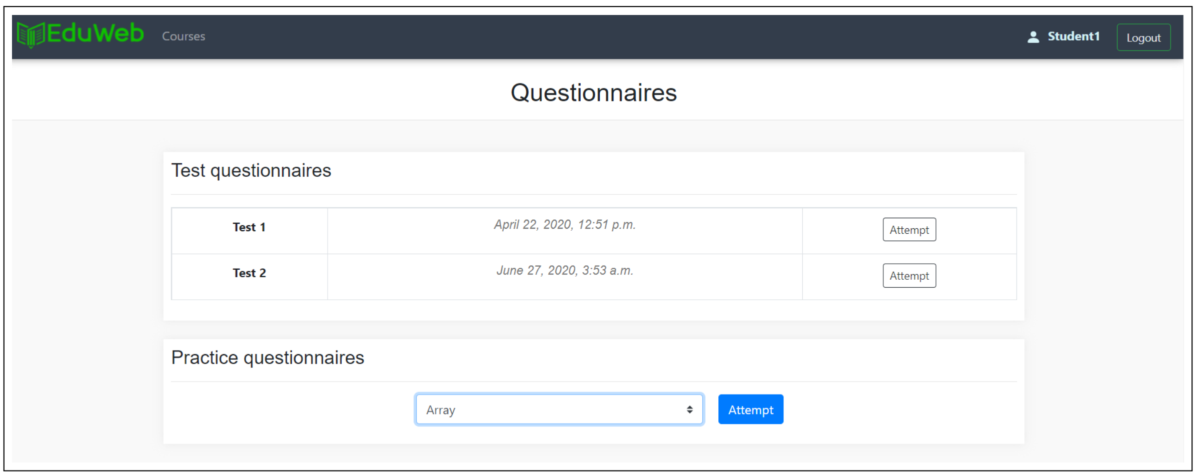


Figure 6.29: Student view for questionnaires

Once the student switches to the course and clicks on the questionnaire, two questionnaires will be visible to the student: *Normal Tests and Practice Tests.* The corresponding interface is shown in Figure 6.29. After this, the test related instructions will be visible to him as shown in Figure 6.30.

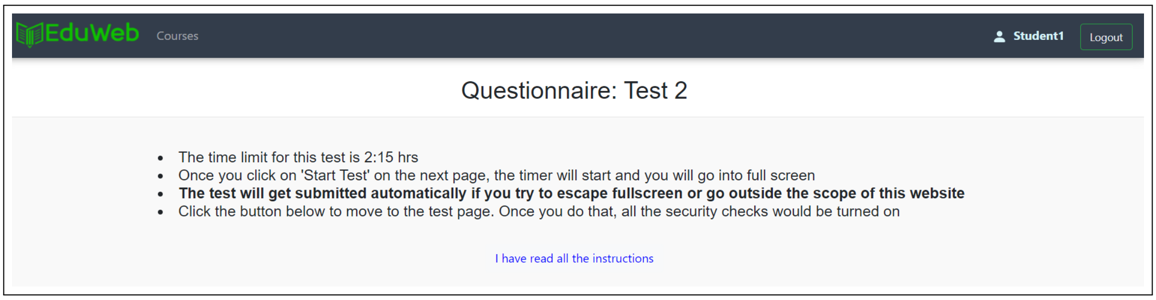


Figure 6.30: Student test attempt instructions page

Once he accepts the instructions he will be taken to security check. This is taken in care with respect to the online environments tests. His all unfair attempts like tab switch, full screen exit *etc.* are traced by the system. if the student exceeds the forbidden move threshold the test automatically terminates for him, considering unfair means.

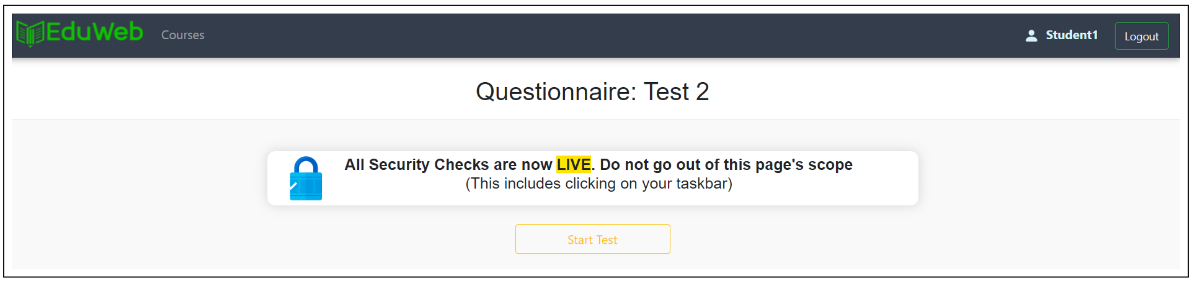


Figure 6.31: Student test attempt embedded security features interface view

Once the student starts the test, the test opens in full screen mode. Total time left and total number of questions are displayed on the top. Forbidden move count is traced. As of now, one page per question appears on the interface as shown in Figure 6.32. The student also has the option of exiting the test in between. In case the student chooses to exit, the remaining unsolved questions are only visible to him in his next attempt of same course test with adjusted other parameters.

Similarly, the student can give practice tests too. But there are no security checks are there as these questions are for self-assessment of the students. Here while solving practice questions, the student is told with the correct or wrong answer through color change and respective feedback is made available for the respective questions. The practice question interface for the student is shown in Figure 6.33.

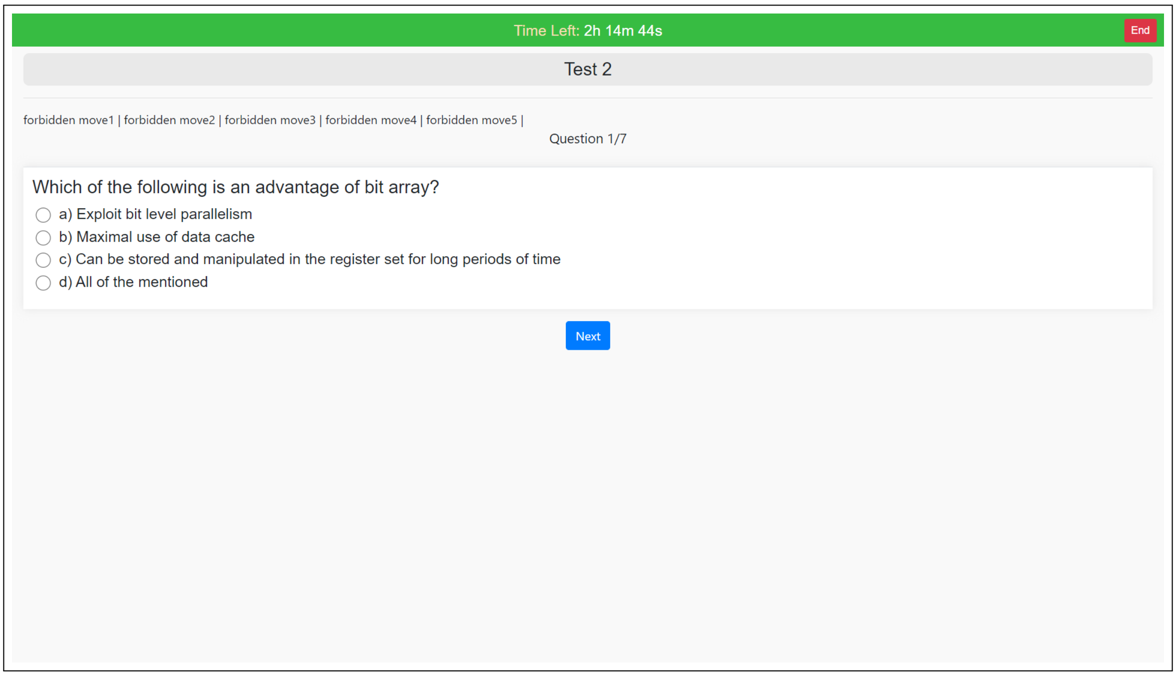


Figure 6.32: Student test attempt interface view

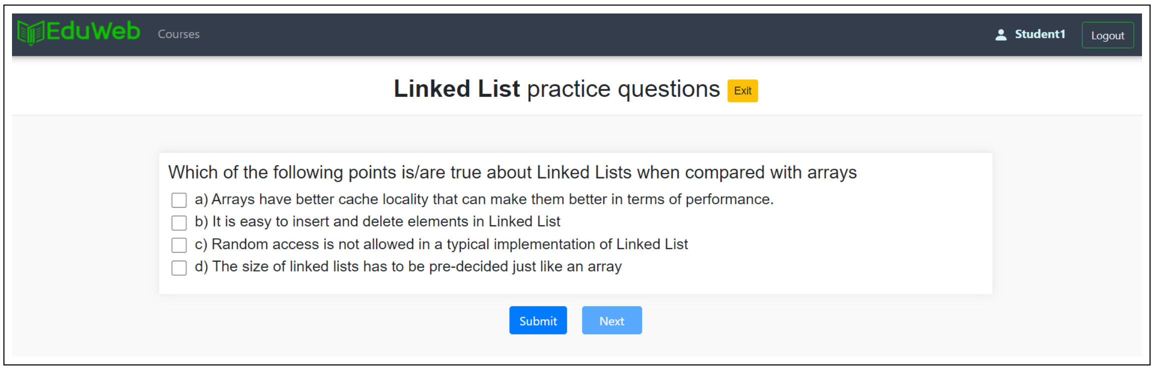


Figure 6.33: Student practice question attempt interface

Till here, the discussion regarding attempting of the normal and pratice tests were discussed. Now, the details regarding the student analytical dashboard will be presented.

The students course-wise dashboard is shown in Figure 3.34. The student can choose the course from the drop-down box present at the top of the dashboard. The corresponding dashboard will be presented as per the course choice. The upper part of the dashboard represents the class wise student performance based on tests that the student has attempted. The meter represent the bars where the student stands after attempting the tests. The answer-sheets for the associated tests can also be viewed by the student for analysis purpose.

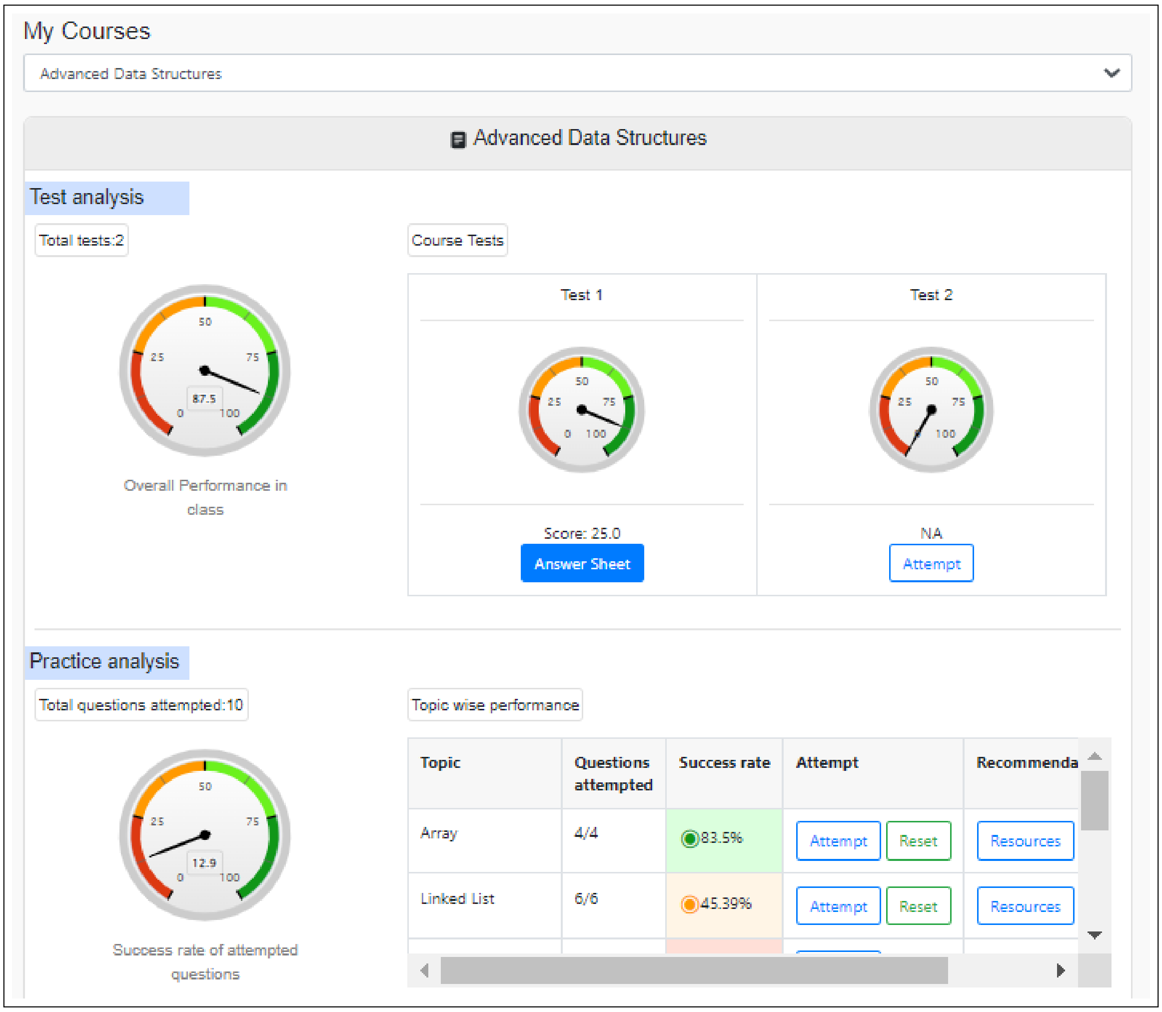


Figure 6.34: Student dashboard complete view

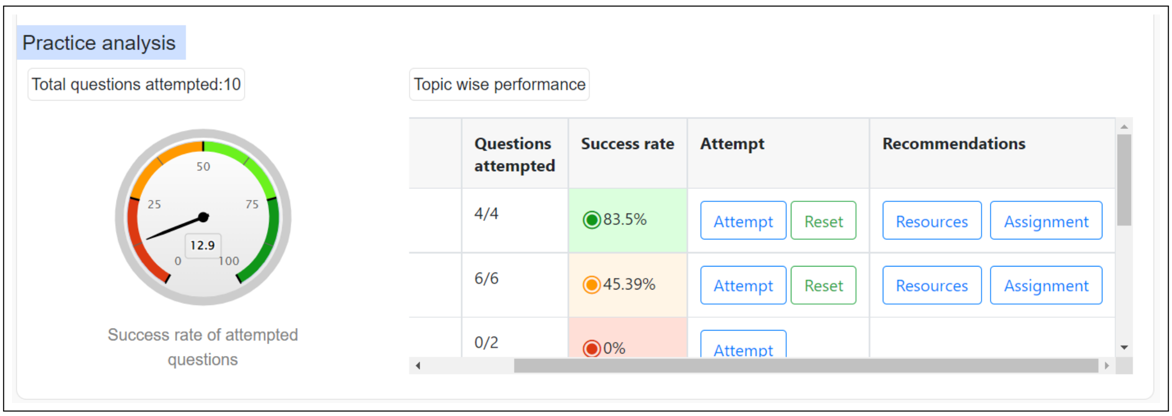


Figure 6.35: Student adaptive learning dashboard

The lower part of the dashboard represents practice tests analysis. As per the earlier discussion regarding the student i-th knowledge building equation and recommendation algorithm, once the students attempts complete questions of a topic the knowledge level of the student is estimated. Then according to the rules the corresponding educational content or resources and assignments are recommended to the student for i-th topic. Figure 6.35 shows the course-wise practice based analysis and recommendations interface for the student.

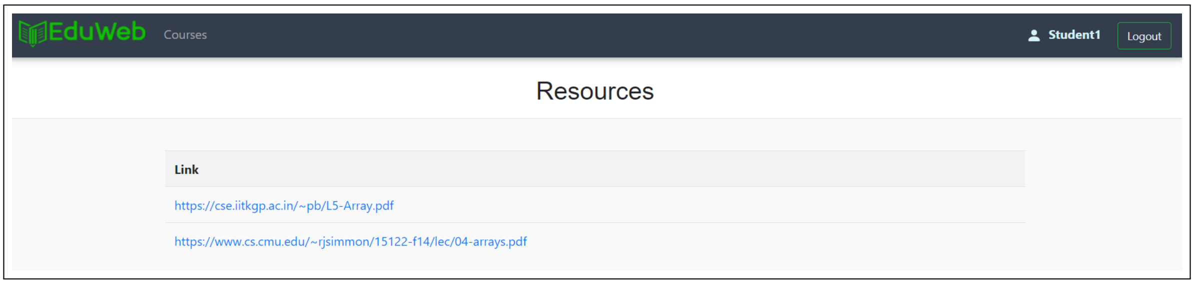


Figure 6.36: Student recommended topic based educational course content

However, if the student has scored very low in knowledge estimation and have been made basic recommendations, then he is allowed to reset the test. This allows to build in flexibility within the system for re-assessing the student knowledge and if student scores well and crosses the easy level threshold, then the student will be recommended with medium level resources and assignments and similarly he can reach one higher level. Figure 6.36 and 6.37 represent the recommended resources and assignments for a specific topic of a course.

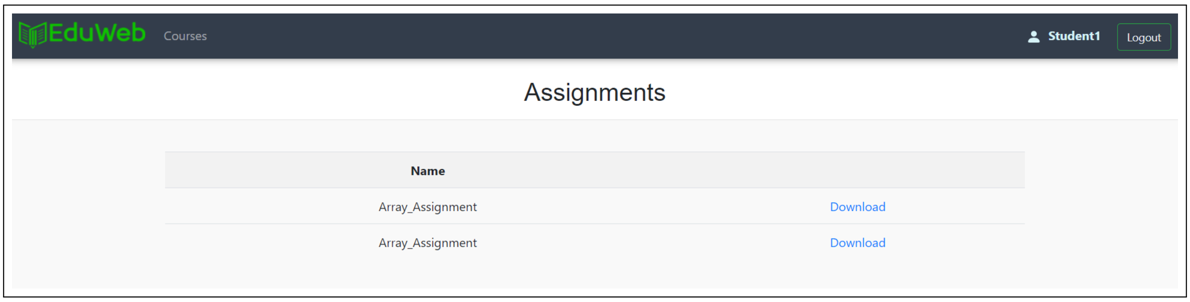


Figure 6.37: Student recommended topic based course assignments

But here, the assumption is made that student is always honest while attempting the practice tests and do not apply any unfair means and gamification within the system.

This section discussed the complete working of the proposed ALS. In the following section the final at-risk module integration is discussed.

6.6 At-Risk Prediction Module

For at-risk module integration within the above proposed system, the basic course access and assessment logs are required. For this, the provision of downloading the course different types of logs (access, tests, practice tests, external tests *etc.*) have been done. The instructor is given the functionality of downloading the associated courses logs from specific dates to specific dates in CSV format. Figure 6.38 represents the course logs downloading interface.

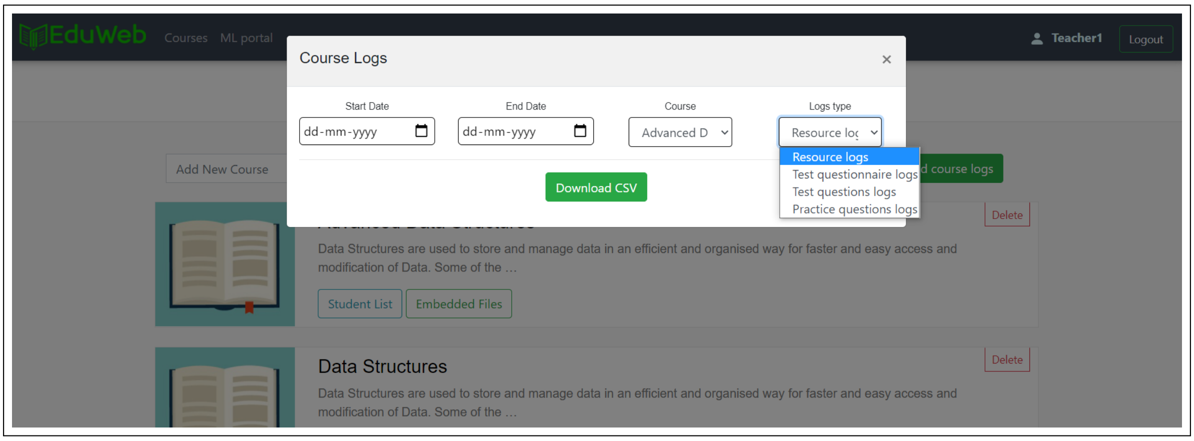


Figure 6.38: Different types of course logs

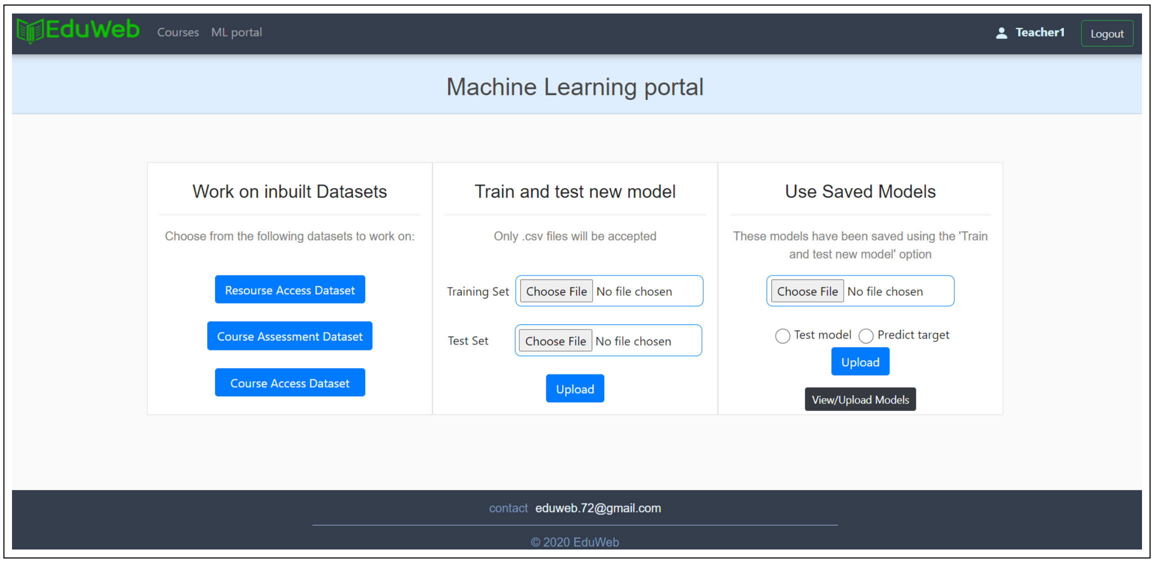


Figure 6.39: Course at-Risk machine learning portal

With the help of these course logs the instructor can further click on the machine learning portal. The proposed machine learning portal for the instructor is shown in Figure 6.39. It consists of three parts. First part again helps to download multiple course logs across the courses along with course access logs containing information about the timings the courses were accessed. For example, while clicking on the course resource logs the basic analysis of the datasets along with top 10 rows list view is presented as shown in Figure 6.40.

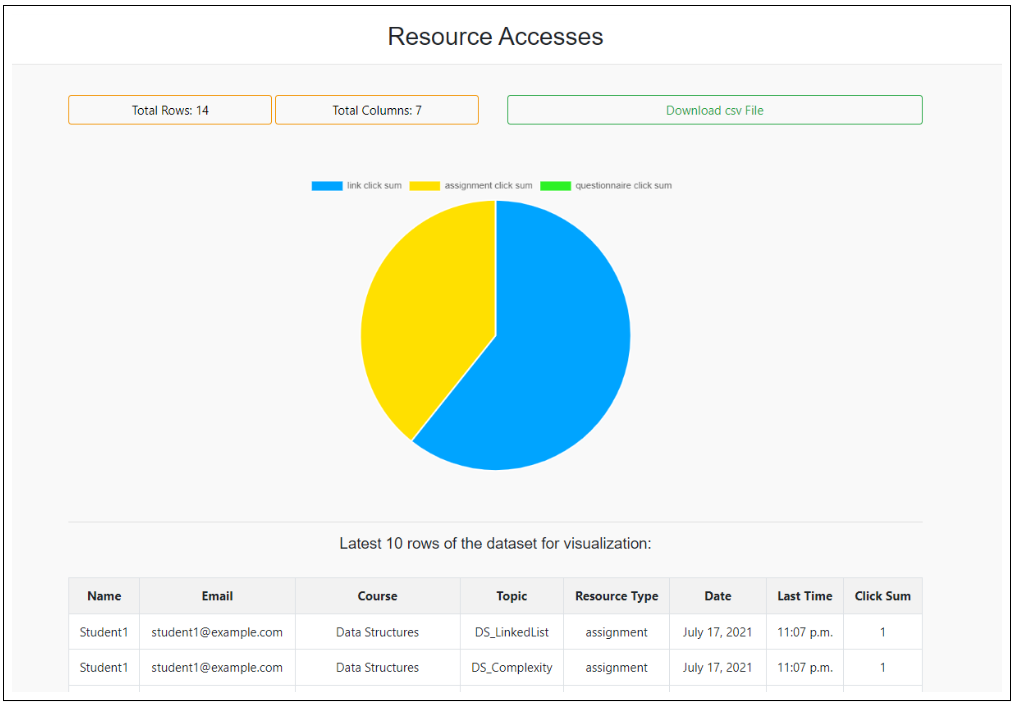


Figure 6.40: Course detailed resource access data analysis view

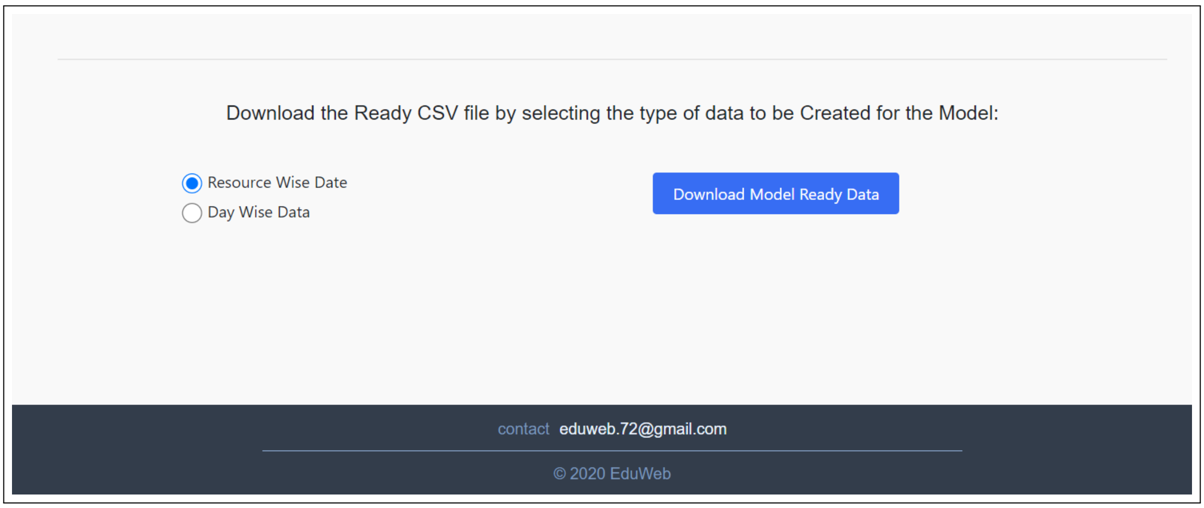


Figure 6.41: Course model ready reasource format file download

Further below, instructor is also provided with model ready data download of the CSV such that each parameter is listed separately in one column, ready to be pre-processed further for the machine learning models. Figure 6.41 shows the snapshot of downloading model ready CSV file for the resource logs.

Similarly model ready assessment data can also be accessed and corresponding CSV file can be downloaded as shown in Figure 6.42.

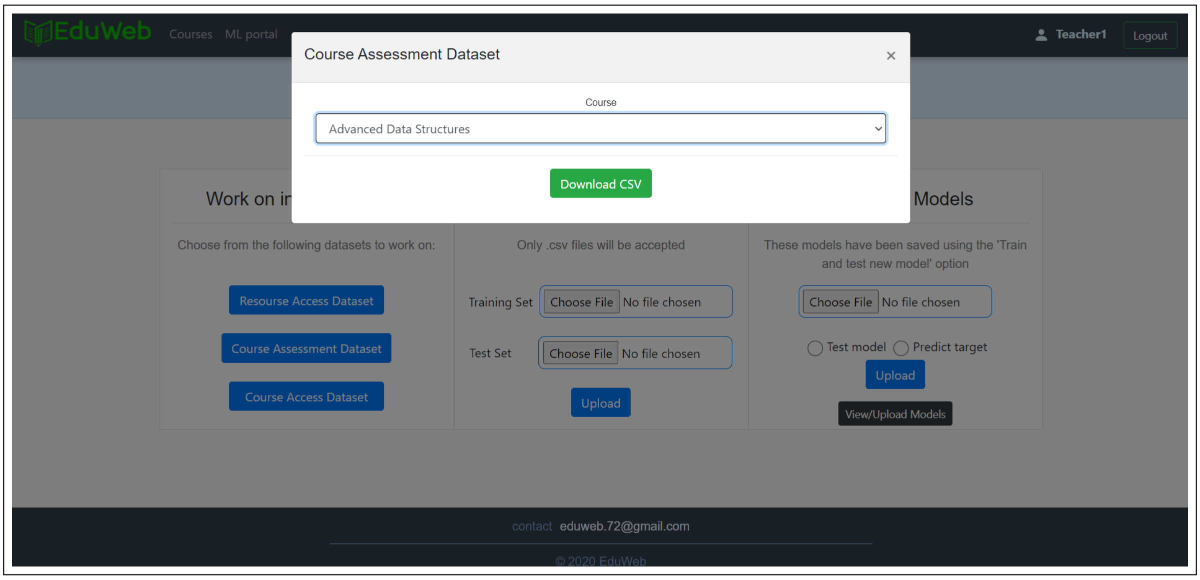


Figure 6.42: Course assessment data download

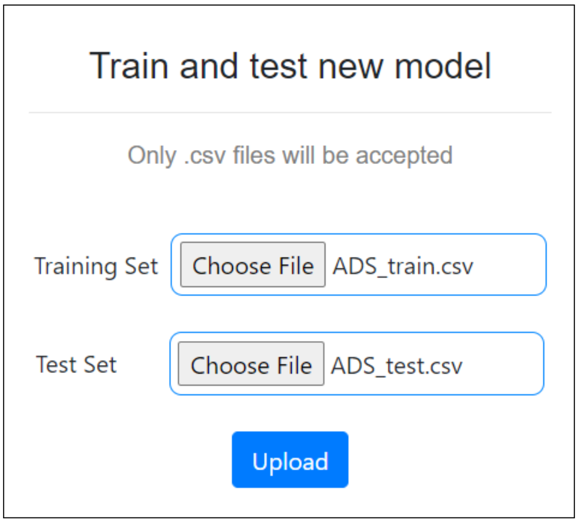


Figure 6.43: Test and train new model on downloaded data

Second part deals with online training and testing of the downloaded datasets. Here the instructors can train machine learning models on their course datasets and test them for new datasets. The interface for training and testing of the new model using downloaded dataset is shown in Figure 6.43. It allows only CSV files to be uploaded. It further asks for two separate files for training and testing. The system is designed considering the fact the previous iterations of courses are used for training the model and latest iteration unseen data is used for testing the model. However, the evaluation models can also be calculated on training dataset, described later.

On clicking the upload option, the training dataset details in list view (top 10 rows) are displayed for confirmation as shown in Figure 6.44.

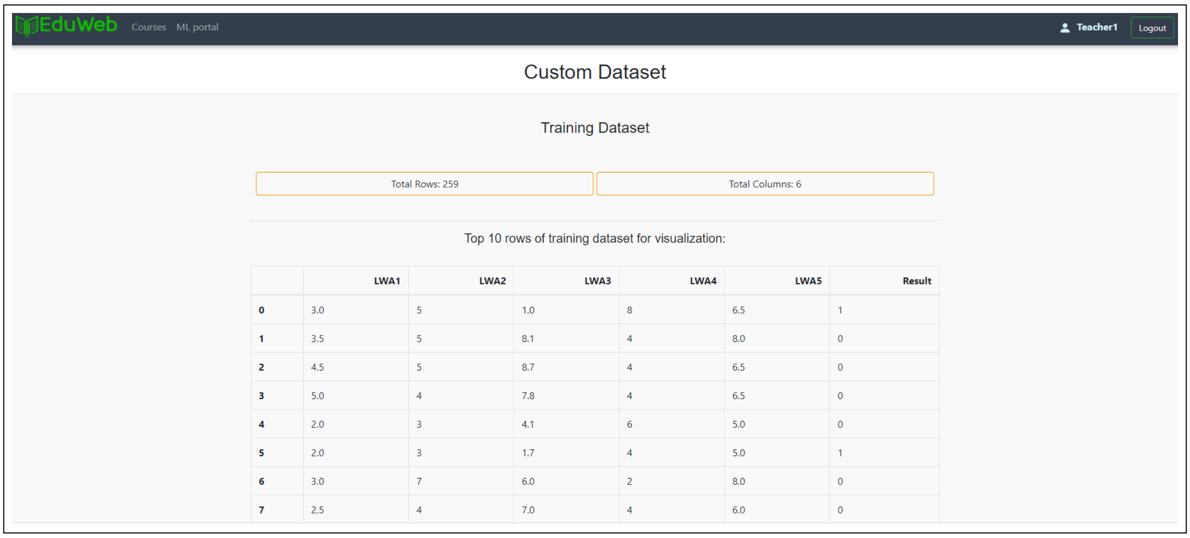


Figure 6.44: Training dataset detailed view

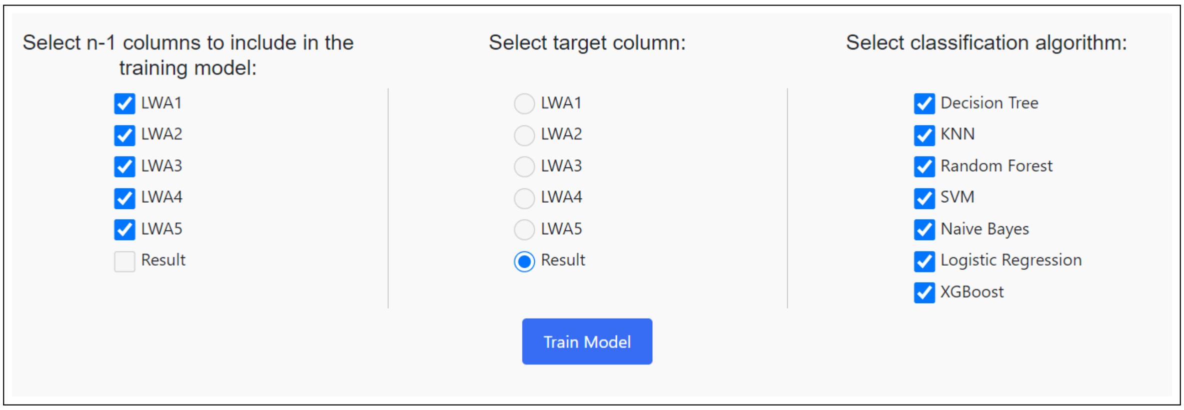
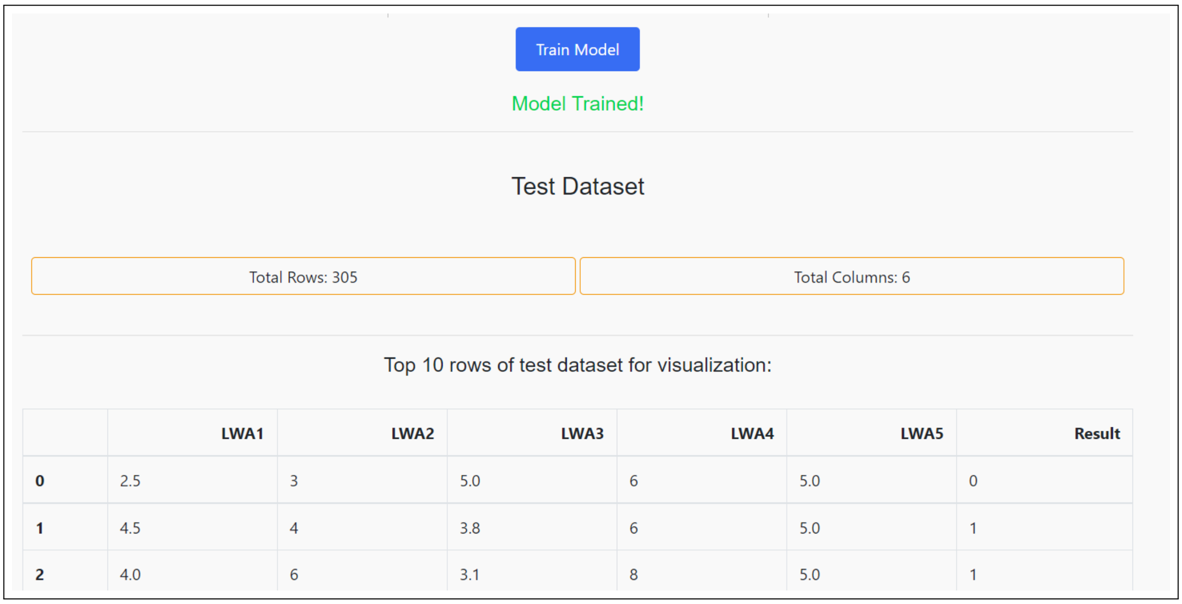


Figure 6.45: Choosing input parameters and classification algorithms for training dataset

After this, the instructor is allowed to choose the input parameters out of all the options as uploaded through the CSV file. The instructor is given the choice of including input features along with the target column. The option for choosing the various machine learning models is also given. As of now the available options of machine learning models are: *Decision tree, KNN, Random Forest, SVM, Naive Bayes, Logistic Regression, XGBoost*. All parameters are reset to their default values and are implemented using python scikit-learn. The corresponding interface is shown in Figure 6.45.

After choosing the respective models, the instructor can click on train model. After some time, the interface acknowledges that the model is trained and displays the test dataset list view as shown in Figure 6.46.



	LWA1	LWA2	LWA3	LWA4	LWA5	Result
0	2.5	3	5.0	6	5.0	0
1	4.5	4	3.8	6	5.0	1
2	4.0	6	3.1	8	5.0	1

Figure 6.46: Test dataset view after training of the model

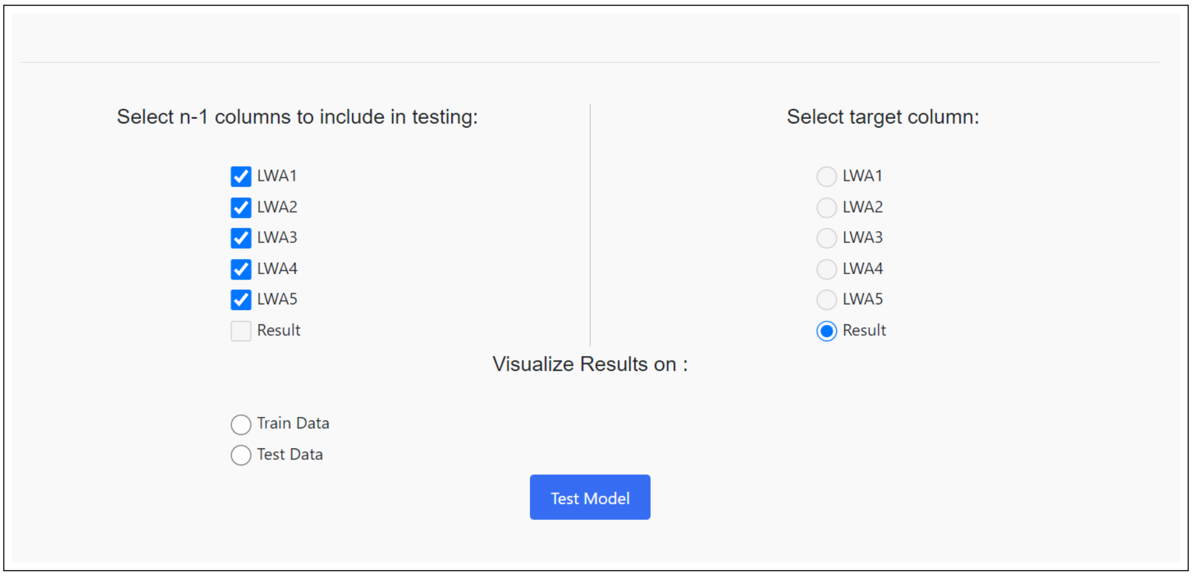


Figure 6.47: Choosing input and predicted parameters for test dataset

If earlier the instructor has made some alterations in choosing the parameters and target column, then directly using test dataset can create inconsistency. So, considering this fact, after the model is trained the instructor is again asked to choose the input parameters and target column for test dataset. Once the choice is done, the system asks for visualization of the results on train or test dataset as shown in Figure 6.47. The interface then shows the selected models evaluation results as shown in Figure 6.48.

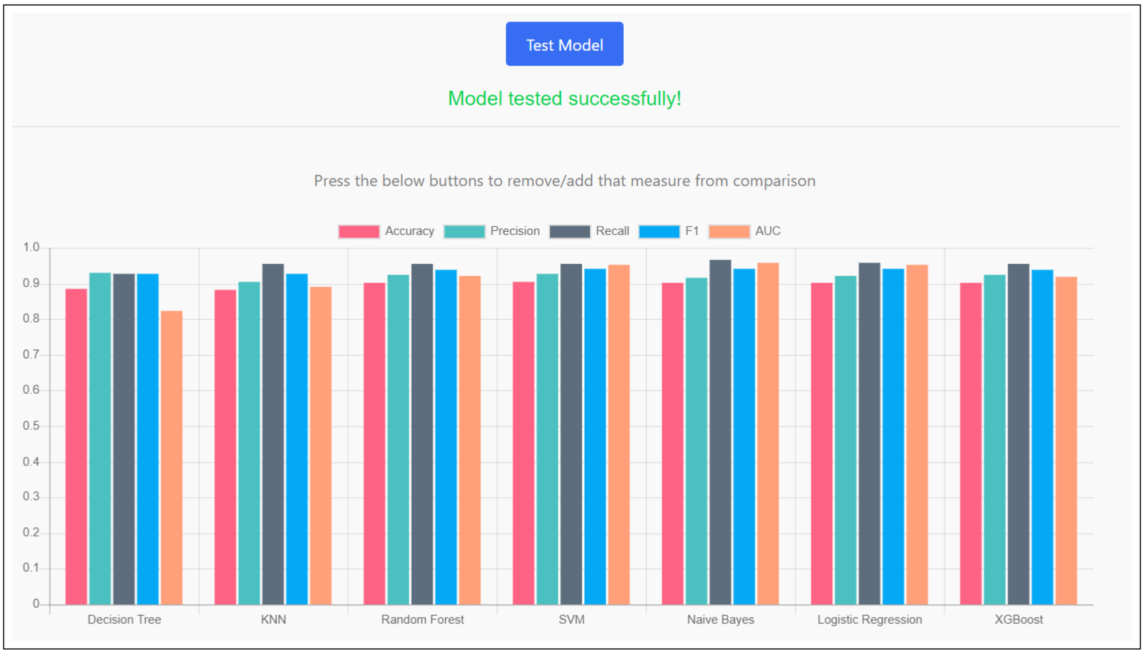
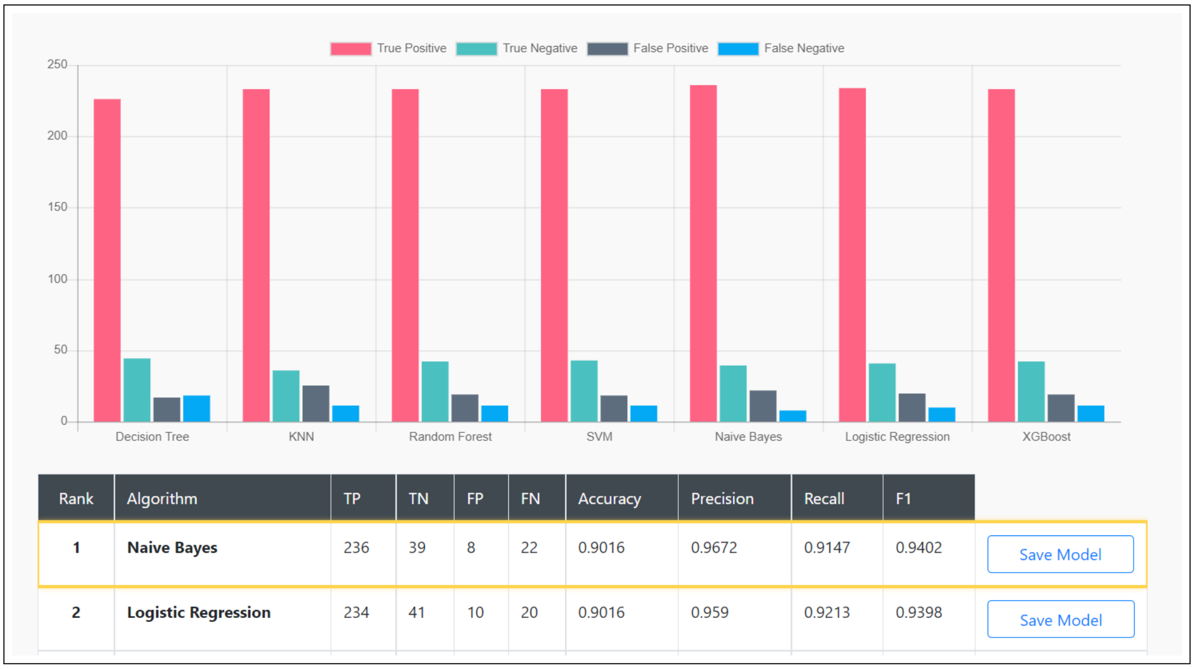


Figure 6.48: Tested model evaluation parameters



Rank	Algorithm	TP	TN	FP	FN	Accuracy	Precision	Recall	F1	
1	**Naive Bayes**	236	39	8	22	0.9016	0.9672	0.9147	0.9402	Save Model
2	**Logistic Regression**	234	41	10	20	0.9016	0.959	0.9213	0.9398	Save Model

Figure 6.49: Best model suggestion with topsis analysis

The considered evaluation parameters are: *Accuracy, Precision, Recall, F1 and AUC*. The system also suggests the best model. The underlying algorithm used for deciding the best model is the topsis analysis [23]. Based on the topsis analysis the algorithm ranks the models and the highly preferred model is shown first. The corresponding best suggested model for one such course is shown in Figure 6.49. The system also allows to save the trained model for future use by clicking on the save model option. This completes the second functionality of the machine learning module.

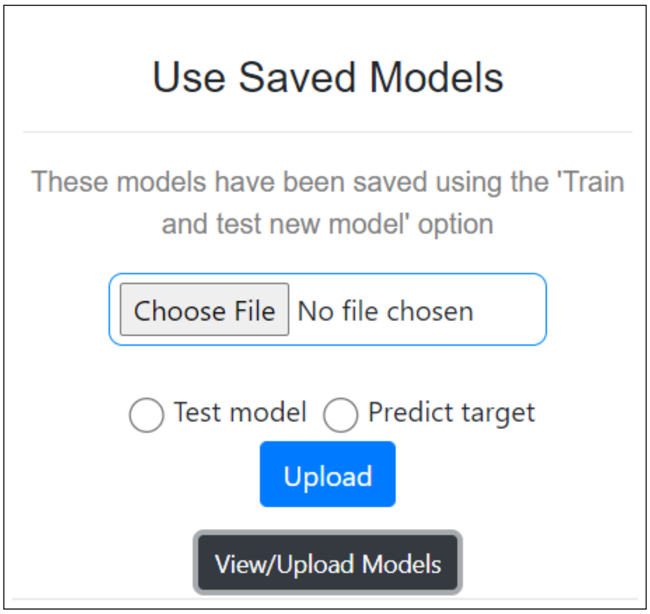


Figure 6.50: Choosing already trained model for testing

Third functionality of the machine learning model allows the instructor to work on already saved models or importing .pkl files of external models into the system as shown in Figure 6.50.

The already uploaded models can be viewed by clicking on the upload models. The corresponding models along with details are visible as shown in Figure 6.51. The system also allows to upload new external models by choosing the corresponding file and clicking on *Upload Model* button. These save models can be used to testing new datasets on various evaluation parameters (if the results are known) and making required comparisons. the steps are same as discussed above for testing a model on testing datasets. The difference is only that here, the model is already trained and saved within the dataset and selected from the given options.

Secondly, it also provides an option of making in-between or early predictions for real-time student status through at-risk predictions. The corresponding option is shown in figure 6.52.

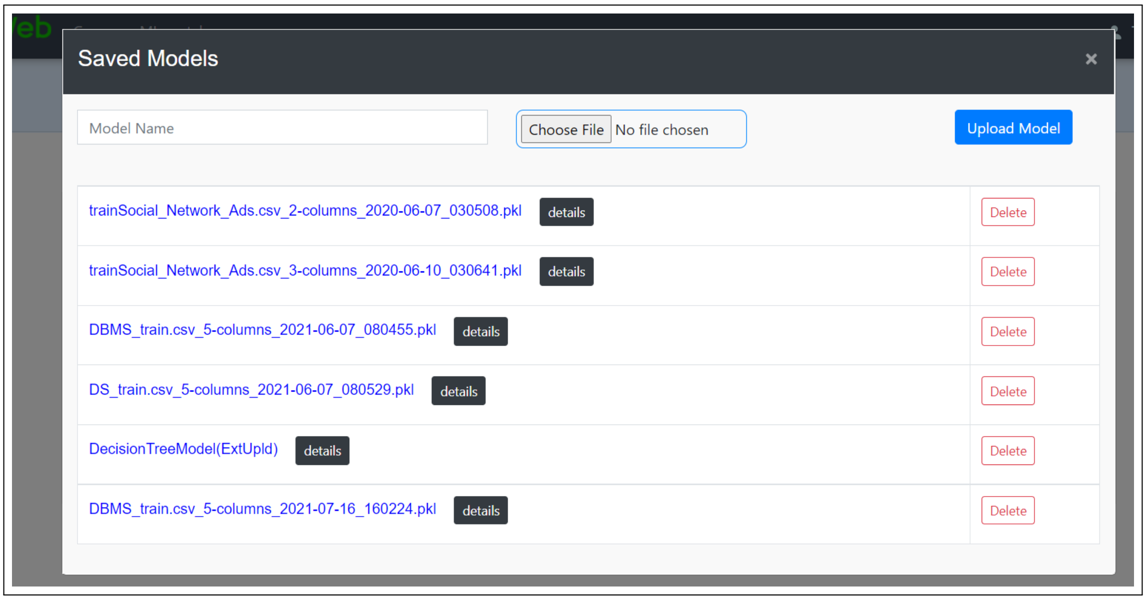


Figure 6.51: Viewing saved trained machine learning models

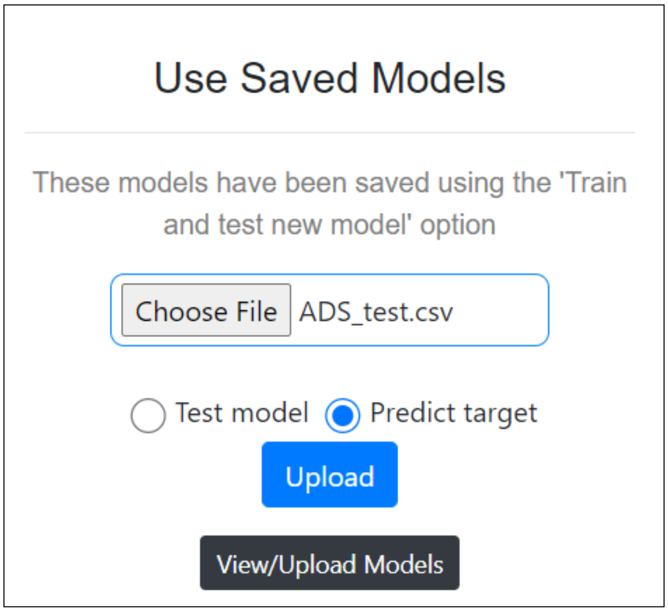


Figure 6.52: Choosing already saved model for at-risk predictions

Here the instructor is asked to upload only the test file. Once the test file is uploaded and predict target option is marked, the system allows the instructor to choose the corresponding trained models and input parameters. Then by clicking on *Predict* button the instructor can make the desired predictions. the successful predictions sample interface is shown in Figure 6.53.

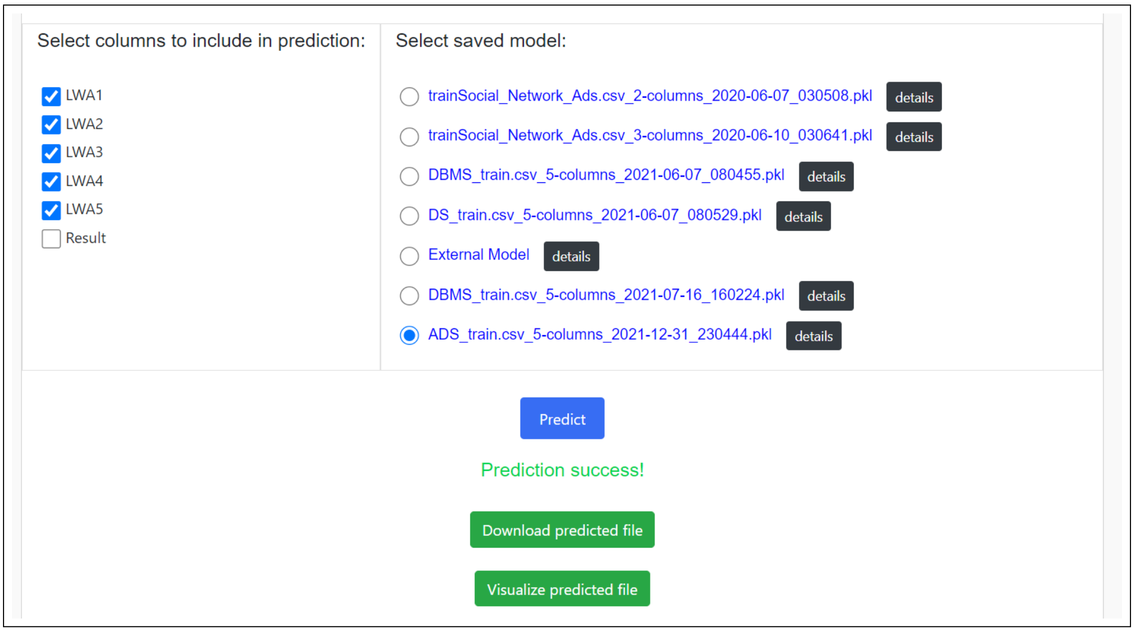
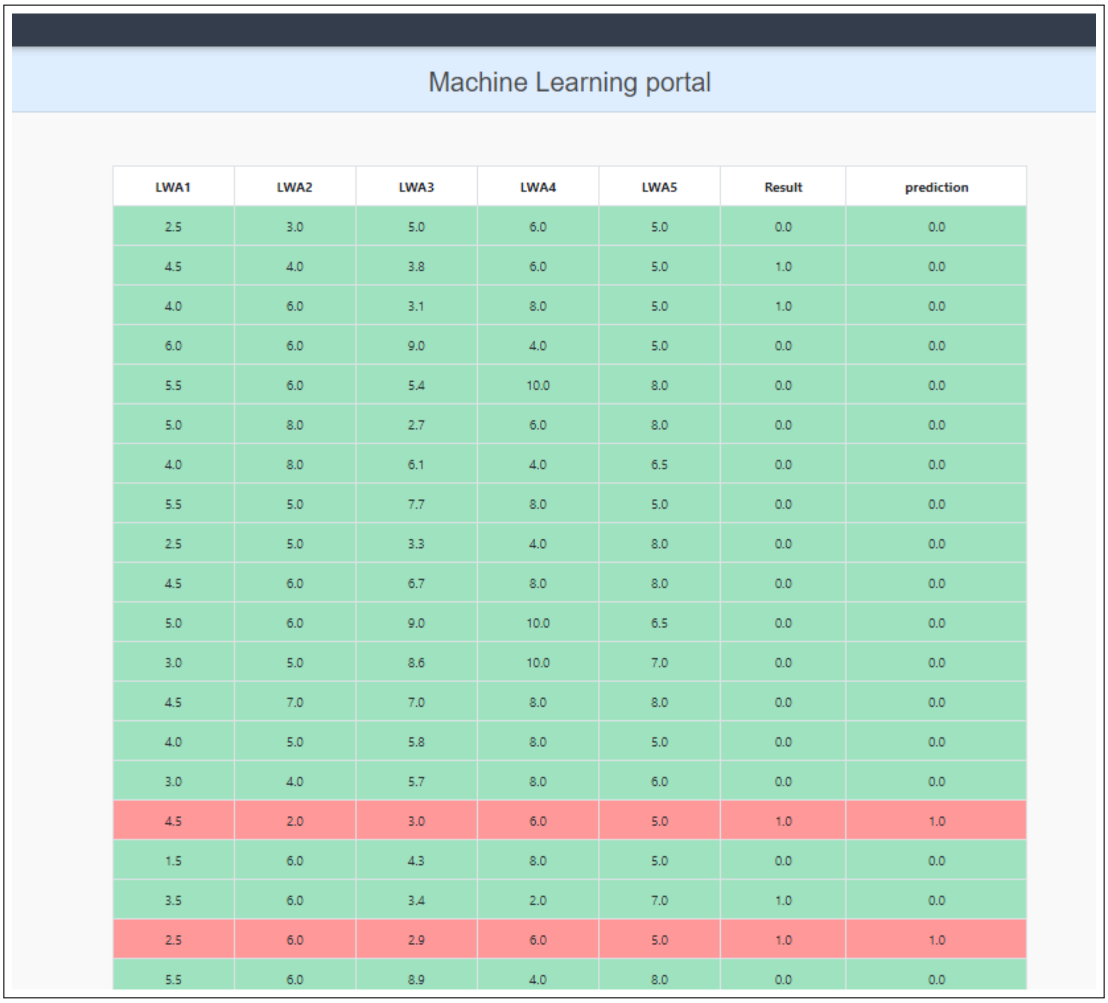


Figure 6.53: Predicting at-risk students with chosen input parameters and saved model

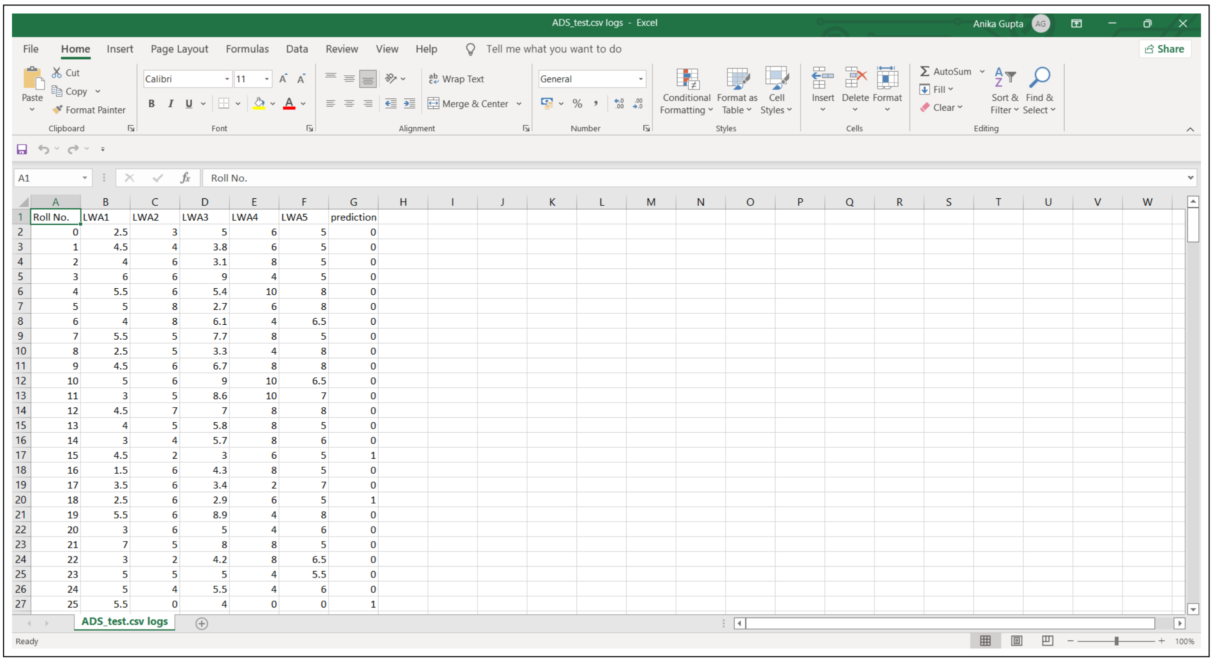

Machine Learning portal

LWA1	LWA2	LWA3	LWA4	LWA5	Result	prediction
2.5	3.0	5.0	6.0	5.0	0.0	0.0
4.5	4.0	3.8	6.0	5.0	1.0	0.0
4.0	6.0	3.1	8.0	5.0	1.0	0.0
6.0	6.0	9.0	4.0	5.0	0.0	0.0
5.5	6.0	5.4	10.0	8.0	0.0	0.0
5.0	8.0	2.7	6.0	8.0	0.0	0.0
4.0	8.0	6.1	4.0	6.5	0.0	0.0
5.5	5.0	7.7	8.0	5.0	0.0	0.0
2.5	5.0	3.3	4.0	8.0	0.0	0.0
4.5	6.0	6.7	8.0	8.0	0.0	0.0
5.0	6.0	9.0	10.0	6.5	0.0	0.0
3.0	5.0	8.6	10.0	7.0	0.0	0.0
4.5	7.0	7.0	8.0	8.0	0.0	0.0
4.0	5.0	5.8	8.0	5.0	0.0	0.0
3.0	4.0	5.7	8.0	6.0	0.0	0.0
4.5	2.0	3.0	6.0	5.0	1.0	1.0
1.5	6.0	4.3	8.0	5.0	0.0	0.0
3.5	6.0	3.4	2.0	7.0	1.0	0.0
2.5	6.0	2.9	6.0	5.0	1.0	1.0
5.5	6.0	8.9	4.0	8.0	0.0	0.0

Figure 6.54: At-risk students prediction visualization

The predictions made by the model are binary and map to binary classification. These are in the form of either 0 or 1. Here zero represents Safe status of the student and one represents the at-risk status of the student. The system provides an online prediction visualization iterface for viewing the student's status online. The other option is to download it as CSV file and use it for further analysis.

Figure 6.54 represents the visualization of the at-risk student predictions, as made by the desired model. Figure 6.55 represents the downloaded CSV file view for the corresponding at-risk students predictions.



Roll No.	LWA1	LWA2	LWA3	LWA4	LWA5	prediction
0	2.5	3	5	6	5	0
1	4.5	4	3.8	6	5	0
2	4	6	3.1	8	5	0
3	6	6	9	4	5	0
4	5.5	6	5.4	10	8	0
5	5	8	2.7	6	8	0
6	4	8	6.1	4	6.5	0
7	5.5	5	7.7	8	5	0
8	2.5	5	3.3	4	8	0
9	4.5	6	6.7	8	8	0
10	5	6	9	10	6.5	0
11	3	5	8.6	10	7	0
12	4.5	7	7	8	8	0
13	4	5	5.8	8	5	0
14	3	4	5.7	8	6	0
15	4.5	2	3	6	5	1
16	1.5	6	4.3	8	5	0
17	3.5	6	3.4	2	7	0
18	2.5	6	2.9	6	5	1
19	5.5	6	8.9	4	8	0
20	3	6	5	4	6	0
21	7	5	8	8	5	0
22	3	2	4.2	8	6.5	0
23	5	5	5	4	5.5	0
24	5	4	5.5	4	6	0
25	5.5	0	4	0	0	1

Figure 6.55: At-risk students prediction downloaded CSV view

This chapter represented the proposed adaptive learning system with educational data mining and learning analytics through three different modules. First one described the basic topic based learning management system basic functionalities. The second module described the extended part in the form of adaptive learning interface where topic-wise student knowledge is estimated and recommendations are made based on the knowledge level of the student. This module will provide the students with self-assessments. These self-assessments will help the students to assess their knowledge and also assist them with personalized recommendations.

The third module dealt with integrating the ALS with at-risk model for better adapting to the blended learning environments. The instructor can download course logs, train and test new models or make predictions on pre-defined or external models. Instructor can use these at-risk predictions for timely interventions and help in reducing failure or dropout rates for blended learning environments.

6.7 Limitations

The proposed ALS is for blended learning educational environments. When compared to the present learning management systems like Google Classrooms, Moodle, Blackboard *etc.*, the system supports the basic functionalities of these learning management systems like course management, students management, educational content management, assignment management, test interface, manual feedback *etc.* [25, 35, 167]. It scores over these basic learning management systems via its effective knowledge tracing, automated adaptive content alignment, learning analytics dashboard, machine learning model training and testing interface for instructors and machine learning based at-risk predictions. However, it lacks the following additional functionalities like discussion forums, answer sheets detailed analysis, sub-group management *etc.*

In the proposed system, each topic is linked with individual knowledge component. At present, complex topic with more than one knowledge components are not covered. The future work may extend this to include complex topics. There are pre-defined threshold values for easy, medium and difficult level content and assignment recommendations. This dimension may be extended further to include, dynamic setting of the threshold values, as per the student cohort knowledge level. As of now, manual tagging of easy, medium and difficult level educational content and assignments need to be in place for the system. This also can be altered and extended in future research.

There are limited number of machine learning models available for online training of the datasets. The list can be extended to include more enhanced models. Also, currently no alteration of hyperparameters is allowed for online training. In case of any alterations, the system assumes that the instructor will upload the trained model to the interface and use it separately, for making the predictions. However, in future research, separate interface for altering of the hyperparameters, can also be developed. A pre-processing interface can also be included. The graphical user interface can be further extended for more functionalities like discussion forums, answer sheets analysis, inbuilt chatbots, automated feedback *etc.*

6.8 Major Outcomes

This complete research study proposes a research based learning management system for blended learning environments. It possess the basic learning management system functionalities. Along with these, it also supports additional functionalities like adaptive learning for students and machine learning analytics based interface for instructors. The system is expected to help the students and instructors of blended learning environments, in improving the quality of education for blended learning environments of higher education.

The major outcomes of the research study can be represented as follows.

- Topic based learning management system for posting the required educational content with proper interfacing. For this, the topics directly map to the knowledge components.
- Adaptive learning interface for personalized learning support for the students. The interface facilitates non-weight and light-weight assessments or tests.
- Adaptive learning analytics dashboard for students, for effective knowledge representation. The interface estimates the topic-wise current knowledge level of the student. According to the rule based adaptive learning algorithm, it then provides adaptive educational content to the respective student.
- Machine learning at-risk interface for instructors for easy analysis. The instructors can get a glimpse of different course workings through its descriptive analytical interface.
- Online training and testing of the available machine learning models on contextual course datasets. The instructors can train, test or import external trained models for course based analytics.
- Early prediction interface of at-risk students for instructors, for timely intervention. The instructors can visualize at-risk predictions and export them for further usage.

- One-stop adaptive learning system for students and instructors, with educational data mining and learning analytics for blended learning environments. It will help in increasing the student retention rates by decreasing dropout rates and assist in improving the quality of higher education.

Chapter 7

CONCLUSION & FUTURE SCOPE

The research focuses on development of adaptive learning system with proper support of educational data mining and learning analytics for blended learning environments. This chapter concludes the research work presented in this thesis and presents the future scope of the work.

7.1 Conclusion

For the development of an efficient adaptive learning system with educational data mining and learning analytics for blended learning environments, in this thesis a detailed description regarding the existing terminologies, objectives, systems and challenges is provided. At first the studies mapped to the research objectives related to these fields are discussed. In this thesis, a comprehensive literature review for existing research studies mapped to the field of educational data mining, learning analytics and adaptive learning systems research objectives are presented. Existing methodologies for exploring the learner's statistics, behavioural patterns, performance prediction, analysis, visualizations, different types of adaptive learning algorithms *etc.* are studied in detail. The publically available datasets, tools and technologies for carrying out research within the corresponding field are also explored. An extensive list of existing analytics based systems at international and national level are presented.

Further the research is narrowed down to the present context specific research studies related to the present research and development of the desired system. Here, at first behavioural analysis related studies for exploring the learning behaviour of the students are studied. The behavioural analysis based studies were conducted in two parts. The first one, involved consisted of studies that helped in identifying the unusual learning behaviour of students through direct parameters whereas the second one involved, reliability testing of the feedback for checking the existance of biases. The behavioural pattern analysis is done to hunt for reliable parameters that can trusted by the stakeholders of blended learning environments. As per the latest trend of the research studies, the students are either studied in its entirety or are usually traced for their unusual behaviour like absenteeism, lower class engagements, low performance *etc.* For further utility of these reliable and trustable input parameters, further studies related to the automatized detection of unusual learning behaviour of students through early warning systems, are studied. These systems have been explored in various aspects like based on their objectives, input parameters, datasets, machine, sequential and deep learning models, computer science and engineering domain based studies. The latest research studies along with commonly used evaluation parameters are discussed and research gaps have been identified.

In order to bridge the gap, the present research is carried out in three phases. During the first phase the behavioural analysis of blended learning environment students is performed through indirect and direct parameters. First analysis focussed on the unusual behaviour of the students and efforts are put to find the reasons behind this unusual behaviour through direct interviews. The study revealed that the 21^{st} century learners can often risk their academic performance in order to achieve their long-term prioritized goals. The factors that they may be interested in and often keep them on track are related to peer instructions, clickers, small quizzes, assignments, practice problems *etc.* The second study checked the reliability of the student's feedback for biases. While performing reliability testing for a large cohort of students data, it is identified that relying only on the feedback may not be a good choice, as there exist biases within the system. So, apart from feedback other parameters also need to be considered for identifying the learning patterns of the students.

After the discovery of probable reliable input parameters, the second phase involved the building of efficient models that help in identification of low-performing students through early warning systems. The focus is on building generalized models that can be used for all irrespective of the environments, so online available public datasets across the institutions are used for system validation. The generalized models are built using the two most common input parameters: clickstream data and performance data, independently. Both the models utilized the sequential and relative nature of the educational datasets. For both the models, the educational data is modelled as time series data. For extracting out the relative nature of the educational dataset, gaussian transformation is applied as pre-processing phase. Once the data is pre-processed, the sequential models are utilized for building up the binary classifications of safe and at-risk category students. For clickstream data model as the educational data was sufficient for deep learning models, sequential three-layered LSTM model is utilized as a subpart of the model, due to its outperformance. Whereas for performance (light-weight assessments) data, discrete HMMs outperformed the other sequential models and helped in efficient classification of at-risk and safe category students. The HMMs further added interpretability to the predictions. These models evaluation results along with comparative analysis with present systems is discussed in detail, for online datasets.

As an outcome of the first and second phase, the trustable and more probable parameters for blended learning environments are the performance parameters. Based on the students direct interactions, model efficiency and better prediction interpretability, performance parameters are explored further, for blended learning environments. The pedagogical space for the utilization of these light-weight assessments within the blended learning environments is explored. Considering the integration of effective pedagogy and machine learning model for efficient model building, short-lightweight online formative assessments are implemented. As a pedagogical initiative, these were applied across three different core computer science and engineering courses, for effective teaching. In-turn the input parameters obtained through these assessments, helped in at-risk students model building at backend for the instructors. As an output of this third phase, a new pedagogy for the implementation of these short-lightweight online formative assessments within the present blended learning environments, is proposed. Along with this, an efficient ensemble model that builds upon these assessments is also presented. The results are compared with the existing computer science and engineering domain based studies, and are found to efficient enough in early identification of at-risk students.

An output of the three phases, the reliable parameters for blended learning environments are proposed to be the short-lightweight assessments. Utilizing these as input parameters, efficient online and blended learning models can be built. This is highlighted via the comparative analysis with various state-of-the-art techniques, that shows the efficiency of the proposed systems. Finally, a topic based weighted adaptive learning system for students with integrated at-risk module for early identification of at-risk students is proposed. The system relies as well as utilizes these input parameters and helps in making efficient predictions along with the recommendations. This can be concluded that the results given by the proposed systems are very promising which can be used for the benefits of the society in the educational field.

7.2 Future Work

The developed topic based adaptive learning system with educational data mining and learning analytics can benefit the educational researchers of blended learning environments in considerable amount. However, the present system can also be extended further for enhancing its utility as well as generalizability across the domain.

- *Cross-domain Studies:* The system is tested and validated only on the computer science domain of one educational institute. More cross-institution studies throughout the nation or at international level, will add more value to the present research study. Similarly, cross-domain based studies will also add more generalizability to these results.

- *Datasets:* Due to the non-availability of sufficiently large light-weight assessment online datasets, the deep learning sequential models were not applied on the performance data. As per the availability of such datasets in sufficient quantity in near future, this dimension can be explored further.

  Future research may even be redirected to create such datasets for blended learning environments. This may help the educational researchers in better understanding of the basic requirements of the blended learning environments.

- *Diversified Parameters Integration:* The present study focussed on each of the input parameters like clickstream data, performance data independently. The studies integrating the usage of these as collective measures, can add further value to the results. Also the additional contextual information like demographic data, students earlier performance data, personal data like family status, income range, caste *etc.* can be added along with these parameters for efficient model building.

- *Extending Graphical User Interface:* The proposed system has limited number of machine learning models available for online training of the datasets. The list can be extended to include more enhanced models. Also, currently no alteration of hyperparameters is allowed for online training. In case of any alterations, the system assumes that the instructor will upload the trained model to the interface and use it separately, for making the predictions. However, in future research, separate interface for altering of the hyperparameters, can also be developed. A pre-processing interface can also be included. The graphical user interface can be further extended for more functionalities like discussion forums, answer sheets analysis, inbuilt chatbots, automated feedback *etc.*

- *Extending Reliable Parametric Search:* In future, apart from the performance parameters, other reliable parameters for blended learning environments can be searched. Exploring different types of activity and contextual parameters that may be effective for blended learning environments, can form part of future research. Further redesigning of the proposed topic based learning management system according to the reliable parameters, may produce more effective results.

- *Mastery based Learning Support for Blended Learning Environments:* The different ways to implement mastery based learning concept for blended learning environments, needs to be explored. This can assist the future students as well as instructors in better skill-building through personalized learning and quality education as per the need of the hour for educational environments.

- *Complex Adaptive Learning System:* In the proposed system, each topic is linked with individual knowledge component. At present, complex topic with more than one knowledge components are not covered. The future work may extend this to include complex topics. Also, there are pre-defined threshold values for easy, medium and difficult level content and assignment recommendations. This dimension may be extended further to include, dynamic setting of the threshold values, as per the student cohort knowledge level.

- *Explainable Artificial Intelligence Interpretations:* The models used in this research are treated as black-box, that includes both: machine learning and deep learning models. The future research may involve understanding the interpretations of these models, for better predictions. These interpretations will add value to the results.

The understandability and interpretability of the model learning may lead to more accurate predictions with higher values for evaluation metrics.

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