An Intelligent Real-time Classroom Visualization and Notification System

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An Intelligent Real-time Classroom Visualization and Notification System

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Dedicated to

Maa (late), Didi (late), Wife, Babu, Family, & Laxmi Kanta Mondal (my first teacher)

For their unconditional love, blessings, and constant inspiration

Declaration

I hereby certify that

- The work contained in this thesis is original and has been done by myself and under the general supervision of my supervisor.
- The work reported herein has not been submitted to any other Institute for any degree or diploma.
- Whenever I have used materials (concepts, ideas, text, expressions, data, graphs, diagrams, theoretical analysis, results, etc.) from other sources, I have given due credit by citing them in the text of the thesis and giving their details in the references. Elaborate sentences used verbatim from published work have been clearly identified and quoted.
- I also affirm that no part of this thesis can be considered plagiarism to the best of my knowledge and understanding and take complete responsibility if any complaint arises.
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Thesis Certificate

This is to certify that the thesis entitled **"An Intelligent Real-time Classroom Visualization and Notification System"** being submitted by **Ujjwal Biswas** to the Department of Computer Science and Engineering, Indian Institute of Technology Guwahati, is a record of bonafide research work carried out by him under my supervision and is worthy of consideration for the award of the degree of Doctor of Philosophy of the Institute.

To the best of my knowledge, no part of the work reported in this thesis has been presented for the award of any degree at any other institution.

Date : ____/_____/______

Place: Guwahati, India

Dr. Samit Bhattacharya
(Thesis Supervisor)

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Abstract

Traditional classrooms are now required to satisfy the demands of teachers and students to fulfill their ever-increasing expectations to provide quality teaching-learning experiences and outcomes. The classroom system uses technology to enrich the students and teachers in classroom teaching and learning. It gives birth to a blended learning platform based on the usage of Information and Communications Technology (ICT), while researchers are also looking for new ways to teach in the classroom. The purpose of a blended learning platform is to incorporate new opportunities like the Bring Your Own Device (BYOD) paradigm and mobile computing into classroom teaching-learning.

In a classroom, teachers face difficulties in monitoring and caring for individual students. Technology-enabled on-demand classroom monitoring can assist the teachers. In real-time classroom status visualization, the major challenges are showing the status and location of a large number of students in a limited display area such as that of a smartphone with minimum additional cognitive load on the teacher working in a time-constrained environment. Here, cognitive load means the metal effort teachers need to understand classroom monitoring information. Researchers are also facing challenges in notifying teachers and students about the students' pitfalls. The notification improves teacher-student interaction and engagement. Usually, receiving notifications about weaknesses or pitfalls requires the teachers' and students' focused attention to comprehend in a real-time classroom environment. This makes it really challenging to design notification systems for in-class use. In addition, classroom visualization and notification demand academic performance metrics (APMs) in tracking student performance. However, performance assessment and prediction depend on the challenges of selecting metrics.

To address the challenges of classroom visualization and notification, this thesis contributes to determine metrics, and define academic performance state, and introduces the concepts of a classroom visualization including notification techniques. We provide an up-to-date literature survey to use the APMs and strengthen the state-of-the-art. This survey helps in defining and predicting student performance states for real-time classroom visualization and notification. In addition, we determine the APMs through a field study to validate and compare the metrics in the Indian context. The aim of our classroom visualization is to display the large data on students' performance state in a limited available display. A two-level visualization scheme is developed to display the state of one hundred or more students on a desktop and/or smartphone screen the teacher might have. Our goal is to display the status of the entire class, location of the student, and detailed state information of the in-class students. In order to prevent disruptions to the usual flow of instruction, it should also be simple for the teacher to check student performance state. We

propose an intelligent notification system for real-time classroom use. The system generates automatic notifications to the user depending on students' performance status in real-time. The challenge here is ensuring the teacher's primary task (lecture delivery) should not be hampered. The notification also makes sure that instructors and students are aware and focused throughout lectures, even in the face of the busy schedule in the classroom. In this scenario, we developed a peripheral notification technique, which helps to reduce the cognitive load and time to get the feedback of a teacher working in busy everyday classroom activities. The system is designed to deliver notifications to students to analyze and understand their performance at an early stage and on time.

We developed Android applications for implementing visual monitoring and notification systems to evaluate usability. The high System Usability Scale (SUS) scores, perceived usability, and the positive feedback from the users (teachers and students) point to the fact that the proposed visual monitoring and notification system are likely to result in higher learning outcomes.

Keywords: Academic metrics, Academic performance, Blended learning, Classroom status, Classroom monitoring, Classroom-centered feedback, E-learning tool, Machine learning, Overview+details, Peripheral alert, Predictive model

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List of Algorithms

List of Acronyms

Acronym	**Expansion**
2D	Two Dimensional
APM	Academic Performance Metrics
BL	Both Level
BYOD	Bring Your Own Device
C	Critical
CGPA	Cumulative Grade Point Average
CLR	Critical Literature Review
DT	Decision Tree
FL	First Level
FUM	Frequently Used Metrics
GPA	Grade Point Average
GUI	Graphical User Interface
HCI	Human-Computer Interaction
HEIs	Higher Educational Institutions
IA	Internal Assessment
ICT	Information and Communications Technology
ITS	Intelligent Tutoring System
KNN	K-nearest Neighbors
LA	Learning Analytics
LB	Learning Behavior
LC	Likely to be Critical
LED	Light-Emitting Diode (LED)
LR	Logistic Regression
ML	Machine Learning

N	Normal
NB	Naive Bayes
NN	Neural Networks
OFS	Online Field Study
PC	Personal Computer
PEQ	Perceived Efficiency Questionnaire
PG	Postgraduate
PLQ	Perceived Learnability Questionnaire
RF	Random Forest
RFID	Radio Frequency Identification
RI	Relative Importance
RQ	Research Questions
SD	Standard Deviation
SL	Second Level
SOQ	Students Open-ended Question
SUS	System Usability Scale
SVM	Support Vector Machine
TOQ	Teachers Open-ended Question
TSQ	Teacher Satisfaction Questionnaire
UCD	User-Centered Design
UG	Undergraduate
WAN	Wide Area Network

List of Symbols

Symbol	Description
(F_S)	Feedback Score
(I_S)	Instantaneous Score
$ASCT_{T_i}$	Computed the average time taken to perform tasks i successfully
$CS_{M \times N}$	Classroom seating matrix
D_H	Display height
D_W	Display width
$DG_{R \times C}$	Display grid matrix
E_F	Elevation Factor
F_{fact}	Feedback Factor
F_C	Feedback Content
F_M	Feedback Modality
$M \times N$	Classroom size
$P_{O+D\_level\_col})$	Number of columns of students in the second level
$P_{O+D\_level\_row}$	Number of rows of students in the second level
P_{O+D_level}	Performance at the Second Level
$P_{Overview\_level}$	Performance at the First Level
$R \times C$	Maximum grid size for first level
$SS_{M \times N}$	Student state matrix
T_{i+1}	$(i+1)^{th}$ Feedback Interval

T_i	i[th] Feedback Interval
T_W	Weighted Threshold
TCR_{P_i}	Task completion rate in percentage for i^{th} participant
WCS_{R*C}	Weighted criticality score matrix
D	Euclidian distance between the 3 grid elements
P	Performance
TCR	Task completion rate

Chapter 1

Introduction

Since ancient times, traditional classroom instruction has gained popularity. In the past, India was well-known for its traditional teachings taught in Ashrams (Gurukuls). A traditional classroom is a teaching and learning environment where students receive instruction from teachers face-to-face. Teacher and student interactions take place in person. There are many advantages of face-to-face teaching and learning in a classroom. The traditional face-to-face classroom is beneficial because it gives a fixed and dedicated time for teaching and learning. Most students believe that traditional classroom settings are good for learning because they can easily interact with classmates and teachers. Students can gain deeper knowledge, real-world examples, and stories from their teachers and classmates.

Despite the fact that traditional classroom settings support teaching and learning in many ways, there are still a number of crucial needs that must be met to improve learning outcomes. In a traditional classroom, the following challenges are observed:

- **Clear audibility:** Clear audio enhances the learning outcomes for both teachers and students. Even if a student has not yet received a hearing impairment diagnosis, there are a number of things that can affect their capacity to listen and hear clearly. Such examples are the distance between teacher and students, classroom size, and noisy environment.

- **Visibility of the board:** Teacher's handwriting impacts the visibility of the teaching content. However, it depends on various factors. A common factor affecting the visibility of the board is the distance between the board and the students which directly depends on the class size. When the class size is large, obviously the distance between students and the board increases.

- **Individual attention:** It can be challenging to interact with every student daily in every class. Even in smaller classes, it is not easy to interact with every student due to the teacher's teaching in a time-constrained environment. There are various ways teachers can improve interaction with individual students, including their time, learning feedback, relationships, team-building, and peer support. Unfortunately, it is not always possible to do so, especially in large classrooms.

- **Measurement of Learning at Real-Time:** In classrooms, it is difficult to measure the performance of learning that happens during teaching. Teachers must ensure that their students have not been left behind before moving on to the next topic. It is crucial to conduct a brief check-in to make sure everyone is getting the concepts, particularly after introducing a new topic. If not, additional explanations could be based on faulty assumptions, which could make some students lose interest, get confused, or begin to question their abilities.

In order to address these challenges traditional face-to-face classrooms are adopting projectors, smartboards, sound amplifiers, and other technologies to improve teaching and learning. Researchers attempt to adopt new technology in classroom teaching-learning to get the advantages of both traditional and technology-enabled classrooms [3]. Many forms of classroom settings have been created using Information and Communications Technology (ICT) and other intelligent solutions [4, 5].

Nowadays, classroom systems focus on monitoring, controlling, and motivating students to improve teaching and learning process [6]. Modern technology aids the classroom system in providing quality teaching-learning [3]. The technology-enabled on-demand classroom analytics can assist the teachers in monitoring and improving student-teacher interactions [7]. In classroom monitoring, the challenging task is to convey the overall classroom status, academic performance, and student position in a classroom during lectures. Moreover, proper classroom monitoring and Learning Analytics (LA) demand quality academic performance metrics in quantifying student performance. The identification of state needs influential metrics that can help researchers, academicians, and students, keeping assessment and prediction as a key to student performance [3].

In a time-constrained large classroom environment, real-time monitoring becomes more challenging for teachers while minimizing their cognitive load. Here, cognitive load means the *metal* effort teachers need to understand classroom monitoring information. The most substantial challenge in classroom visual monitoring is representing large performance data sets that satisfy specific classroom needs. There are challenges in designing an adequately simple system concerning better interaction and user experience for visual monitoring. To make such a visualizer usable, it must be designed using User-Centered Design (UCD). The principal intuition is to develop a visualizer to explore and understand the data by a non-expert user. Good data visualization also concerns design decisions such as data abstraction as per the user's cognitive ability or load and clustering of data into groups as per reasonable goals.

Moreover, active research in classroom settings faces challenges in notifying teachers and students about students' difficulties and pitfalls [8]. In this research direction, the choice of blended learning in a classroom environment can assist in receiving notifications about the weaknesses of students. Therefore, intelligent classroom monitoring and notification will continue to develop due to the rapid growth and increasing popularity of ICT and innovative tools. It is also crucial to have a valuable strategy to enable future classroom systems to achieve the quality of teaching-learning experience [4, 5].

1.1 Role of ICT in Teaching and Learning

Classroom teaching has been using ICT to strengthen the degree of the teaching-learning process [9, 10]. At the current stage of technological development, a new form of classroom teaching can be created. Advanced technology-supported classroom teaching helps access educational resources, presents effective teaching content, and promotes teachers-students interaction with the context of monitoring [6] and notification environment management [8]. The use of ICT enhances interactivity and introduces accessibility of performance metrics and learning materials provided by the classroom system to improve system usability [10, 11].

The present-day learning platform and pedagogical objectives require teaching-learning tools that are interactive and adaptable enough to meet the present demands using ICT into classroom settings [10, 12]. The research showed that inadequately designed and inefficient classroom systems did not consider the utilization of ICT tools in the education process [4, 5]. Some recent attempts are also made to present advanced technologies in classes [5]. The effectiveness of the ICT tools benefits current endeavors to reduce the challenges of real-time classroom monitoring and notifications. The solution needs to address a fundamental problem: the excessive complexity of advanced technology in classroom teaching often makes it difficult to adapt effectively in achieving educational goals [3, 13]. The issues of technical complexities are common in blended classes, and a good solution would enhance learning outcomes [3].

1.2 Blended Learning Systems

Nowadays, technology-enabled classroom settings solve many of the difficulties a teacher faces in a traditional face-to-face class. These classroom systems integrate technology into classroom settings to improve learning outcomes. These forms of classes are also known as blended classes. The ICT, Bring Your Own Device (BYOD) paradigm, and mobile computing accelerate the research in setting up a blended classroom environment.

Blended learning is also known as the hybrid or mixed-mode of learning [14]. According to Osguthorpe and Graham [15], blended learning combines physical classroom teaching with computer-supported instruction. The phrase was redefined by Hoic-Bozic et al. [16] as various combinations of classical classroom teaching, the Internet, and learning support with advanced technologies, producing an efficient teaching-learning environment. Conceptually, blended learning may combine various teaching-learning methods, different modes of learning, and different interaction strategies.

The use of different learning methods such as e-learning, utilizing modern technologies, and traditional classroom teaching-learning may be combined in this platform. Researchers also blended various modes of learning methods in classroom teaching such as one-to-one and group learning. In one-to-one learning modes (e.g., 'individual learning'), a private tutor or machine takes additional care of a student. In "group learning" a teacher partitions students into groups and takes care of the groups. Researchers also incorporate and/or mix different classroom interactions, such as 'synchronous' and 'asynchronous' interaction

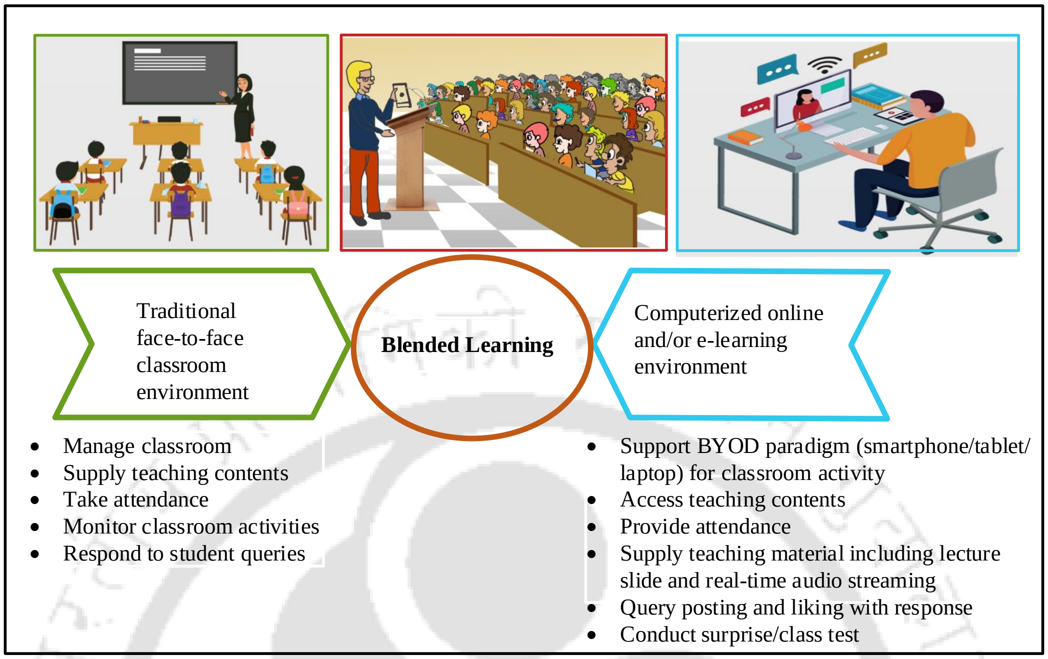


Figure 1.1: Basic building blocks of a blended learning environment.

schemes. Synchronous interaction is all about real-time engagement between the teacher and students. In the asynchronous interaction scheme, live interactions do not occur, but the students can post queries that the teacher can address at their convenience. The primary focus of blended learning is to determine an appropriate blending of this technology, online and traditional classroom teaching methods, group and individual modes of care, and synchronous and asynchronous schemes to design an intelligent learning platform. The actual aim of mixing these techniques is to improve pedagogy in terms of better learning experiences and outcomes [12, 17, 18, 19, 20, 21]. The goal of a blended learning platform is to incorporate new options into classroom teaching and learning, such as the BYOD paradigm, e-learning, and mobile computing. Figure 1.1 illustrates the concept of blended learning setting.

The blended learning is advantageous over e-learning and classroom teaching in terms of students learning achievements and outcomes [17]. Gitinabard et al. [18] reported that students achieve better grades in this learning environment compared to the conventional classroom teaching and e-learning system. The study by Nortvig et al. [21] further indicates that blended learning leads to positive outcomes in terms of student satisfaction, learning achievement, and enhanced engagement in the teaching-learning process. Tikadar et al. [12] found that classroom interactions have a beneficial impact on teaching-learning efficiency when using a blended learning platform.

1.3 Difficulties in ICT enabled Classroom

The classroom is a physical platform used to deliver lectures or share knowledge [12]. The use of learning tools is steadily expanding and is now prevailing in most of the education systems [3, 8]. Technology-equipped classrooms introduce a new way of teaching-learning into education. The design of classroom tools using UCD approach further enhances user satisfaction and interaction leading to improved learning outcomes. Through such improved interactions, the teacher is able to give timely feedback to the students, which leads to an ideal classroom teaching environment for future classes. Nowadays real-time and offline interactions between teachers and students are possible using advanced tools in teaching and learning.

Identifying the possible hurdles to using ICT in educational institutions would be a crucial step in enhancing the quality of teaching and learning. Academic researchers have realized the importance of ICT in society and its potential for the future of education. Educators appear to recognize the usefulness of ICT in institutions and suggest that challenges persist in adopting these technologies [10]. There are several difficulties teachers and students face in ICT-based blended classrooms. Some of the difficulties that need to be overcome in improving learning outcomes in such classrooms are as follows.

- **Support individual students:** There is an issue with providing individualized student support in a classroom teaching-learning environment. It is becoming more obvious in all educational settings, particularly when the number of students in a class increases. The primary challenges are determining and understanding the learning issues different students experience during lecture. The focus is on what happens when students have problems and become confused.

- **Class size:** Only a certain number of students can be present in the classroom at any given time. The growth in the number of students in the class necessitates increased quality resources with more teachers, classrooms, and reliable classroom infrastructure. As a result, responding to students who are stuck or confused with guidance or feedback to help them grow might be difficult.

- **Implementing blended learning:** The challenge in implementing blended learning is acquiring new technology and skills. Such examples include fostering understanding, facilitating classroom discussion, and managing students. There are challenges in minimizing teachers' time and effort to understand the classroom and real-time monitoring during class on a regular basis. The complexities of adaptation of new technology is the common problem and a simple solution would help to improve learning outcomes.

- **Teachers' effort:** The teachers must put a lot of effort into designing the course and lecture materials. The outcomes of the live class depend on the presentation and flow of teaching and learning. The flaws in presentations and teacher performances can result in significant problems. Therefore, it is vital to meet various difficulties regarding the adaptation of innovative ICT tools.

An ICT-enabled learning environment demands teachers' and students' attention to operate and interact in a real-time class lecture on monitoring and getting notification information. It has the potential to disturb teaching-learning. An effective data visualization for real-time classroom monitoring according to logical goals and data abstraction can help to reduce user cognitive load [6]. In case of notification management, one solution is to use peripheral interaction to minimize the disturbances [22]. The concepts of visualization methods in a limited display and notification system design using peripheral interaction are required to meet the state-of-the-art challenges. Therefore, an effective data visualization for real-time classroom monitoring and notification system design using peripheral interaction is required to meet the state-of-the-art challenges.

1.4 Motivation

The usage of advanced technology in education has increased exponentially to improve teaching-learning. It helps to utilize and adopt technology in our everyday routine to improve learning outcomes. Nevertheless, we still encounter performance issues in the utilization of smart devices in education. Of course, BYOD does have its advantages for other tasks.

Its portability and flexibility can be great for staying productive on the go or accessing information quickly. However, it's important to be aware of the limitations when considering BYOD for specific classroom activities. Also, there are risks to using these devices to perform tasks that are outside the classroom activities. Here, we must think of alternatives to streamline and enhance user experience in a smart classroom system [3]. Advanced tech-driven smart classroom systems adopt new interaction, input methods, and feedback approaches toward devising modern teaching methodology. Suitable classroom feedback to teachers and students, including comprehensive information about difficulties, plays a crucial role in quality teaching. On-demand visualization of the real-time classroom status can assist teachers in monitoring students using advanced technology. However, several challenging issues still exist, including processing raw inputs (e.g., data about students' criticality in terms of performances) and rendering in a limited display area. It helps the instructor customize the lecture better and nurture the students overall academic growth. Additionally, real-time feedback in the form of notifications concerning exceptional situations to teachers and students can enhance engagement in teaching and learning.

One of the growing areas where digital technologies can play a significant role is in classroom teaching and learning. The rapid growth of mobile technologies helps in effective teaching for omnipresent use [23]. Various digital environments and technologies are being used to improve academic performance, attendance, and other behavioral aspects during a particular course [24]. These technologies are primarily used as supportive tools for the teacher to effectively deliver the lecture (primary task) and improve teacher-student interaction (secondary tasks). However, quality teaching is expected to know students' progress, achievements, and difficulties to provide positive encouragement and to inform students about anything wrong on the fly [6]. Furthermore, these systems require the teacher's focused attention to operate a Graphical User Interface (GUI). Thus, using GUIs and technologies with regular teaching activities puts an additional cognitive load on the teacher. Current research has focused on representing students' learning states and performances meaningfully to the teacher [6, 25, 26, 27]. However, to improve teaching-learning, students' classroom performance and engagement in learning must be visualized [6]. The visualization is likely to help a teacher understand learners' difficulties and the need for the teacher's attention and subsequent intervention [6, 27]. In the literature, we found a few approaches for monitoring and visualizing in-class students. However, there are limitations to using important Academic Performance Metrics (APM) in identifying students' real-time difficulties and performances. In the classroom, real-time metrics on the quality of instructional episodes let the instructor adjust the lecture and nurture the academic progress of all students. However, several challenging issues include processing raw inputs (e.g., data about students' criticality in terms of performances) and rendering in a limited display area.

Earlier research has also explored peripheral interaction, ambient display, and tangible user interface to know the classroom's pulse. These techniques are used to minimize teacher's additional cognitive load. These are used in designing innovative classroom settings [22]. There are many interactions in real life (during classroom teaching) that a teacher needs to be aware of. For example, monitoring remaining lecture time or purposefully sipping water or tea, can be seamlessly integrated with lectures and discussions work while not considerably increasing their cognitive resources. Blending seamlessly these activities into everyday classroom activities required minimal mental workload. The authors have shown that these actions are required to shift attention when desired. However, performing a teacher's secondary or supporting tasks (e.g., knowing the students' pitfalls) required shifting the center of attention. The blending of these concepts in classroom settings design requires less mental effort of the teacher. In this scenario, the peripheral interaction can allow the teacher to provide quality teaching in a classroom. Additionally, the real-time feedback in the form of notification concerning exceptional situations to teachers and students can enhance engagement in teaching-learning.

1.5 Thesis Objective

The teacher in the classroom plays a significant role in teaching and learning. Quality-teaching demands to know students' performance states whether students are getting the concepts or not. These data are crucial to provide more attention for a student or group of students in the class. Nevertheless, the teacher needs performance information about an individual student a group of students, or an entire class of students to enhance the learning experience. These data are possible to access and comprehend faster using advanced technology in a classroom teaching-learning process. In improving the instructor's teaching quality, it will be required to understand the student's academic performances on the fly during lecture delivery. However, tasks may be overburdening when the classroom strength is large (e.g., more than 100 students). Hence, expecting the instructor to manually glean the real-time performance metrics of the classroom, which incurs a significant amount of cognitive load, is unreasonable for the individual instructor, not scalable across society, and a disservice to students. Therefore, designing a classroom monitoring tool is challenging.

To comprehend the classroom status information in an available or frequently used display (such as that of a smartphone) demands real-time visualization techniques. Precise visualization methods from a classroom perspective can reduce teachers' cognitive load to employ primary tasks (e.g., teaching). Like the traditional visual representation of complex data sets in the form of pictures, charts, diagrams, and animations reduce human time and help quickly perceive the entire data content. Researchers used visualization techniques because the instructor needs a conscious thought process to comprehend what is happening inside the lecture hall while delivering the lecture. Therefore, the teacher has a limited time to visualize all the details. However, an extensive group of information, such as performance, activity, attendance assessment, and records, must be shared with the instructor to enhance teaching quality. Therefore, identifying academic performance and difficulties for classroom systems demands influencing APMs to use visualizing or other real-time feedback systems.

Another challenge is that the students' monitoring activity primarily relies on the instructor's visual attention on a device. As a consequence, the teacher can overlook the visualizer in their busy time-constrained schedule. However, visual resources are limited and need focused attention on teaching. In this scenario, we must render an alternative to bring students' states to the attention of the teacher. A peripheral interaction can reduce the teacher's cognitive load to utilize in the primary task. We can use intelligent techniques to give feedback to teachers and students to improve student's learning outcomes. Educational apps on mobile devices can track student progress and provide actionable feedback in real-time, leading to better learning outcomes. Feedback in the form of notifications can help the instructors and the students in the classroom environment. Furthermore, on-demand systems to address real-time proactive alert generation need to motivate the students for active classroom participation in an available device in a classroom environment.

As we have already introduced, the challenging task in monitoring students is to show both the status and location of many learners in a limited display area. Furthermore, the representation of such situations and location information is challenging without putting an additional cognitive load on the teacher working in a time-constrained environment. A well-thought notification on the available device (e.g., smartphone or tablet) can improve the teacher's interaction with students. However, understanding in-class status and notifications needs teachers' and students' focused attention on seeing the information on the display. As a consequence, interaction with smartphones or tablets requires users' concentrated attention. This attention-shifting may interrupt the lecture's progress. Therefore, designing a real-time notification system is important and challenging [8]. However, quality teaching-learning demands knowing students' progress, achievements, and difficulties to provide positive encouragement and to inform students of anything wrong during lectures [6, 26, 27]. We extend and explore visualization techniques and peripheral notifications using influencing APMs in classroom settings to address these challenges. Here, another important note is that identifying academic performance and difficulties for classroom systems demands important APMs to be used in classroom visualization and notification systems. We describe the following research problems to address the research challenges.

- Problem #1: A systematic study on academic performance metrics for assessing and determining students' difficulties in higher education to better monitor and know learning pitfalls.
- Problem #2: Designing an intelligent system for the instructor, as part of the classroom system, to visualize potential learning pitfalls of the students at an individual or overall classroom level.
- Problem #3: Designing an intelligent notification system for the instructor and students, as part of the notification, ensures that the teacher's primary task is not hampered. The system notifies on peripheral device and acts on it for engaging and motivating in-class students in teaching-learning.

1.6 Summary of Contributions

The aims of the thesis are to develop and validate an intelligent real-time classroom monitoring and notification system in a blended learning environment. We made three key contributions to achieve our ultimate goals. The major contributions of the thesis can be summarized as follows:

Thesis goal

Improve the teaching-learning experiences and learning outcomes in a blended learning platform using real-time in-class students' visual monitoring and intelligent notification to both teachers and students.

- Our research methodology identifies trends in using academic performance metrics and methods to assess and predict academic performance over time. The classification of students based on academic performance metrics to real-time monitoring and notifications.
- We propose a novel interactive visualizer and monitoring dashboard, the Manas Chakshu, for large blended classrooms to improve teaching-learning experiences.
- We present an in-class intelligent notification method that uses peripheral device and interaction for teachers and students to tackle poor students in a blended classroom.

1.7 Thesis Contributions

The above contributions were made which effectively lead to ultimate goal of the dissertation. Below, we describe about the contributions in brief.

1.7.1 Comprehensive Study on Academic Performance Metrics

We aim to use our findings to assess and predict academic performances in a course in higher educational systems. We have reported a comprehensive study to select metrics for assessing and predicting academic performance to address these challenges. We performed a critical literature review (CLR) and identified 62 articles to determine metrics and their categories using existing terminology. The categories helped to define frequently used metrics. Our critical literature review also shows the role of the metrics' relative importance in academic performance assessment and prediction.

The major contributions that we made are as follows:

- This CLR identified 62 primary articles to show the importance of the APMs. Initially, we searched five known databases and got 45 articles. In the final stage, we followed the forward snowballing [28] scheme of article search and got an additional 17 articles.
- We proposed *eight* best-suited categories to understand the broader aspects of the *academic metrics* using on-dated terminologies.
- This CLR also determined *frequently used metrics* and described the role of *relative importance* of the academic metrics.
- This CLR also reported seven recommended Machine Learning (ML) models to predict students' academic performance based on literature.

A better understanding of those academic performance metrics helps effective decision-making in day-to-day classroom activities. We use three states, namely, C: critical, LC: likely to be critical, and N: normal to real-time in-class monitoring and notifications. Some students perform well in all aspects and require very less intervention, we term these students to be of the N-type. There might be some students for whom intervention is desirable. These are the LC-type students. There can also be students who must be given special attention. We call them the C-type students. In this thesis, we considered forty-eight states which is practically a bit tricky and complicated [29]. That is why we have combined these states into three simpler states to easily remember and comprehend the states.

1.7.2 Real-time Interactive Classroom Monitoring

In order to address issues of classroom monitoring, we propose a real-time interactive visualizer. The visualizer consists of two levels, implemented as a sequence of four algorithms. In the first (overview) level, the entire classroom status is visualized using a grid structure. An optimum grid size is computed first (first algorithm), keeping in mind the issue of "clickability". Each grid element indicates a cluster of students. A second algorithm was proposed to compute the *criticality* of each cluster for subsequent visualization. Three colors are used to visualize the classroom. Red indicates a *critical* cluster of students that require immediate teacher intervention; yellow denotes a *likely* to be *critical* cluster, which has the potential to turn critical; and green indicates a *normal* student cluster. The rendering of the clusters with colors is done with the help of another (third) algorithm. The final (fourth) algorithm is used to obtain the details of each cluster in the second (details) level. In this level, student details (including state information) are displayed in the form of a grid of pre-stored images of the students belonging to particular clusters.

To further refine the visualizer, we design the "Manas Chakshu" - a real-time visual monitoring dashboard for blended classrooms. The proposed dashboard is based on the basic concept of a two-level dashboard, with significant optimization and non-trivial challenges. The optimization pertains to the screen-area utilization at both the overview and display levels. The major non-trivial challenges include a better strategy for calculating classroom status utilizing weighted states and an improved method for identifying critical classroom regions.

In order to carry out the experiments, we developed an application for the visual monitoring system. The inputs to the same are the classroom configuration matrix and the corresponding state matrix in the visual monitoring application. In this, we assumed the classroom as a rectangular seating arrangement, which is the general convention. The application uses four proposed algorithms to process these inputs and generate the visual interface. To perform the experiments, we assigned the aforementioned three states to the students (C, LC, and N).

1.7.3 Intelligent Notification System

We reported a notification system design that includes complex alert scheduling during lecture delivery, both for the teachers and the students. The system design is real-time feedback-driven for the blended classroom settings. The system notifies teachers when students are at risk, not engaged in learning, and/or not participating in real-time classroom discussions. The system will take care of notification fatigue and disturbances in lecture flow due to the feedback in real-time using available peripheral devices and interaction. The notification helps the instructors evaluate themselves and change their teaching patterns to make the class more engaging. Therefore, the solution provides the teacher and students with a digital notification to monitor the students' activity and provide real-time feedback automatically.

To validate our notification system, initially, we did an empirical study using a system prototype. Finally, we implemented the notification system as an Android application based

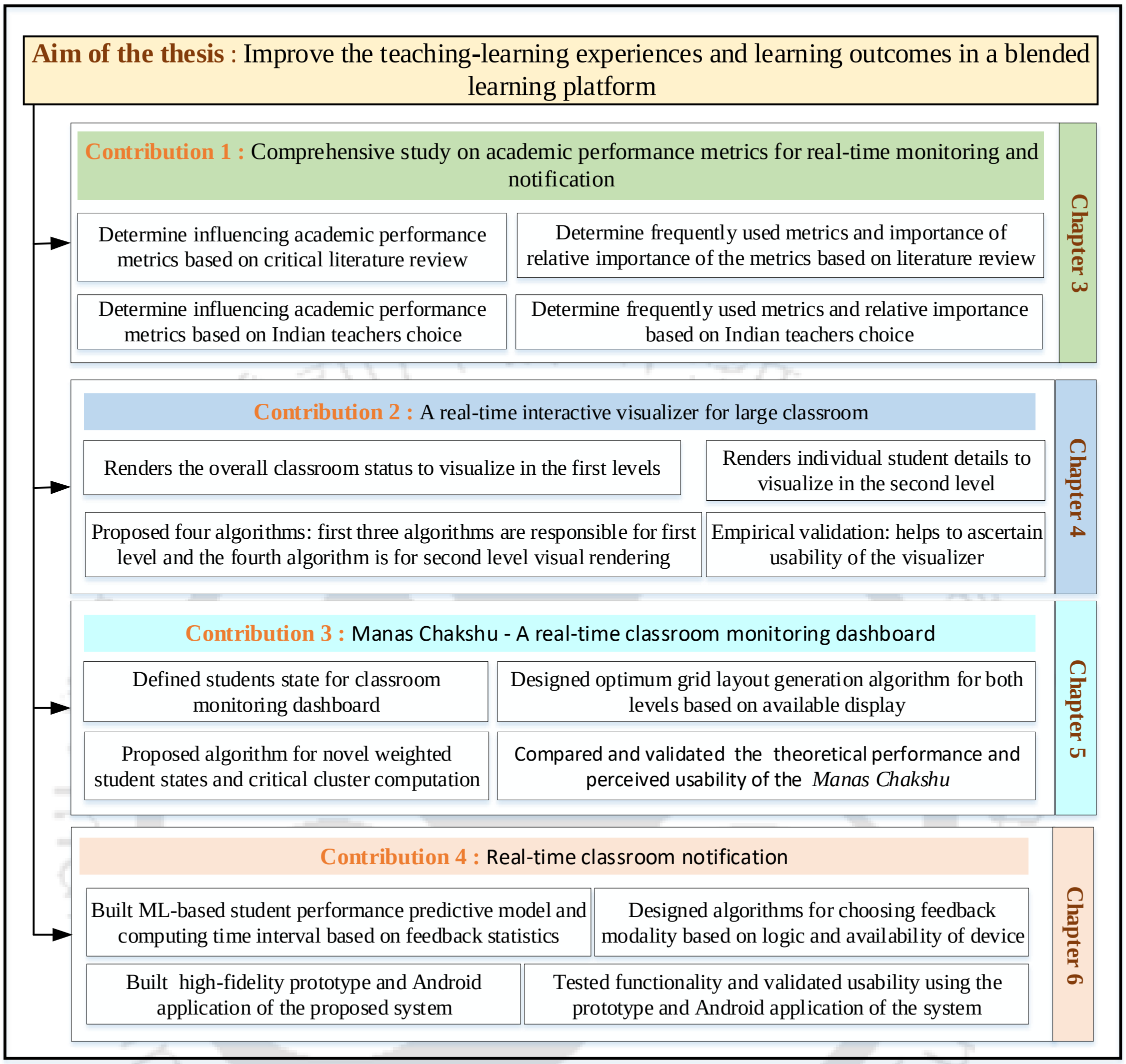


Figure 1.2: Summary of the contributions

on user preferences and requirements identified in the empirical research.

1.8 Organization of the Thesis

Figure 1.2 depicts a visual representation explaining the contributions of the thesis. The chapters are mapped onto the contributions of our work. This thesis is divided into seven chapters. The organization of the thesis and details of chapters in brief are as follows.

Chapter 1: entitled "Introduction", introduces the basic terms needed to comprehend the entire work. The motivation, objective, brief discussion of the problems addressed in the thesis, and contributions of the thesis are presented in this chapter.

Chapter 2: entitled "Related Work", presents the literature review which are relevant to the proposed intelligent real-time classroom visualization and notification system. This chapter describes previous classroom monitoring and notification systems and their related works, as well as critical studies of these works, in order to demonstrate the novelty of the proposed system.

Chapter 3: entitled "Comprehensive Study on Academic Performance", reports an up-to-date critical literature review on the academic performance metrics. Moreover, we take Indian teachers' choices of frequently used metrics through an online field study to reuse them. The survey helped to validate the importance of these metrics in the Indian context.

Chapter 4: entitled "A Real-time Interactive Visualizer for Large Classrooms", presented the design and validation of an interactive visualizer for large classrooms. The visualizer is intended to aid classroom instructors in more effective teaching. It is designed for relatively small displays as well, making the system useful for the instructors who can use it on a smartphone or tablet that they might be carrying.

Chapter A: entitled "Manas Chakshu - A Real-time Classroom Monitoring Dashboard", describes the intelligent classroom visualization in detail to monitor in-class students. We propose a novel interactive and dynamic visual monitoring dashboard, the Manas Chakshu for large classrooms to overcome the present difficulties.

Chapter 6: entitled "Intelligent Real-time Classroom Notification System", reports a notification system design in detail that includes complex alert scheduling during lecture delivery, both for teachers and students. The system design is real-time feedback-driven for the blended classroom system.

Chapter 7: entitled "Conclusions and Future Work", concludes this thesis with a summary and functional prototype of an intelligent classroom visualization and notification system, including its scope. It also discusses the research directions for future work.

Chapter 2

Related Work

This chapter describes related work on deploying intelligent real-time classroom visualization and notification systems in a technology-enhanced classroom. This study on related work brings together a set of contributions that form the backbone of this research. The related work consists of three parts: the description of the role of metrics in academic performance assessment and prediction, the importance of classroom monitoring and visualization, and intelligent notification to expand the existing system.

2.1 Role of Academic Performance Metrics (APMs)

The following subsections review the importance of *academic performance metrics*. We ascertain the need for *metrics* to explore the present need.

2.1.1 Influential Metrics

Colleges and universities collect reams of student educational data to evaluate student performance. The metrics include various internal assessment marks and attendance [30]. Current studies also show that behaviors and affective states are also recorded over the course using the digital back-channel concept [31]. The use of these metrics in real-time decision-making for large classroom teaching-learning has many benefits [32]. The academicians and teachers use a few of these APMs pro-actively to guide students. Nowadays, the ICT and BYOD paradigm allow teachers and students to utilize these APMs and become more active in the classroom. Recently, numerous data visualization efforts have attempted to provide teachers and administrators with student performances summaries to monitor and increase student interaction [1, 33]. Adopting ICT and BYOD concepts with traditional face-to-face classrooms has been used as influential metrics to support students and teachers [3]. The various possible approaches have already been developed to become reactive in their classrooms. Such systems have gained their place. However, they are limited to adopting change in day-to-day face-to-face real-time blended classroom activities. Therefore, more data-driven decision-making and real-time tools are required to empower blended classrooms, which have been ignored to date.

In this area, researchers are looking for available metrics that may be used for performance predictions, search algorithms that can improve predictions, and quantify aspects of student performance. Furthermore, research into student performance prediction aims to find interconnected metrics and the underlying reasons why influential APMs work better than others. In this respect, the APMs and selective metrics (i.e., frequently used metrics and their availability) play a crucial role.

2.1.2 Academic Performance Assessment

Presently, assessment in student learning is an extensive research topic [34, 35, 36]. Assessments have a significant impact on student learning [35]. The learning and co-curriculum assessment helps to measure a student's academic performance. Higher educational systems use the final grades to assess students' performance. The summative assessment is an essential part of the process of verifying a student's knowledge [37, 38]. The summative tests are typically performed on paper with representatives during specific periods, identifying potential academic difficulties. Given the importance of assessments in computing, researchers are concentrating on the practical challenge of grading with limited instructor resources [30]. In terms of grading, computer science educators have devised techniques to enhance the grading process for a range of evaluations. Harrington et al. [39] assessed the accuracy of manual TA markings during marking parties and advised organized group exam marking sessions in a recent study on test grading.

The grades are based on course assessment marks, exam scores, and students' activities [40]. Teachers monitor student academic performance using these internal assessment metrics. The grades of any student depend on different metrics like internal assessment (including laboratory file work, class tests, and viva-voce). However, some papers describe academic performance more broadly. The study [41] defines academic performance as measuring a student's activities and competence in courses. Students typically strive for good study efficiency by aligning their studies as closely as possible to expected assessment criteria [42, 43]. Students can use formative exams to discover areas of difficulty and to help them self-regulate their learning [44]. Designing systems to improve grading for coding assignments is another topic of research [45]. For example, Dewey et al. [10] employed constraint reasoning from the programming language literature to create auto-grading test suites. This review article on project auto-grading [46] is recommended to readers. Automating the grading process saves teachers significant time and effort, freeing them up to focus on more productive tasks like providing in-depth feedback, facilitating discussions, and providing personalized support. However, most systems use multiple-choice and true-false tests to evaluate when it comes to exam grading automation. Typical exams include code and brief responses, which are not always multiple-choice and true-false-based. However, it is feasible to take tests solely on computers. To address the challenges, researchers use internal course performance metrics to predict academic performance [30, 47].

2.1.3 Academic Performance Prediction

Choosing metrics for predicting students' academic performance has become more challenging due to the availability of a large volume of data [30, 48]. Literature reveals that ML is present everywhere in everyday life (e.g., product selection, which movie to watch, and what product/food to order), more importantly, from educational problem-solving [49] to recommender systems (e.g., e-learning material) [50].

In recent years the application of ML algorithms has drawn researchers' attention in academic performance prediction [51], which supports teachers, and tests students [52] in education. In teaching-learning, the use of ML is increasing that identify the quality of teachers [53, 54]. The colleges and universities are using ML for early intervention [55, 56], and prediction for a better quality of learning outcome [50]. It also covers different educational problems, such as learning product selection [57, 58], examination time scheduling, assessments [59], course planning, and academic advancing system [60, 61]. We have observed many ML algorithms are commonly used in students' performance prediction. The

Support Vector Machine (SVM), Neural Networks (NN) [60], K-nearest Neighbors (KNN), Naive Bayes (NB), Decision Tree (DT), Logistic Regression (LR), and Random Forest (RF) classifiers are very important [51].

2.1.4 Use of Academic Performance in Blended Learning

According to Osguthorpe and Graham [15], blended learning combines physical classroom teaching with computer-supported instruction. Blended learning is also known as the hybrid or mixed-mode of learning that requires student performance state to improve teaching-learning [3].

ML is currently being used extensively to predict students' academic performances [49]. The prediction can assist in the development of computerized adaptive evaluations [51]. The ML-based evaluation offers teachers and students continuous feedback on how they learn, the help students require, and their progress toward their learning goals [52]. One of the most potential application areas that use ML in education is the early warning system [62]. Early warning will also help to improve students' retention rate in a course or program. Universities and teachers can reach out to “at-risk" students using advanced tools and provide them with the support they need to succeed [63]. Teachers and institution personnel can use machine learning-based algorithms to classify students' performance and provide better assistance to students.

Predictive models are now used in many educational institutions to improve students' engagement in teaching-learning [64]. ML algorithms can automatically extract complicated patterns from existing data attributes, allowing them to make intelligent decisions using currently available *academic performance metrics* [65].

2.1.5 Role of an Intelligent System in Education

Researchers are more focussing on building various intelligent systems in diverse educational settings. Many intelligent systems use Artificial Intelligence (AI), Intelligent Tutoring Systems (ITS), Learning Analytics (LA), and Educational Data Mining (EDM) systems in education. Contribution to this field can be improved using well-defined APMs in tracing students' regular performance. Without dependable APMs, optimizing these intelligent systems is like taking a chance. We cannot successfully identify areas for development or personalize learning experiences unless we have precise data on what works and what does not.

The application of AI become an emerging field of research to meet modern learning and instructional needs in blended classrooms [66]. The AI-enabled Machine Learning (ML)-based predictive models for Student performance can reduce teachers' effort and time in real-time decision-making to improve learning outcomes [67, 68]. An ITS in blended learning settings can use ML techniques to acquire real-time student-related performance data that helps teachers intervene during the early phases of a course [69, 70]. LA is a popular classroom monitoring tool [29]. LA helps teachers collect, interpret, and analyze students' performance data generated during the teaching and learning process. However, designing interactive LA is challenging for real-time blended classroom use due to the busy schedule of the teachers [71]. EDM is a growing discipline that combines education and informatics. Its significance in today's educational scene arises from the numerous advantages it provides institutions. EDM enables educators to maximize learning outcomes by evaluating large educational data sets using a variety of data mining approaches. One key issue addressed by EDM is predicting student performance before final exams [72]. With such insight, educators can intervene proactively to improve student progress and reduce dropouts. As a result, research in EDM is mainly focused on constructing advanced student performance prediction models.

As a result, models that predict student performance and classify performances are very useful in teaching and learning. However, selecting metrics that determine the achievement of the course and program remains a challenging issue. Particularly, the challenges are to assess the potential of using available influential metrics and utilizing machine learning algorithms in a blended learning platform.

2.2 Student Monitoring and Visualization

There is a spurt in interest in technology-enabled visual monitoring of students to support teaching and learning in live classrooms [3, 6], particularly in the context of the blended-learning environments [73, 74, 75]. Efforts have been made in this direction to provide the teachers with visual aids for real-time student monitoring [6, 76, 77, 78]. Such tools aim to draw the attention of a teacher to the difficulties faced by the students and subsequent intervention [6, 27], leading to a possible fine-tuning of the teaching-learning strategies [1].

Research on data visualization has witnessed a growing interest in building interactive user interfaces to comprehend complex data [6, 79, 80, 81, 82]. One of the major challenges in interactive visualization of large-scale datasets is to visualize the data in a relatively smaller display. To address the challenge, a set of approaches are widely used that include the focus+context, overview+details, fish-eye view, and, other distortion-based methods [83, 84, 85, 86, 87]. Literature reveals that increasing interest in visualization research has given rise to a variety of visualization tools, models, and systems designed to address visualization challenges in different domains of application [81, 88, 89]. Classroom teaching is one of the potential application areas of student performance visualization.

2.2.1 Methods of Real-time Classroom Monitoring

Classroom monitoring can aid teachers in perceiving the real-time performance and critical states of students. Creation of classroom monitoring aid for educational purposes in general and real-time classroom use, in particular, is gaining popularity in recent times [6, 25, 90, 91].

Diana et al. [92] reported a real-time learning analytics tool for K-12 teachers. A similar attempt was made to design Lumilo [7], a wearable and real-time learning analytics tool. Mathioudakis et al. [26] reported a system to identify and perceive the weaknesses of individual students and the overall classroom status. Harfield et al. [93] introduced a supportive environment for teachers in a classroom. The settings integrate the BYOD paradigm with regular teaching [94]. The environment combined supportive tools for monitoring the progress of the students. Chiou and Tseng [25] proposed a wireless sensor and network-based classroom system. The system allows detecting real-time classroom status and individual student progress. The proposed classroom system allows a teacher to monitor the student states. Other notable works in this direction include the EduSense [95] and the iKlassroom [96].

The EduSense [95] is a classroom sensing system that provides theoretically-motivated metrics using an array of commodity cameras. The concept of automated classroom analytics promises to provide fidelity, scalability, and temporal resolution that are impractical with the existing method of in-class observers. The study offers the Learning Dashboard for Insights and Support During Study Advice (LISSA) [76], a learning analytics dashboard that was created, refined, and tested with the help of study advisors. The evaluation, gathering, analysis, and reporting of information on students and their environments for the purpose of comprehending can lead to cognitive load. Therefore, use of this system for real-time classroom use to improve learning is limited. A wireless sensor network-based intelligent classroom management system [25] with context awareness is suggested and put into practice. It is built up with a variety of sensors and actuators that regulate the feedback devices. The system helps to monitor students' states through learning behavior management. The classroom size they considered was 24 intelligent desks. Therefore, setting up such a system required huge infrastructure costs and did not consider addressing the challenges of representing the states when the number of students is more than 50 or a few hundreds. The real-time analytics [92] have various components of the teacher's dashboard. The system consists of a timeline for classroom replay controls, a class summary with estimates of student progress, and a visual representation of students. The visual representation of students has not considered the time to comprehend the students' states. Moreover, all the information is displayed on the screen at a time, which may increase valuable time for comprehending student state when the number of students increases. Authors [93] reported on a system that allowed the teachers an "open monitoring environment". This system lets one to check a group status as a bar chart. There is no way of checking individual students' states and their location in the class. The idea of iKlassroom is a real-time teaching analytics solution [96]. The iKlassroom reported a usage scenario for classroom practice, exhibited design sketches and screenshots, and they indicated possible contributions to enhance monitoring of students. The authors did not address the challenges of locating students and the overall status of the class, but rather the challenges of individual students' state identification.

Raja et al. [6] presented a Radio Frequency Identification (RFID) based visualization and activity monitoring system. The system allowed a teacher to identify the level of involvement of the students in a classroom. Therefore, classroom visualization is an important research topic.

2.2.2 Methods of Real-time Classroom Visualization

It is well-known that a good visual representation reduces the human cognitive load to comprehend the data [97, 98, 99]. The most challenging task in developing a real-time visual classroom monitoring system is to represent learning performance and behavior in a meaningful way [6]. A quality visual monitor can aid teachers in quickly observing student learning performance and behavior [100, 101, 102]. In order to comprehend the state of the students, the student states must be retrieved and represented suitably [3]. Overview+details is a visual representation technique in which two parallel views are combined simultaneously on a single display device [103]. The technique is particularly suitable for information visualization on small-sized display devices, such as those of smartphones or tablets. In such devices, highlighting details about some information or data about an object of interest improves user performance [103].

The idea of a real-time student locating system using RFID is reported for a real-time student visualizing system [6]. The visualizer is suitable for desktop-based applications to locate students. Moreover, the system uses symbols to represent 28 students' status. Therefore, for a larger number of students and available devices like smartphones, the utility of the system is questionable. A student can be represented in a classroom environment in different ways. Two basic methods are the representation of each student with a square grid element [25] and another is using Chernoff faces which are basically smiley-like face representations of students. The emotions on Chernoff face visualize the state of the student. The emotions change based on students' activity [104]. Some implementations of visualization techniques group students by their current state as in [104] while some represent them as their physical position in a classroom [25].

However, none of the previous studies dealt with large classrooms. In such classrooms, the primary challenge is to be aware of the status of a large number of students continuously and in real-time, to take effective and quick corrective actions, if needed. The reported systems were not designed to help the teacher identify problem cases effortlessly and quickly during lectures.

2.3 Notification for Blended Classroom

The automated notification system is essential to manage classes effectively to enhance teaching-learning [105]. However, the effective integration of the student's academic performance metrics to identify at-risk students in a course and give both the students and teacher feedback is challenging. But the real-time feedback helps to learn from the mistakes of both instructors and students. There is a lack of real-time decision-making and motivation to enhance teaching and learning using timely notification at the institutional level.

2.3.1 Multimodal Notification for Classroom Use

Singley et al. [105] reported a system that is designed to understand what is happening in a class. The system identifies unusual learning patterns during lecture delivery. The system generates an alert to the teacher on a stationary device (desktop) based on the specified pattern. Chiou et al. [25] suggested a wireless sensor-based classroom application that detects the real-time condition of the classroom and the student's status. The system comprises a subsystem that delivers alerts when students are inattentive. The light-emitting diode (LED) flashlights were used to alert learners in a classroom. However, with this signal, the challenging task is to present students' deficiencies in instructors' notice and motivate them towards classroom learning outcomes. One particular challenge is that using light signals to indicate understanding can be distracting for other classmates. A potential solution is providing timely alerts [26]. The commonly used smartphone and wearable alerts ensure timely feedback without hindering classroom interactions.

One of the current research studies reported that multimodal smartphone-based alerts and awareness are potentially better for understanding real-time circumstances. The multimodal alert (sound and visual in combination) types can affect user acceptability and usability [106]. There are studies on sound alerts to inform the user of critical situations. The sound alert gained popularity in various fields such as hospital intensive care units [107], atomic power plants [108], aviation [109], and alert vehicle drivers [110]. The visual alert and awareness represented in the form of colors, shapes, and text improve the intelligibility of the feedback [106] when using smartphones and wearable devices.

These techniques, e.g., smartphones and wearable devices, usually require users' focused attention to perceive alert and awareness contents. Extensive research is required to utilize the concepts of real-time multimodal alerts in appropriating them for classroom use.

2.3.2 Technological Distractions on Notification

Earlier research studies in the fields of Human-Computer Interaction (HCI) and ubiquitous computing reported the bad effects of technological distractions or interruptions in different situations (e.g., driving, walking, academics) [111, 112, 113]. Leiva et al. [111], in their research study, observed that interruptions caused by app-switching and incoming phone calls have interruption costs. Levine et al. [112] have mentioned in their research studies that disturbances varied on tasks and situations. Mehrotra et al. [114] reported the smartphone interruption measurements based on notification content and context. However, some research studies suggest suitable moments (e.g., appropriate time, multitasking, synchronizing interruptions with user behavior and cognition) for interruptions to optimize distractions [114, 115, 116].

Bakker et al. [117, 118] outline how technology is adopted to develop such a system to reduce teaching-learning disturbance in HCI. The key idea was that the teacher could interact in their background or periphery to know the students' difficulties, thereby reducing her/his cognitive load while teaching. Moreover, peripheral interaction is used in human attention management [118]. Recent works [119, 120] explored a generalized strategy to investigate three system designs (CawClock, NoteLet, and FireFlies) on peripheral interaction. Based on their studies, they suggested some characteristics and their practical development goal to optimize distraction. Olivera et al. [121] aim to present how multitasking (e.g., parallel) interaction and natural interaction are favorable in HCI. The work uses the tangible user interface to identify advantages in Personal Computer (PC) based systems. Bakker et al.[122] explained an interactive system design called "FireFlies" through a system prototype. The system supports a primary school teacher to interact in the periphery of their attention to know the in-class student's needs. The system integrates information, such as light and audio signals, through the peripheral device. The experimental study permits the teachers to control the mentioned signals through physical interaction and shows how it can become a part of everyday teachers' routines. Doris Hausen [123] builds peripheral interaction as a secondary task carried out in the user periphery. The author recommended a classification approach to avoid disruption by peripheral tasks. Verweij et al. [22] adopted peripheral interaction in a regular classroom setting as the upgraded version of FireFlies called "FireFlies2".

To address the challenges of digital distractions and cognitive overload in classrooms, we have investigated the potential of utilizing peripheral selection for feedback delivery and optimizing alert fatigue management strategies. This approach aims to minimize disruptions to learning while keeping teachers and students informed about their real-time performances.

2.3.3 Studies on Alert Fatigue

Alert fatigue is the notion of supplying a large number of frequent message content on user devices [124]. Fatigue is one of the human psychomotor qualities [125], which controls our cognitive functions that affect productivity, decision-making [126], and memory [127]. However, fatigue can negatively influence attentiveness, resulting in a slowdown of reception times [124].

Cognitive load and alert fatigue are closely related to each other. The cognitive load increases when we use more cognitive resources of our working memory to memorize or perceive information. Alert fatigue happens when an individual receives a large number of alerts [128, 129]. It also becomes difficult when forwarded with inadequate time or requires more cognitive resources to differentiate relevant from irrelevant content. Alert information that is not informative contributes to this overload. Uninformative alert contents are similar to false alerts. In the human factors literature, it is well established that false alerts reduce responsiveness to Wide Area Network (WAN) and negatively affect overall task performance [130, 131]. The replicated appearance of alerts leads to decreasing responsiveness due to alert fatigue [132, 133, 134]. An alert, or awareness is useful when first noticed but becomes less effective as the recipient becomes accustomed to the alerts over time. Alert fatigue has the potential to desensitize teachers and students in classroom teaching-learning. Fatigues have become our focus of consideration to alert teachers and students to reduce their cognitive load, freeing up mental resources. In face-to-face teaching-learning in a class, alerts can help customize lectures and motivate users to actively participate in classroom teaching. We believe structural and sensible notification management can help optimize alert fatigue in the classroom and extend the research field.

2.4 Summary of the Chapter

In this chapter, we have reported the related works for academic performance metrics, classroom monitoring, and notification for blended learning. We have observed that the existing work on academic performance metrics can be used to determine students' performance standards and assess and predict the states. After the crucial studies of the literature, we have found that academic performance metrics, determination of performance, and prediction methods are important in the current context. However, selecting metrics that determine the achievement of a course and program remains a challenging issue. Particularly, the challenges are to assess the potential of using available influential metrics and utilizing machine learning algorithms in a blended learning platform.

The metrics and the predictive models need to be adapted to the real-time performance monitoring in our assumed blended learning system to improve learning outcomes. Thus, we aimed to build real-time classroom monitoring and validate the real-time classroom visualization to address all the classroom visualization issues so that we can utilize academic performance states for building an intelligent real-time classroom visualization system that is able to detect the performance states of the students based on their academic performance metrics. To gain more meaningful use of that data demands effective decision-making instruction in a day-to-day classroom activity. One of the solutions is to create new technology-enhanced notification tools to address the challenges of alerting and giving feedback to support teachers and students in a blended classroom [67].

Research is limited in the direction of real-time proactive notification generation to motivate students for active classroom participation on an available device in a classroom environment. The exciting peripheral interaction techniques can support the instructor in perceiving the updated status of the classroom [22]. However, the existing methods still have some significant shortcomings: (i) the use of LEDs or flashlights in a classroom setting that may disturb students or teachers. (ii) teachers' focused involvement is required to comprehend the notification (iii) the existing research does not consider the critical component of quality teaching for lecture flow, the variation of the modality and content, or the timing to deliver the notification. The proposed novel interactive visualizer and notification are presented in the subsequent chapters to address the challenges.

Chapter 3

Comprehensive Study on Academic Performance

3.1 Introduction

Academic metrics are crucial in interpreting and predicting student performance to improve teaching and learning in blended learning environments. However, there are challenges in determining the metrics and improving prediction accuracy to quantify students' performance. We have reported a critical literature review (CLR) with a field study on the usage of *metrics* for interpreting and predicting academic performance to address these challenges. Our CLR includes 62 articles for determining influential metrics and their categories using existing terminology. The CLR helps to show the importance of academic metrics, select category-wise *frequently used metrics*, and their *relative importance* in performance interpretation and prediction. In addition, we have conducted a field study to test the usage and applicability of *academic metrics* for performance prediction. In this field study, we received 369 teachers' responses from 109 reputed higher educational institutions on the usage of *academic performance metrics*. Based on these responses, we determined 18 influential *academic performance metrics*, including nine *frequently used metrics*. This research summarizes our findings using 3-level tags to choose metrics with relative importance based on CLR and field study. We have reported seven recommended machine learning models based on CLR in predicting academic performance. This contribution offers a comprehensive examination and analysis of CLR, field investigations, and prediction models. The precise insights provided can enable the use of academic metrics for monitoring and predicting student achievement and performance in blended learning environments.

3.2 Research Questions and Methodology

We aim to use our findings to assess and predict academic performances in a course in higher educational systems. This study addressed three research questions using a three-fold systematic methodology.

3.2.1 Research Questions (RQ)

Academic performance assessment and prediction became the focus of many researchers and studies [30, 3, 47]. We studied the following research questions to contribute to understanding the influential metrics and techniques in students' academic performance assessment and prediction.

RQ1: Which academic performance metrics (APMs) are used to assess and predict student performance based on CLR?

RQ2: Which ML models are explored in academic performance prediction in the literature?

RQ3: Which of these APMs are adopted and preferred by Indian teachers?

3.2.2 Overview of the Research Methodology

To address the above research questions RQ1 and RQ2, the major contributions which we made are as follows:

- This CLR identified 62 primary articles to show the importance of the APMs.
- This study provides details on important *academic performance metrics* for assessment and prediction of students' performances.
- We also determined *frequently used metrics* and described the role of *relative importance* of the academic metrics.
- This study explored different ML models that are used in academic performance prediction.

Table 3.1: Search results based on keywords, inclusion and exclusion criteria

Source	Raw results	Inclusion or exclusion criteria
IEEE Xplore	523	72
ACM digital library	570	78
Google Scholar,	470	60
Scopus link	453	42
Springer link	463	33
Total	**2479**	**285**

Table 3.2: Details of our inclusion, exclusion, and quality criteria for literature search

Inclusion	Exclusion	Quality
The research addresses determination of academic metrics, assessment and prediction. The research discuses an empirical study. The research is on academic performance prediction for supporting teaching-learning.	The paper have no abstract. The paper is published before 2013. The paper is not published in English. The paper is not a research or peer-reviewed.	Should clearly address a research problem. Should contain clear objective/aim of the research. The research contains adequate description on research methods The research clearly explain academic metrics used, data analysis and findings on academic performance prediction.

CLR Methodology

We use five common online bibliographic databases to get the research articles. The databases are *IEEE Xplore, ACM digital library, Google Scholar, Scopus Link, and Springer Link*. The articles were searched based on search keywords **academic performance** AND **metrics** OR **assessment** OR **prediction**. This search approach produced a total of 3352 hits, which included 2479 different papers based on the *search keywords* (see Table 3.1 middle column). Then, we scanned the papers based on inclusion/exclusion criteria (see Table 3.2) and selected 285 papers (see Table 3.1). Finally, we scanned the full text of those studies on quality criteria (see Table 3.2 right column) and selected 45 primary papers discarding 240 articles from our initial search. In addition, we follow the forward snowballing scheme for searching valuable articles to strengthen the search. The term *snowballing* refers to finding articles using the reference list or citations from source papers [28]. A total of 62 articles are used for our study, out of which 45 were from the initial search and 17 using the snowballing approach. The outcomes were obtained by reviewing and analyzing those selected articles. The detailed summary of the CLR and the key outcomes are shown in Figure 3.1.

Online Field Study (OFS) Methodology

The primary objective of the OFS is to answer the RQ3. Figure 3.2 shows the data collection method and finding steps. We used online platforms and email as a comparatively

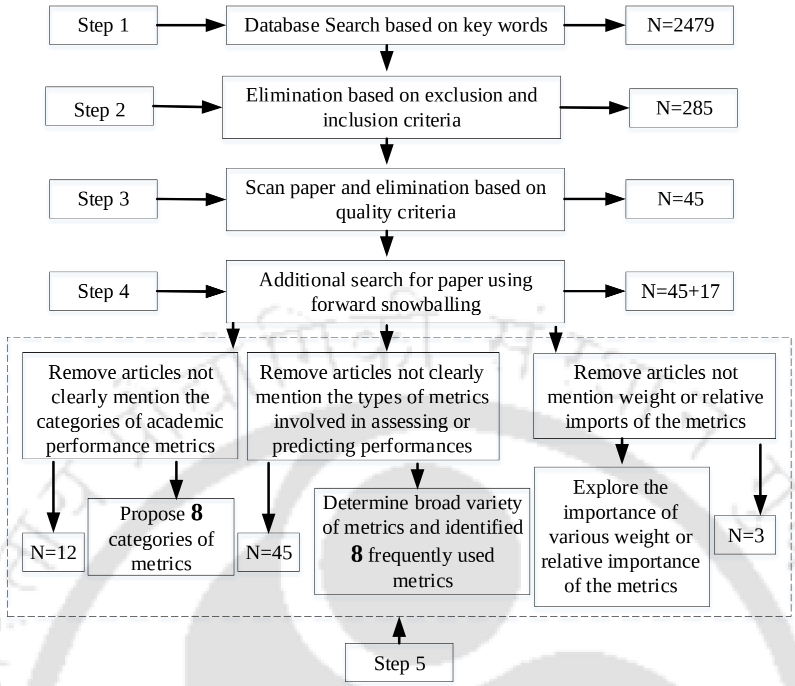


Figure 3.1: Details of the critical literature review process and key outcomes based on N number of existing works.

cost-effective OFS alternative. The systematic steps help collect a large data sample from participants in a short duration. The OFS assists in avoiding the challenges of approaching professors and academicians in person in widespread geographical locations. Section 3.4 helps in gathering data on teachers' sensitive grading and evaluation schemes and determines our OFS outcomes. The major contributions are summarized as follows:

- We carried out the OFS using Google Forms[1] with survey questionnaire to reuse the available metrics, test the applicability of *frequently used metrics*, and *relative importance* for better performance assessment and prediction in the Indian context. We selected four most distinguished categories of HEIs having higher national importance and reputation all over India for our OFS.

- We collected mailing addresses of institute administrators and faculties. These mailing addresses cover 146 reputed HEIs, all 30 states (including union territories), and 6 disciplines spread all over India.

[1] `https://docs.google.com/forms/d/e/1FAIpQLSfuIuqrhyE-WwQ0VI2i64O0adwtJXzEAkWl4FfM1ywkHMiuhw/viewform`

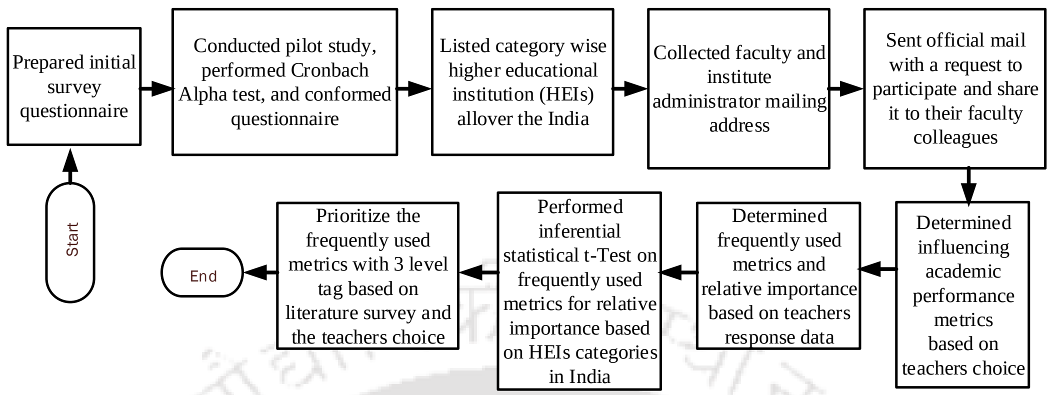


Figure 3.2: Major steps of our field study methodology and finding process.

- We received responses from 369 teachers about the available performance metrics and *relative importance* usages for academic assessment in India. We identified 18 metrics and determine nine *frequently used metrics* out of 18 metrics considering at least 130 teacher participants (above 35%) usage the metrics to assess students' performance. We reported the *relative importance* of the nine *frequently used metrics* based on teachers' choices.

- Statistical t-Tests were performed to observe the significant difference between the mean *relative importance* for the *frequently used metrics* in various categories of HEIs in India. Finally, we prioritize metrics using a 3-level tag, i.e., high, medium, and low, using citation count (based on CLR) and empirical evidence (collected by OFS). The tags helped to select *frequently used metrics* based on availability.

3.3 Critical Literature Review (CLR)

The following subsections review the importance of *academic performance metrics*. We ascertain the need for *frequently used metrics* and their *relative importance* to explore the present need.

3.3.1 Influential Categories of Academic Performance Metrics

Influential categories of APMs can help researchers and academicians to reuse them [135] keeping assessment and prediction as a key to student performance. Categories help researchers and academicians to understand the nature of metrics [30]. Therefore, we have identified the APM categories based on their importance and the data source used. We determine APM categories to provide a new understanding of the field using state-of-the-art terminologies. After carefully analyzing 62 publications, we identified 12 that conveyed a clear summary of the metrics categories. The remaining 50 have reported *important academic performance metrics* without categorizing them. Their research objective was not the categorization of the academic metrics Table 3.3 outlines the list of these articles in detail with a count of metric categories. Most of the other studies are older than a decade. Also, the studies did not even mention the categorization of metrics. Table 3.3 shows that the number of categories of APMs varies widely (3 to 10). The variations indicate researchers assume various levels of abstraction while categorizing APMs.

Furthermore, we observed that some of these categories could merge [40] or expand for very less number of categories [41] using state-of-the-art terminologies. Therefore, we propose 8 APM categories using existing terminologies to understand the performance metrics better (see Figure 3.3). These 8 categories are primarily a combination of the findings reported in the studies [30, 40, 139]. We observed that the learning behavior and affective states are closely related. However, learning behavior and affective state metrics are two separate components. Na and Tasir (2017) [143] reported that learning behavioral metrics include interactions collected within students and their learning environments (e.g., task time and the number of clicks). The affective states metrics are learning emotional data collected from the physiology of the students (e.g., moods, feelings, or expressions) during teaching-learning [3, 143]. Therefore, learning behavior and affective state metrics are two separate categories of APM that are justifiable. All other APM categories and their names are self-explanatory (see Figure 3.3).

We have identified 5 influencing categories of APMs (1 to 5) based on citation count (see Figure 3.3). The maximum citation count is 12 (out of 12) for the categories related to external assessment and students' demographics. The second highest citation count is 11 for the internal assessment APM category. The minimum citation count is 7 out of 12

Table 3.3: Summary of the Categories of Students Academic Performance Metrics (APM) Used in Existing Literature

[S.L. No.] Authors [Citation]	Categories of APM used to assess and predict academic performances	Count
[1] Alamri and Alharbi (2021) [136]	pre-course data, current course data, demographic data, personality metrics, and engagement levels	5
[2] Ameri et al. (2016) [56]	demographic attributes, family background attributes, pre-enrollment attributes, financial attributes, enrollment attributes, and semester-wise attributes	6
[3] Chitti et al. (2020) [137]	behavioral, academic, demographics, and psychological	4
[4] Francis and Babu (2019) [138]	behavioral, academic, demographics, and extra	4
[5] Hellas et al. (2018) [30]	demographic (e.g., age, gender), personality (e.g., self-efficacy, self-regulation), academic (e.g., high-school performance, course performance), behavioral (e.g., log data) and institutional (e.g., high-school quality, teaching approach).	5
[6] Hu et al. (2017) [139]	demographic, student history record and performance, student record and performance in current course, activity and course performance, learning behavior, self-reported metrics, and others	7
[7] Kumar et al. (2017) [140]	personal attributes, family attributes, academic attributes, institutional attributes,	4
[8] Lei et al. (2015) [41]	academic performance, socio-economic, personal information	3
[9] Muthukrishnan et al. (2017) [141]	basic information- students profile, current and past grades, basic family details extended information- parents' education, income level, siblings and etc. holistic information- locality, school / university status, social recognition and rest	3
[10] Papamitsiou and Economides (2014) [142]	demographic characteristics, grades (in pre-requisite courses, during assessment quizzes and their final scores), students' portfolios, multimodal skills, students' participation, enrollment and engagement in activity and students' mood and affective states	7
[11] Saa et al. (2019) [135]	students e-Learning activity, students previous grades and class performance, students environment, students demographics, instructor attributes, course attributes, students social information, course evaluations, students experience information	9
[12] Shahiri et al. (2015) [40]	internal assessment, external assessment, extra-curricular activities, psychometric, students' demographics, engage time, family demographics, institutional background, social network interaction, and other (soft skill)	10

(approximately 60%) for learning behavior and affective states categories. The crucial point is to note that external assessment, particularly pre-course data is a commonly used APM category [41, 135, 136, 141]. Student demographics, such as gender, are often considered in educational research to predict academic performance [30]. Some studies suggest that female students may exhibit certain learning styles that are associated with academic success, such as being more organized and conscientious [30, 40]. The internal assessment category gains popularity because the HEIs can easily access the APMs that the instructor had collected and recorded [144]. The trend of using learning behavior and affective state gaining recently, are still relatively new and rare [3, 143, 145]. However, family demographic and institutional background are rarely used APM categories [40]. Therefore, the first 5 categories of the APMs (1 to 5) are considered as the influencing APM categories (see Figure 3.3). In the

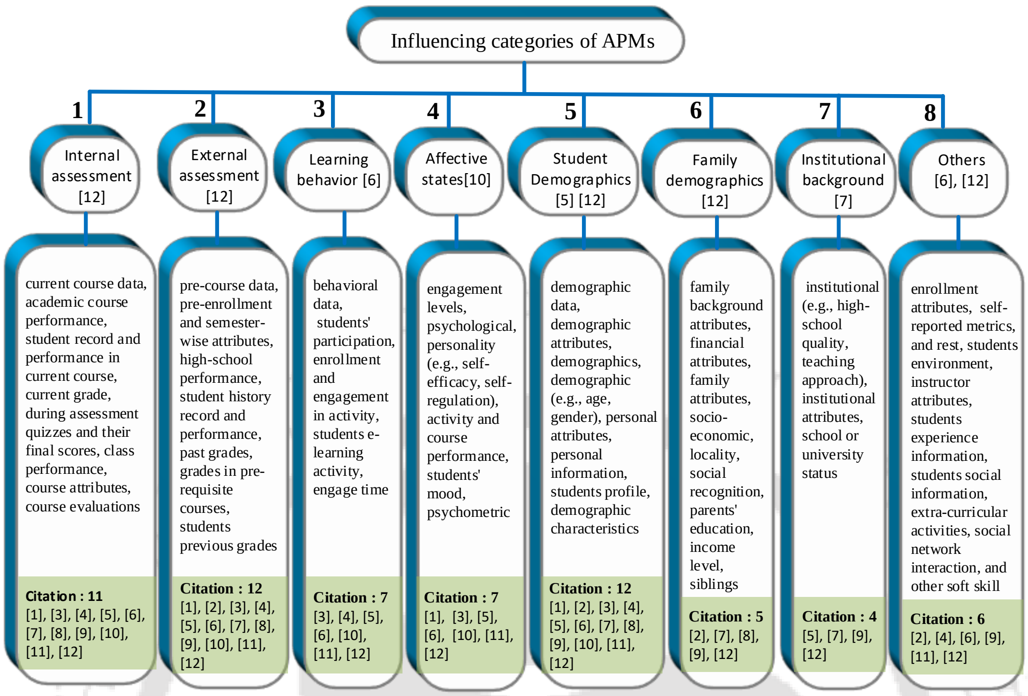


Figure 3.3: Categorization of APMs that can help to understand metrics used for assessment and predicting performance of the students from the articles listed in Table 3.3 [Number indicates the Article S.L. No.] from Table 3.3.

following subsections, we reviewed another important component *students monitoring and visualization*.

3.3.2 Frequently Used Metrics (FUM)

The FUMs help to assess and predict student academic performances [30, 146, 147, 4, 148]. We observed a crucial contribution reported in [30] to identify FUMs. Hellas et al. (2018) [30] reported that course grades, individual exam grades, GPA/CGPA, and assignment performance metrics are the preferable FUMs. Table 3.4 shows 5 influencing categories of APMs and the wide variety of metrics found in related work.

We have selected 45 out of 62 articles based on three essential aspects to review on FUMs (see Figure 3.1). These 45 articles include nine out of 12 mentioned in Tables 3.3 (Chapter 2). Table 3.4 summarizes the wide variety of metrics that have been used to assess and predict student academic performance. The metrics are sorted in the descending citation count. The count indicates the number of unique metrics used in the literature

Table 3.4: Top 5 APM categories and the broad variety of metrics utilized in existing literature to assess student performance

(No.) Category	Broad Variety of Metrics (Sorted with Descending Citation Count)	Metrics Count
(1) Internal Assessment	Assignment Performance [146, 149, 150, 147, 151, 138, 40, 30, 144, 152, 143, 51, 153, 135, 154, 155], Class Test Marks/Scores [156, 146, 157, 149, 150, 147, 151, 40, 158, 47, 51, 153, 154, 155], Attendance [146, 56, 150, 147, 138, 41, 40, 30, 143, 153, 154, 155], Quizzes [150, 138, 144, 40, 142, 143, 159, 153, 135, 154], laboratory test grade/score [147, 160, 40, 152, 154, 155], Mid-term Assessment [146, 4, 30, 144, 143], Seminar Performance [146, 147, 155], homework [146, 144], race calculated based on internal input metrics [156], credit hours attempts, percentage of passed credits, percentage of dropped credits, percentage of failed credits [56], subjects studied currently [160], end-semester marks [147, 155], viva-voce and sessional test, PostCourse Performance and Course Performance [30], one key course marks and one fundamental course marks [41]	20
(2) External Assessment	University Course GPA/CGPA [156, 161, 157, 56, 150, 160, 147, 138, 41, 40, 158, 4, 148, 162, 152, 143, 51, 135, 154, 163, 164], High School Marks/Grade [156, 157, 56, 165, 160, 41, 158, 30, 51, 163], Previous Course Internal Marks [161, 157, 41, 40, 4, 148, 30, 51, 154, 163], Admission Score [157, 41, 148, 30, 163], and Number of Previous course Failure [41, 30], marks include in 3 subjects: Malay Language, English, Mathematics [156], composite ACT (American College Testing) score, Math ACT score, English ACT score, reading ACT score, Science ACT score [56], previous semester marks[147], pre-course Performance [30], past grades [141], a particular subject score [40]	18
(3) Learning Behavior	Total Time Study Material Viewed [157, 56, 151, 138, 148, 162, 166, 30, 152, 143, 142, 159, 153], Number of Log in [157, 56, 138, 148, 166, 30, 152, 143, 142, 159, 153, 135], Participation in Classroom Discussion [157, 56, 138, 166, 30, 152, 143, 142, 159, 153], Assessment Activity [157, 150, 162, 166, 143, 51, 159, 153], Task Time [151, 166, 30, 142], responses for a course [149], participation in the course [146], raised hands [138], concept assessment, browsing history[30], 4 questionnaire-based learning behavior assessment [47]	14
(4) Affective State	Self-regulation [157, 149, 162, 30, 142, 47], Student Engagement [149, 30, 143, 142, 47, 154, 159], Stress or Anxiety [157, 162, 30, 47], Student Interest [149, 162, 30, 154], Student Mood [167, 142], self-efficacy [30, 167, 143, 135], log data on affective state [30, 167], general proficiency performance [147], students self-confidence [149], 7 psychometric APM on uploaded lecture materials [47]	13
(5) Students' Demographics	Gender [156, 161, 157, 56, 168, 149, 150, 165, 138, 148, 162, 30, 158, 41, 163, 135, 154], Age [161, 157, 56, 150, 165, 162, 30, 41, 163, 135, 154], Nationality [168, 138, 158, 163, 135], Hometown [156, 138, 158], Traveled Distance [157, 148], Marital Status [163], Address [149, 150], birth year [158], disability [41, 154]	9

to assess and predict students performance. The first two categories of APMs, namely, internal assessment and external assessment, have the highest number of metrics counts (see Table 3.4). The counts are 20 and 18, respectively. The higher number indicates that the researchers used a broad variety of metrics to predict and assess academic performance. The metrics counts are relatively lower for the remaining categories (see Table 3.4 right column).

Figure 3.4 summarizes the category-wise citation counts of the FUMs to understand the importance of the metrics given in the literature. Our findings considered a metric to be a FUM if its citation count is more than 35%. Figure 3 illustrates the category of the APM and the individual FUM. We identified 8 FUMs having at least 16 citation counts. The 3 FUMs out of 20 metrics is from the internal assessment. The metrics are assignment performance, class tests marks/scores, and attendance. The citation counts for these 3 FUMs varied between 16 to 23 (i.e., 35.56% to 51.11%). The FUM in the external

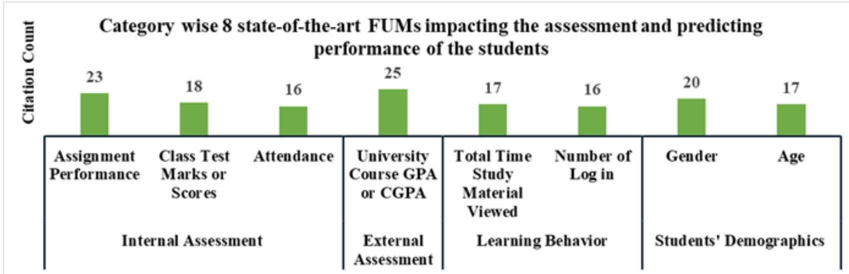


Figure 3.4: Details of influencing categories of APMs and the FUMs with citation count impacting the assessment and predicting performance of the students

assessment category consisted of 1 out of 18 metrics. The FUM in this category is university course Grade Point Average (GPA) or Cumulative Grade Point Average (CGPA), and the citation count is 25 (i.e., 55.56%). In learning behavior, we identified 2 FUMs. The citation counts are 16 and 17 (i.e., 35.56% and 37.78%). The FUMs are total-time study material viewed and the number of log-ins for various learning activities. In students' demographics, we identified 2 FUMs (citation count 20 and 17). The FUMs are student gender and age (citation count 44.44% and 37.78%). One crucial fact is that no FUM from the affective state APM category was selected based on our citation count constraint. The primary reason is that the usage trend of the affective state APM is relatively new [3]. However, Table 2 can help in choosing any number of FUMs based on the category of APM and citation count. The popularity of using metrics like learning behavior and affective state have increased in recent years to predict the performance of students in blended learning settings [3, 143, 159].

In the Indian HEI context, we found three valuable contributions related to the use of FUMs. Baradwaj et al. (2012) [147] evaluated the end-semester examination performance using 8 FUMs. Kumar et al. (2017) reported 10 crucial FUMs applied to predict student performance. All the metrics are included in Table 3.4. The study [144] hints us *relative importance* or weights of the FUMs are another crucial factors for the evaluation and prediction of student performance. However, the above studies overlook the analysis of the *relative importance* among the metrics to predict and assess student performance [4]. The details about *relative importance* are explained in the following subsection.

Table 3.5: Details of the APMs with RIs or weight and their categories

Authors	Metrics used in assessing and predicting student academic performance	RI or weight of the metrics	Category of the APM
Huang S. and Fang N. (2013) [4]	cumulative GPA, statics grade, calculus I grade, calculus II grade, physics grade, dynamics mid-exam #1 score, dynamics mid-exam #2 score, dynamics mid-exam #3 score, dynamics final exam score	4, 4, 4, 4, 4, 15, 16, 15, and 100	The first 5 APMs are External Assessments, and the remaining 4 APMs belongs to Internal Assessment.
Hussain et al. (2019) [169]	Assessment Marks: semester #1, semester #2, semester #3, semester #3, semester #4, semester #5, semester #6	20, 20, 40, 40, 80, and 80	All APMs are related to the External Assessment category.
Meier et al. (2016) [144]	Homework Assignments: homework #1, homework #2, homework #3, homework #4, homework #5, homework #6, homework #7, midterm exam, course project, and final exam	20, 20, 20, 20, 20, 20, 20, 25, 15, and 100	All APM are of the Internal Assessment category.

3.3.3 Relative Importance (RI) of the APMs

RI is the weight of the APM that may vary based on the teacher's evaluation strategy and courses taught [144]. The RI of metrics directly connects with the data recorded by the teachers in assessing academic performance [144, 4]. Meier et al. (2015) [144] pointed out that there are higher chances of changing in RIs of the APMs over the year/time. One of the objectives of using varied RIs for APMs is to prioritize teachers' assessment strategies. We observed that dynamic RI values are rarely used in assessing and predicting performances. Table 3.5 summarizes 3 crucial contributions to the metrics with their RI values using course data. All the APMs belong to the Internal Assessment and External Assessment categories.

However, timely assessment and prediction based on the course data are challenging for many reasons. The primary reason is that at the beginning of the course, performance assessments (e.g., quizzes) are weakly correlated with marks in later in-class exams and the overall assessment score [144]. Moreover, if we consider that a course instructor uses the same teaching material over the year, there is still a chance that the assignments and exam patterns may change. Therefore, there are higher chances that RIs for APMs will vary. In this direction, the identification of RIs for APMs has paramount importance. All the studies mentioned earlier are connected, valuable, and encouraging as their key focus is to determine student performance. Moreover, existing studies show that APMs, FUMs, and RIs play a pivotal role in performance assessment and prediction. A limitation of using the current metrics is that they are challenging to apply in diverse education scenarios. Metrics such as GPA, learning behavior, self-efficacy, and affective states (see Table 3.4) are not readily available to the teachers. Some metrics have not been collected and the rest are not

Table 3.6: Recommended ML models after conducting the critical literature review

Model	References (n=32)	Count
Support Vector Machine (SVM)	[3], [30], [40], [51], [55], [4], [138], [141], [135], [150], [164], [60]	12
Naive Bayes (NB)	[3], [139], [40], [160], [51], [55], [137], [138], [135], [143], [148], [150], [152], [156], [158], [163], [165], [168], [170]	20
Decision Tree (DT)	[3], [30], [139], [171], [40], , [160], [51], [56], [151], [49], [136], [137], [138], [141], [135], [143], [147], [150], [156], [157], [164], [165], [168], [60], [170], [172]	27
Artificial Neural Networks (ANN)	[30], [139], [40], [160], [51], [137], [138], [141], [135], [147], [150], [157], [165], [168], [60], [170]	17
K-nearest Neighbor (KNN)	[30], [171], [40], [160], [51], [137], [135], [143], [147], [150], [157], [158], [165], [172], [173], [174]	16
Random Forest (RF)	[3],[30], [160], [51], [55], [56], [49], [141], [163], [164], [170], [175]	12
Logistic Regression (LR)	[51], [55], [56], [49], [135], [143], [144], [157], [163], [60], [170], [175],	12
Adaboost (AB)	[56], [49], [143], [169], [175]	5
Rule-based (RB)	[136], [137], [156]	4
Multiple Linear Perceptron (MLP)	[51], [4], [135], [148], [152], [164]	6
Deep Learning (DL)	[51], [136], [169]	3
Linear Discriminant Analysis (LDA)	[51]	1

available due to privacy. Therefore, we focus on identifying APMs, FUMs, and RIs based on some easily accessible metrics, which the instructor collects.

Recent studies do not address the above aspects. Moreover, they are focused on a limited number of disciplines or populations. There is no varied population across a domain, HEIs, and geographical location to replicate studies and extend in reusing the FUMs and their RIs. The FUMs, particularly for internal assessment, are vast (see Table 3.4). Selecting FUMs to assess student performance is a tedious task. Moreover, based on our observation, the RI aspects are neglected mostly in prior studies except [144]. In the Indian HEIs context, studies are limited in number, not up-to-date , and done for a specific discipline or HEIs [162].

3.3.4 Recommended ML Models

The prediction of students' performance helps to track academic performance and achievements throughout the course at an early stage [176, 177]. To predict student performance requires academic metrics and machine learning (ML) algorithms [160, 178]. However, early detection of poor students and providing personalized intervention using frequently used metrics have positive impacts on learning outcomes [30]. As a result, models that predict student performance and classify performances are very useful in teaching-learning. The recommended studies that prefer ML models are given in Table 3.6.

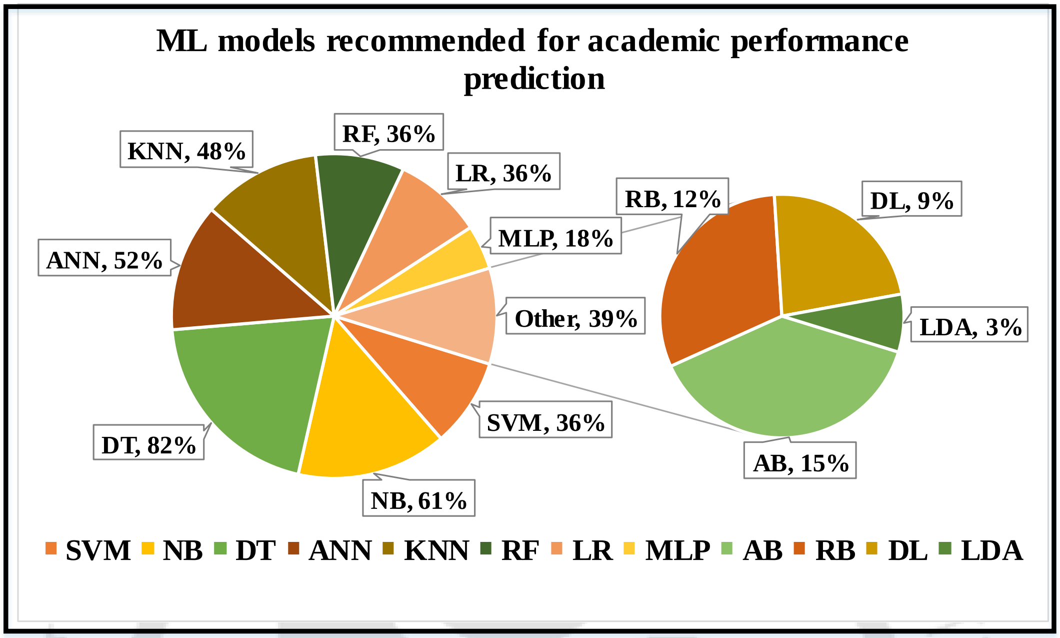


Figure 3.5: Comparative results obtained using support vector machine (SVM), Naive bayes (NB), decision tree (DT), artificial neural network (ANN), k-Nearest neighbors (kNN), random forest (RF) and logistic regression (LR) algorithms for predicting a student's academic performance

The choice of metrics for predicting students' academic performance has become more challenging due to the availability of a large volume of data [48, 30]. In recent years, applications of ML algorithms have drawn researchers' attention in academic performance prediction [51]. We have observed many ML algorithms are commonly used in students' performance prediction. Predictive models are now used in many educational institutions to improve students' engagement in teaching-learning [64]. ML algorithms can automatically extract complicated patterns from existing data attributes, allowing them to make intelligent decisions using currently available *academic performance metrics* [65]. An intelligent tutoring system in blended learning settings can use ML techniques to acquire real-time student-related performance data that help teachers intervene during the early phases of a course [70]. The SVM, NN, KNN, NB, DT, LR, and RF models are very important and recommended based on CLR (see Figure 3.5).

However, the validating applicability of the metrics usages and answer RQ3 in the Indian context needs further studies. We believe that teachers can better answer these questions based on their experiences as they frequently evaluate performances. Therefore, involving teachers in validating the applicability of metrics and finding FUMs and RIs is justifiable.

3.4 Online Field Study (OFS) Methodology

We have conducted a descriptive [179] online faculty survey. This survey determines AMPs, FUMs, and their RIs used in the Indian HEIs. In our study, we have followed the standard survey guidelines [180, 181, 182]. Guidelines help us in various ways to prepare a good survey design, like developing a well-written *questionnaire*, getting a response from a large population, and reporting data with satisfactory research goals and validity [179, 180].

Throughout the research process, great care was taken to ensure the study's ethical integrity. Before participants' involvement in this study, participants were provided with comprehensive information regarding the nature, objectives, and potential implications of the research. Each participant provided their informed permission after being fully informed of their rights, which included the option to withdraw from the study at any moment without being charged. The details of our survey are given in the following subsections (summarized in Figure 3.2).

3.4.1 Preparation of Survey Questionnaire

We have determined APMs, FUMs, and RIs through a questionnaire-based survey. The initial version of the questionnaire was developed using the knowledge of APMs, FUMs, and RIs reported in the literature (mentioned in Tables 3.3, 3.4, and 3.5). We also adopted terminologies found in open-access APMs that are available in various data repositories [30, 48]. The final version of the questionnaire is developed using experienced teachers' opinions and feedback from a pilot study.

We carefully selected the teachers for our pilot study. All teachers have at least five years of teaching experience. The participants were course instructors of reputed HEIs. Teachers, including six males and three females, volunteered for this study. The average teaching experience of the participants is 11.22 years ($SD = 4.99$). In our pilot study, the key focus was to inquire about how a teacher uses different APMs to assess and provide grades. Moreover, we requested all the participants to report honest feedback about the components

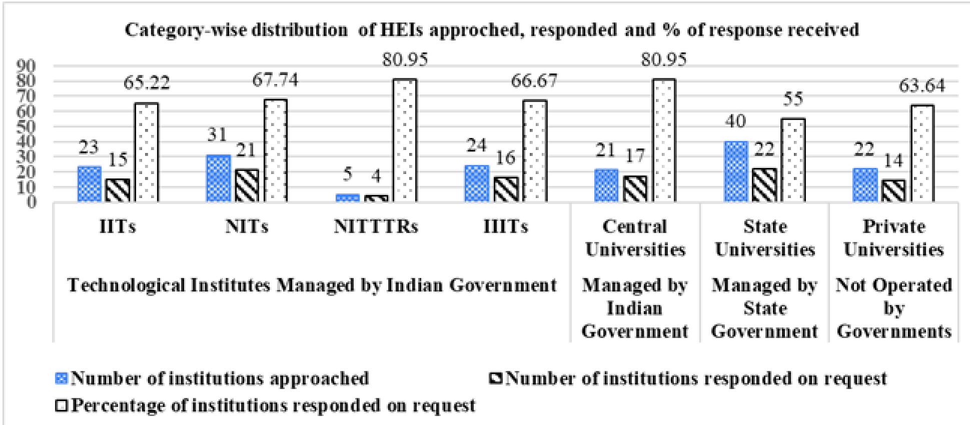


Figure 3.6: Categories of higher educational institutions (including universities) throughout India and their participation in the online faculty survey

of the study and ambiguity in the questionnaire wording (see Chapter 5.6.3, page 121 [179]). The pilot study guided us to get an initial idea about the suitable combinations of survey components and fine-tuning the questionnaire.

We received 7 out of 9 verbal and nonverbal positive feedback on the research study. Moreover, we received 20 encouraging APMs after analyzing feedback from the participants. The positive feedback and the considerable variation of APMs motivate us to conduct further extensive research studies. We finally developed the questionnaire based on the feedback received from the teachers. The questionnaire consisted of a combination of dichotomous, multiple-choice, and open-ended questions [179, 181]. There are two sections in our questionnaire. The first section contains questionnaire statements related to the demographic profile of the teachers. The second section consisted of questions to understand how a teacher uses different APMs and RIs to assess students in HEIs.

The Google form was circulated all over India to receive responses from the participants through email. The form contained questionnaire, including brief information about the importance of their response and the research. We collected data on grading and marking with final grading components using the questionnaire from the teacher participants. The survey data helped to confirm which APMs are reliable in assessing academic performance.

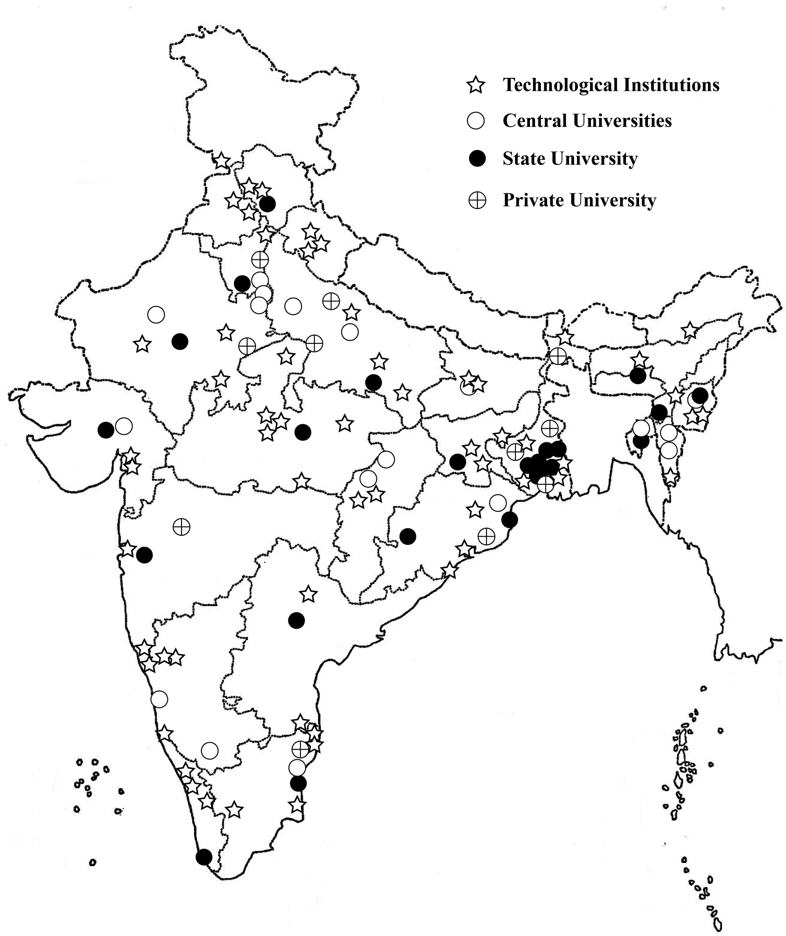


Figure 3.7: Category-wise higher educational institutions and universities throughout India and their participation in the faculty survey.

3.4.2 Approach

We followed a systematic strategy to make the results of the survey valid and reduce bias [179]. We identified 146 HEIs of 4 categories (see Figure 3.6) based on their national importance. The institutions are geographically spread all over India (see Figure 3.7).

In India, HEIs include many technological institutions managed and funded by the Indian government. These are the most competitive, reputable, and nationally/internationally recognized institutes. The institutions are the Indian Institute of Technology (IITs), National Institute of Technology (NITs), National Institute of Technical Teachers Training and Research (NITTTRs), and Indian Institute of Information Technology (IIITs). Out of these, the central universities were established based on a Central Act, whereas the State Act established the state universities. These are funded and managed by the central and state governments, respectively. The state/central government does not fund private universities but recognizes and is regulated by both government bodies.

In our survey, we followed many strategies to minimize sampling bias. Initially, we prepared the category-wise targeted list of HEIs (see Figure 3.6). Then, we visited the websites of institutions to collect the faculty mailing addresses. We followed some strategies to reduce gender bias in the respondent population. We maintain a male-to-female ratio of 1:1 while collecting the mailing addresses. We cover all the disciplines seen in particular HEIs. We collect 1526 e-mail addresses to conduct the survey. Mailing addresses include Institute Directors, Principals, Academic Deans, Heads of Departments (HODs), individual teachers, academicians, and other distinguished administrators. We sent an official request to them to participate in our online survey. We also requested them to share the mail with their faculty colleagues to respond to this survey. The e-mail contains a brief introduction about the purpose of the study, a Google form uniform resource locator (URL) for a response, and our short identity with an internal research website URL to validate and know more about our research activity.

Moreover, we followed some strategies to reduce non-response bias and improve response rates. We requested participants to respond to our survey within a week. If teachers do not respond within a week, we resent the survey request to them. We got a higher response rate with a gentle reminder. After receiving a response, we sent a thanking e-mail requesting them to circulate the survey request to their close contacts. We received positive responses and appreciation from many teachers, academicians, and administrators for conducting the survey. Figure 3.6 shows the number of HEIs we approached with their categories and the number of institutes from which teachers participated in our survey. Figure 3.7 depicts the geographical distributions of the HEIs locations in India.

3.4.3 Participants

Data collection for our survey from participants began on March 11, 2020, and ended on December 28, 2021. Figure 3.6 shows the number of institutions we approached and received responses to our survey. Figures 3.8, 3.9 and 3.10 describe the discipline-wise distributions and demographic information of the participants. All participants who volunteered in the

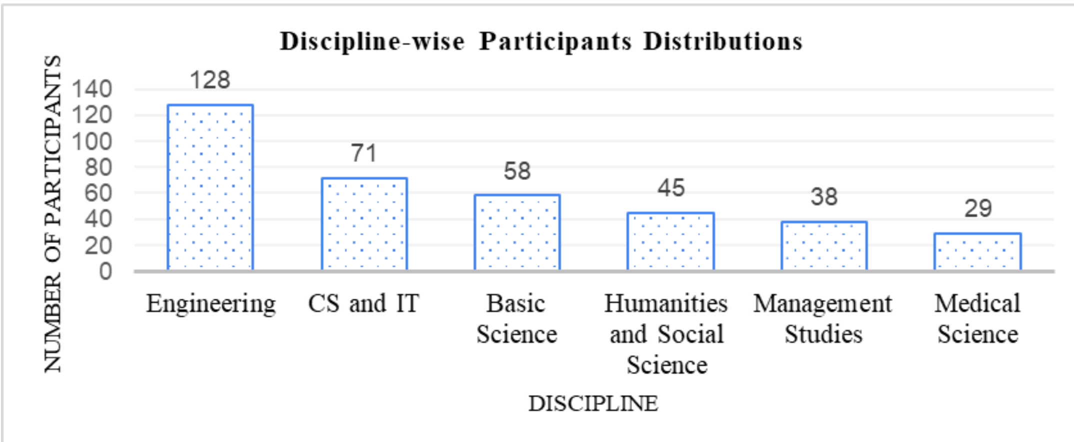


Figure 3.8: Discipline wise participants distribution

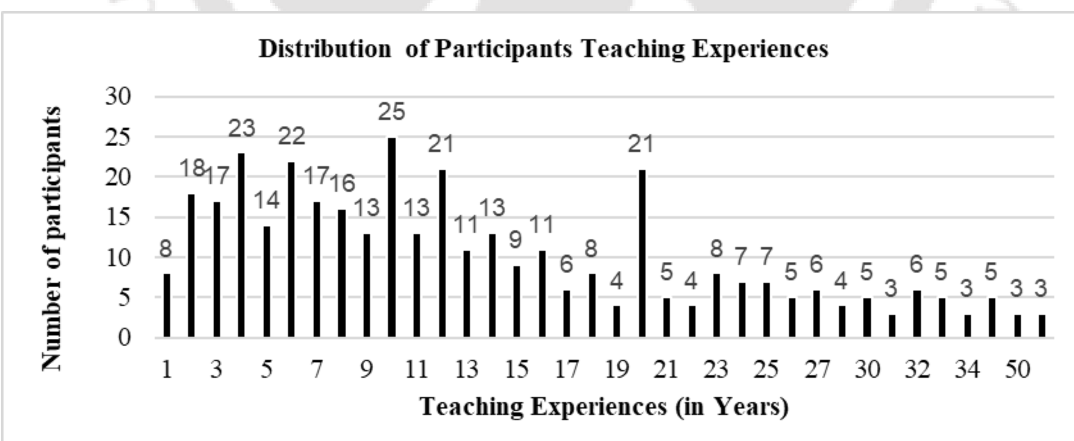


Figure 3.9: Participants teaching experiences

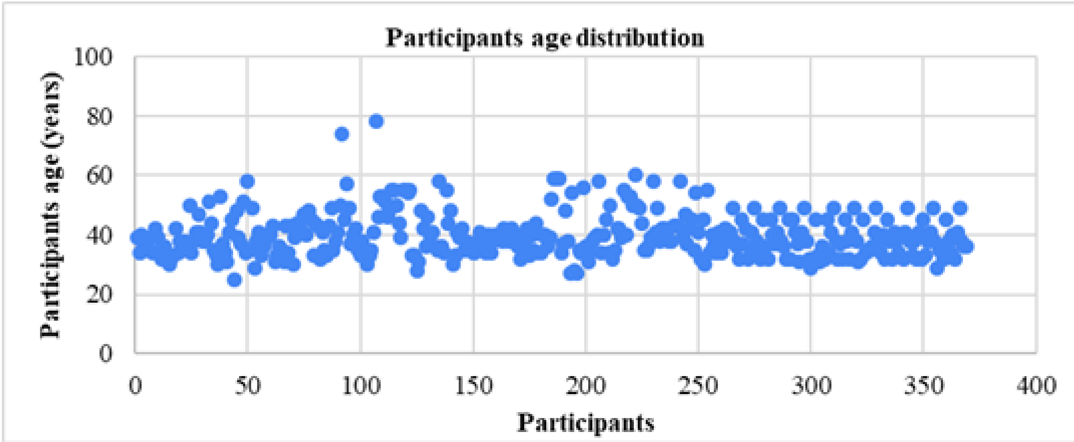


Figure 3.10: Distribution of teachers age who volunteered in this survey

study are from 109 HEIs geographically scattered across India (see Figure 3.7). In this study, we analyzed response data received from 369 teachers employed in HEIs. The response consisted of APMs and their RI values used by teachers to evaluate student performance.

Figure 3.8 shows the discipline-wise number of participants who responded to our survey request. Figure 3.9 shows the statistics of the teaching experiences of all the teachers who participated in this study. The average teaching experience of the participants is 13.78 years. The teaching experience varies between 1 to 53 years. Figure 3.10 shows the age/frequency distribution of the responses received from participants in our survey. The age frequencies of the participants are between 25 - 78 years. The average age of the participants is 40.50 years. The overall gender distribution of the teachers is 65.39% male and 34.39% female.

In summary, the overall statistics of the discipline-wise distribution and demographic information show that our study covers teachers of almost all disciplines, experiences, and age groups. Moreover, the survey covers broader academic classes (HEIs), disciplines, and geographical locations all over India.

3.4.4 Results and Observations

This section investigates various performance metrics to address the research questions (RQ2.1 and RQ2.2) in the Indian context. We characterize the APMs, FUMs, and their RIs preferred by Indian teachers. Table 3.7 demonstrates 24 APMs. We have determined these metrics from the received teachers' responses. We observed that there are some redundant APMs in the list. Therefore, we have revised the APM list based on semantics,

Table 3.7: Broad varieties of 24 APMs based on Indian Teachers Choice

(SL. No.) Academic Performance Metrics (APMs)	(SL. No.) Continuation of APMs
(1) Quizzes Marks	(13) Class Test Marks
(2) Home Work Marks	(14) Assignment on Term Paper Performance
(3) Internal Examination Performance	(15) Practical Examination Marks
(4) Mid-Semester Examination Marks	(16) Class Performance
(5) End-Semester Examination Marks	(17) Presentation on a Project Topic grade
(6) Surprise Test Marks	(18) Class Interaction
(7) Attendance	(19) Observation on Individual's Attention
(8) Projects Performance	(20) Mini Project Performance
(9) Assignments Performance	(21) Viva Voce
(10) Sessional Examinations Marks	(22) Small Write-up
(11) Seminar on a Topic Performance	(23) Presentation Contest
(12) Class Participation Performance	(24) Performance on Audio-Video Recordings

meaning, and the context of the usage of the metrics. Table 3.8 shows the revised list contains 18 APMs. We also reported valuable observations about the APMs while revising the list. Class performance (16) is synonymous with quizzes (APM1) or class test marks (APM3). Similarly, project performance (8), presentation on a project topic grade (17), and mini-project performance are merged and treated as APM8. Furthermore, some APMs convey a similar meaning semantically, like the internal examination (3) and class test marks (13) as APM3, and assignment on term paper performance (14) as assignment performance (APM9).

Table 3.8: Revised APMs and their category information (SL. No. from Table 3.7, IA: Internal Assessment and LB: Learning Behavior)

[Level] Academic Performance Metrics (APMs)	[Level] Continuation of APMs
[APM1] Quizzes Marks (1 and 16, IA)	[APM10] Presentation Performance (23, IA)
[APM2] Home Work Marks (2, IA)	[APM11] Viva-voice (21, IA)
[APM3] Class Test Marks (3 and 13, IA)	[APM12] Class Participation Performance (12 and 18, IA and LB)
[APM4] Mid-Semester Examination Marks (4, IA)	[APM13] Sessional Examinations Marks (10, IA)
[APM5] End-Semester Examination Marks (5, IA)	[APM14] Practical Examination Marks (15, IA)
[APM6] Surprise Test Marks (6, IA)	[APM15] Observation on Individual's Attention (19, IA and LB)
[APM7] Attendance (7, IA)	[APM16] Seminar on a Topic Performance (16, IA)
[APM8] Projects Performance (8, 17, and 20, IA)	[APM17] Performance on Small Write-up (22, IA)
[APM9] Assignments Marks (9 and 14, IA)	[APM18] Performance on Audio-Video Recordings (24, IA)

We also determined categories of the APMs to link with state-of-the-art APM categories. We observed that all APMs except APM12 and APM15 belong to the internal assessment category. The APM12 and APM15 have dual meanings. If a class teacher observes and notes class participation, then it should be an internal assessment. If the system checks the students' activity logs while using technology, then it is learning behavior. Similarly, the observation of individual students' attention should be either an internal assessment or a learning behavior. Moreover, if the APMs are used for future courses, they should be the external assessment category of the APM.

Figure 3.11 describes 18 APMs and the percentage of participants who prefer the metrics for performance assessment. More than 70% of teachers use the 3 APMs, namely, APM4, APM5, and APM9. The APM1, APM3, and APM7 are in favor of using 50% - 70% participants. A range of 30% - 50% participants prefer the APM2, APM6, and APM8. The 10% - 30% teachers adopt the APM10, APM11, and APM12 in assessing students. Below 10% participants choose the remaining APMs (APM13 - APM18).

FUMs to Assess Academic Performances

This survey identified 9 FUMs (FUM1 - FUM9), namely, APM1 to APM9, out of 18 APMs used by the teachers (see Table 3.8 and Figure 3.11). We consider an APM as FUM if it is used by more than 35% of the teachers to assess their students. Moreover, this study and the analysis of the response data help us in characterizing 9 FUMs (see Table 3.9) based on Indian teachers' preferences. Figure 3.11 shows that FUM4, FUM5, and FUM9 are used by above 70% of teachers based on a percentage of the respondent. The 50% - 70% participants favor the FUM1, FUM3, and FUM7. The FUM2, FUM6, and FUM8 are favored by 30% - 50% participants. The APM surprise test mark (FUM6) is selected to evaluate student performance by 36.04% (133 out of 369) participants.

The other crucial point that should be discussed in understanding the FUMs is the RI values for the metrics. We have analyzed FUMs and their RIs with our overall and category-wise HEIs levels in the following subsections.

Relative Importance (RIs) for Frequently Used Metrics (FUMs)

In our study, we found that 85.80% of participants use varied RI for each APM. Therefore, RI is an essential component for APMs as most of the teachers prefer separate RI for each APM. We investigate the relationship between the FUMs and the RIs based on teachers' choices of performance metrics. Table 3.9 shows descriptive statistics in understanding the overall HEIs preferred RIs used in HEIs. It helps to explore the relationship deeply

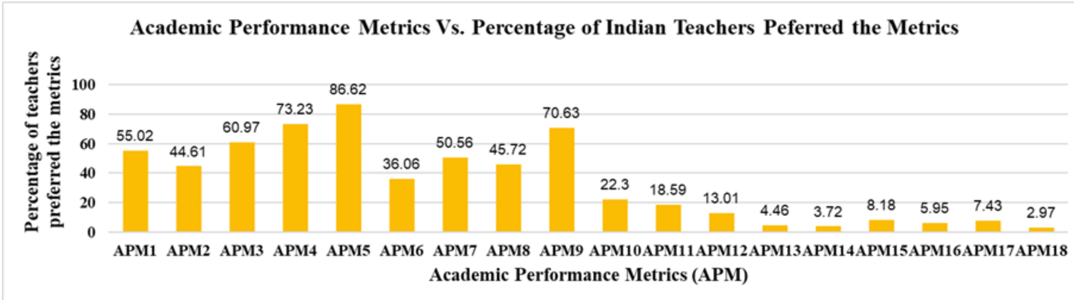


Figure 3.11: Academic performance metrics (APM) and their usages preferences by the Indian teachers in the course performance assessment

Table 3.9: Summary of the percentage (%) of participants preferences and the descriptive statistics of RIs for FUMs.

SL. No. with frequently used metrics (FUMs)	% of preferences	Descriptive Statistics of relative importance (RIs)			
		Mean	Median	Mode	SD
[FUM1] Quizzes Marks	55.02	12.16	10	10	5.84
[FUM2] Home Work Marks	44.61	12.74	10	10	5.84
[FUM3] Class Test Marks	60.97	15.58	15	10	7.63
[FUM4] Mid-Semester Examination Marks	73.23	23.31	20	20	5.51
[FUM5] End-Semester Examination Marks	86.62	37.11	35	30	11.46
[FUM6] Surprise Test Marks	36.06	12.42	10	10	8.9
[FUM7] Attendance	50.56	8.6	10	10	3.83
[FUM8] Projects Performance	45.72	14.94	10	10	10.46
[FUM9] Assignments Marks	70.63	14.52	10	10	9.71

with FUMs based on teachers' responses. The end-semester examination (FUM5) has the highest mean RI value of 37.11. The second highest mean RI value is 23.31 for the metric mid-semester examination (FUM4). The mean RI for "class test marks (FUM3)" is 15.58. The metrics like, "quizzes (FUM1)", "homework (FUM2)", "surprise test (FUM6)", "performance in projects (FUM8)", and "assignments marks (FUM9)" have mean RI values between 10 to 15. The FUM, i.e., "attendance (FUM7)", has a minimum mean RI value of 8.6.

We have identified the 3 highest RI values for FUMs with varied mean median, mode, and standard deviation. They are FUM3 (M=15.58, Median=15, Mode=10, and SD=7.63), FUM4 (M=23.31, Median=20, Mode=20, and SD=5.51), and FUM5 (M=37.11, Median=35, Mode=30, and SD=11.46) utilized by the teachers. However, we have got 7 FUMs with equal median and mode. We have obtained the RI values with an equal median and mode of 10 for 6 FUMs (FUM1, FUM2, and FUM6 to FUM9). We have also observed that the FUM4 has a higher equal median and mode value ($median = mode = 20$).

Table 3.10: An inferential statistical t-Test to observe the significant difference between the means of RIs of the influencing metrics used in various categories of institutions in India.

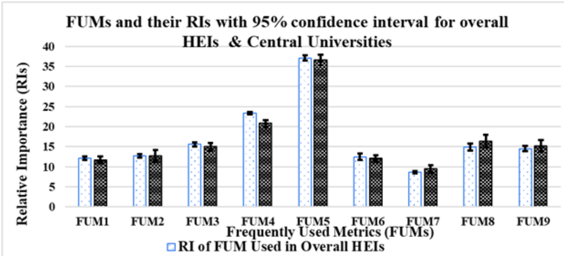
Institutions Compared	No significance difference has been found while tested statistically with RIs of overall HEIs (M=14.91, SD=8.09, n=12) using t-Test with $\alpha = 0.05$)
Central Universities	RIs of Central Universities (M=14.44, SD=8.06, n=12) [t(22)=0.14, p=0.44]
NITs	RIs of NITs (M=14.44, SD=8.06, n=12) [t(22)=0.15, p=0.43]
IITs	RIs of IITs (M=13.87, SD=7.17, n=12) [t(22)=0.33, p=0.37]
IIITs	RIs of IIITs (M=14.41, SD=8.51, n=12) [t(22)=0.15, p=0.44]
State Universities	RIs of state universities (M=13.82, SD=8.91, n=12) [t(22)=0.31, p=0.38]
Private Universities	RIs of the private universities (M=16.27, SD=10.36, n=12) [t(22)=0.35, p=0.36]

Comparison studies on RI for FUM used in Indian HEIs

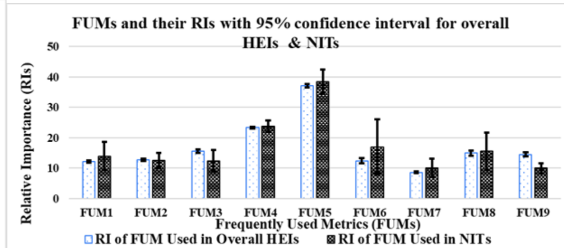
To deeply analyze the importance of FUMs, we have compared the RI values of 9 FUMs and their 95% confidence interval for each HEI. We observed that the overall 95% confidence interval varies based on HEI categories. Figure 3.12 illustrates the findings of RIs used by Indian teachers in a course. We have also performed a significant test on the usage of RI values based on the institution categories to understand the variation across India. In this comparative study, we have not considered the institute category of NITTTRs, as we received responses from only 4 HEIs out of 109 belonging to this category. We determine the overall HEIs preferred RIs for individual FUMs by considering all responses received in our survey. We calculate the RIs for individual FUMs, considering only the institutions' responses from that specific HEI category. We also examine the significance of the RI differences statistically for each type of HEI with overall HEIs' preferred RI. We perform a t-Test (two-sample assuming equal variances) for all statistical tests demonstrated in this section [183].

Figure 3.12 shows the comparison of the overall HEIs' RIs with the individual categories of institutions' RIs usages for individual FUMs. We observed similar RI values for each FUM for all categories of institutions. There are no differences in the 95% confidence interval for both overall HEIs with individual institutions except NITs. Figure 3.12(b) shows there is a higher variation in the 95% confidence interval for all RIs of individual FUMs for NITs. Table 3.10 summarizes the statistical test results. The RIs for FUMs of individual institution categories do not significantly vary with the overall Indian HEIs' RIs.

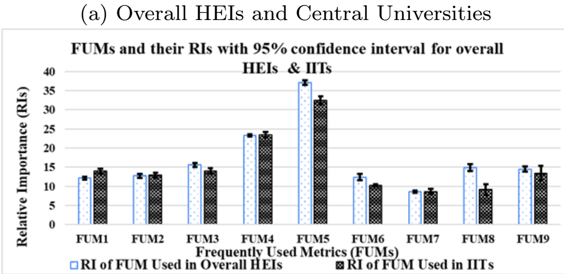
To determine the quality metrics, we summarized our findings with three high-level tags (see Table 3.11). The results show that 3 FUMs (FUM3, FUM7, and FUM9) are common in literature and survey studies. We also observed some dissimilarities in the Indian context.



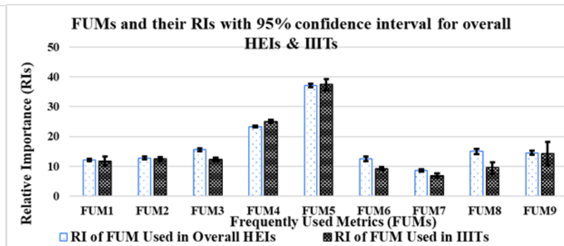
(a) Overall HEIs and Central Universities



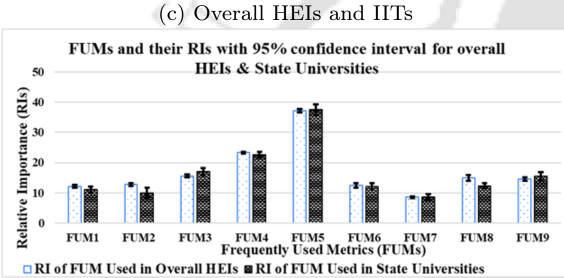
(b) Overall HEIs and NITs



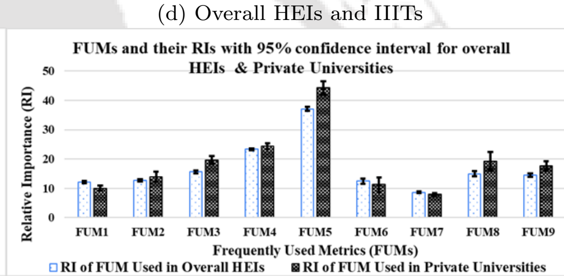
(c) Overall HEIs and IITs



(d) Overall HEIs and IIITs



(e) Overall HEIs and State Universities



(f) Overall HEIs and Private Universities

Figure 3.12: Description of Relative Importance (RIs) of the Frequently Used Metrics (FUMs) and their 95% confidence interval comparison for overall Indian Higher Educational Institutions (HEIs) with (a) Central Universities, (b) NITs, (c) IITs, (d) IIITs, (e) State Universities, and (f) Private Universities.

The findings show that surprise tests (FUM6) and performance in projects (FUM8) are preferred by only Indian teachers as their state-of-the-art citation count is zero. FUM1 and FUM4 have citation counts 10 and 6, which means that existing literature uses these metrics to assess and predict performances like Indian teachers. FUM2 and FUM5 have a low citation count (only 2). The homework marks (FUM2) were preferred by 165 of 369 teachers (45.21%). The 86.72% teachers (320 out of 369) use the end-semester examination (FUM5) as a very high metric preference in India. We have also suggested normalized RIs based on the mean, median, mode, and standard deviation of our empirical data (see Table 3.11). The citation counts help to choose metrics based on the importance given in the state-of-the-art. The participants' preferences and suggested RIs guide to select metrics based on empirical evidence. The high-level tags as low, medium, and high interpretation prioritize the overall

Table 3.11: Summary of the findings about FUMs, suggested RIs, and their interpretation as 3 level tags (high, medium, and low) based on CLR and OFS

FUMs	State-of-the-art citation count out of 48	3 level tag based on citation count	% of participants preferred	3 level tag based on participants preferences	Relative importance	3 level tag based on relative importance	overall impression
[FUM1]	10	medium	55.02	medium	15	medium	medium
[FUM2]	2	low	44.61	low	10	low	low
[FUM3]	15	high	60.97	medium	15	medium	medium
[FUM4]	6	medium	73.23	high	25	high	high
[FUM5]	2	low	86.62	high	35	high	high
[FUM6]	0	low	36.06	low	10	low	low
[FUM7]	13	high	50.56	medium	10	low	medium
[FUM8]	0	low	45.72	low	15	medium	low
[FUM9]	17	high	70.63	high	15	medium	high

importance of the FUMs. The FUM1 to FUM9 are internal assessments APM category. However, the same metrics are considered as the external assessment category while reusing the same for future courses.

3.5 Summary of the Chapter

In this chapter, we have determined the following: *academic performance metrics*, *frequently used metrics*, *relative importance*, and predictive models based on the literature review and an online field study. The prior approaches use various *academic performance metrics* without covering the teachers' actual recorded data and their opinions. In this study, we link the state-of-the-art *academic performance metrics*, *frequently used metrics*, and *relative importance* with teachers' choices of metrics through a faculty survey. The faculty survey covers large geographical locations and diverse populations to find the *frequently used metrics*. Given the potential privacy risks associated with data containing personally identifiable information, we decided not to rely solely on automated logging in our online field study. Instead, we opted to contact teachers individually by email to obtain informed consent before collecting any potentially sensitive information. This allowed us to ensure transparency and respect for participants' privacy throughout the data collection process. This study also identifies an optimized number of *academic performance metrics* termed as *frequently used metrics*. The *relative importance* values and the confidence interval for the *frequently used metrics* help in showing the usage importance and variations of category-wise HEIs in the Indian context. The t-Test shows no significant differences in their *relative importance* values based on the various categories of HEIs with the overall *relative importance* values.

This suggests that the relative importance of these factors is consistent across different types of HEIs. There's no evidence to suggest that the factors are more or less important in one type of HEI compared to others. Therefore, we hope that the suggested *relative importance* of the *frequently used metrics* can help to structure the assessment and predict performances in the Indian higher education systems. The high-level tags for *frequently used metrics* and *relative importance* will help in choosing metrics to quantify student performance for an intelligent tutoring system. We expect that the survey will benefit many multidisciplinary researchers such as intelligent tutoring systems, educational data mining, and learning analytics. Moreover, we believe that the broad familiarity of the *academic performance metrics* and recommended ML models will help to choose suitable metrics and reuse findings in the predictive methods.

The details of publications expected from this contribution are as follows:

Journals Under Review

1. **Ujjwal Biswas** and Samit Bhattacharya, "Usage of Academic Metrics to Predict Student Performance in Blended Learning Environment", ***IEEE Transactions on Learning Technologies***, Revised and resubmitted [Chapter 3]

2. **Ujjwal Biswas** and Samit Bhattacharya, "AI-enabled predictive modeling of student performance using teacher choice of metrics", ***International Journal of Artificial Intelligence in Education (IJAIED)***, [Chapter 3]

Chapter 4

A Real-time Interactive Visualizer for Large Classrooms

4.1 Introduction

Classroom teaching is one of the potential application area of visual monitoring. In a classroom, the teachers are expected to be aware of the attendance level, state of learning and the mental state (e.g., frustrated/excited) among others, of each individual student so as to make the teaching more effective and improve the learning outcome. Usually, acquiring such knowledge is easier in classroom having small number of students (thirty or less). This is so since in a small class, the teachers are likely to be able to "see" all the students and determine the state (physical/mental) from visual inspections. Also, frequent interactions between the teacher and students are more likely to take place in classes with less students, which in turn can also help the teacher understand the mental as well as the learning state of the students. It is also possible to keep track of student records such as attendance or performance in examinations and use those for a better understanding of the state of a student inside the class, without affecting the teaching significantly. For example, it is not very difficult for a teacher to check the records of a particular student *quickly* to know his/her attendance. For larger classrooms with more students (more than fifty), such awareness about the class becomes problematic. For example, if a teacher wishes to know about the attendance record for a particular student, s/he is likely to take much more time to retrieve the record (as compared to a similar task in a smaller classroom), which in turn may "eat away" teaching time (if the teacher needs to do it many times) affecting the overall teaching process (and consequently the learning outcome). The more important of the tasks that a teacher is likely to be interested in doing in a classroom are listed below.

1. The teacher may wish to *quickly* identify the students, who are not engaged in the teaching process (without actually requiring to closely interact with each and every student personally as that is impossible in a large class considering limited teaching periods of typically one-hour duration).

2. The teacher may like to retrieve the allied records (e.g. attendance or past performance in examinations) for such dis-engaged students *quickly* (without having to go through voluminous records).

3. A teacher may also like to learn about particular students/group of students in a particular region of the classroom (e.g., two students sitting in the left corner of the last row) for random check. In a small class, the teacher may walk-up to the student(s) and interact. However, such an approach may not be feasible in large classrooms, as it is likely to reduce available teaching time significantly.

In such situations, the teacher is likely to be benefitted from a visualizer of classroom status. Such a visualizer is expected to ease the effort required to identify problem cases (either systematically as in (1) in the above list or through random checks as in (3) in the list) including retrieval of individual details (as in (2) in the list).

There are several challenges in large classroom visualization. First of all, it is difficult to display the status of the entire class on a relatively small display area (for example, if we wish to display the state of one hundred students on a 21 inch desktop screen or a 10 inch tablet that the teacher might have). This is primarily because the teachers need to see both the state and the location of the students. Moreover, the state information should also be easily identifiable by the teacher so that the regular flow of teaching does not get affected. No present classroom visualizer addresses these challenges. In order to overcome these difficulties, we propose a novel visualizer for large classrooms.

4.2 Design of the Proposed Visualizer

Our proposed visualizer is interactive, it renders the classroom status in two levels, where the change in levels happens through interaction (tap/click). In the first level, a teacher gets to see an overview of the classroom status (with the help of color codes). The individual student details are visualized in the second level. An overview of the visualizer along with the assumptions we made are described next.

4.2.1 Overview and Assumptions

Our first assumption is that the classroom is organized in the form of a two-dimensional matrix. Each cell in the matrix represents a seating position for the student. We have two objectives: to visualize the status of the classroom as well as the details of the individual students. We define classroom status as the aggregation of the individual states of the students. In order to design an efficient and usable visualizer, we propose a set of three states: critical (denoted by C), likely to be critical (denoted by LC) and normal (denoted by N). A student can be in either of these states at any instant of time. When a student is doing well and do not require any intervention by the teacher, s/he is in the N state. There might be some others for whom the intervention by the teacher is desirable. Their states are LC. There can also be students who must be given special attention by the teacher immediately. These students are in the C state.

At any instant, the classroom is likely to contain all the three types of students (considering the classroom to be large). In the first level of the visualizer, we group all the students in the classroom into clusters. Each cluster represents a state type (N, LC and C). We render these clusters on a rectangular grid with color codes. We use three colors to denote the three types: red to indicate the C clusters, yellow to refer to the LC clusters and green to represent the N clusters. The idea is illustrated in Figure 4.1 (first level visualization part).

The grid color is dynamic. It changes every few minutes reflecting the change in the students' state as the teaching progresses. We set a value of fifteen minutes to update the grid colors assuming it to be sufficient to capture any change in the state of the students. However, the fixed value is not necessary and the teachers can set it, based on his/her experience.

In the second level, the teacher can get the details about the students. The information is overlaid on a visual representation of the students. We used a colored bounding box on an image of the student as the visual representation to indicate the exact state of the student.

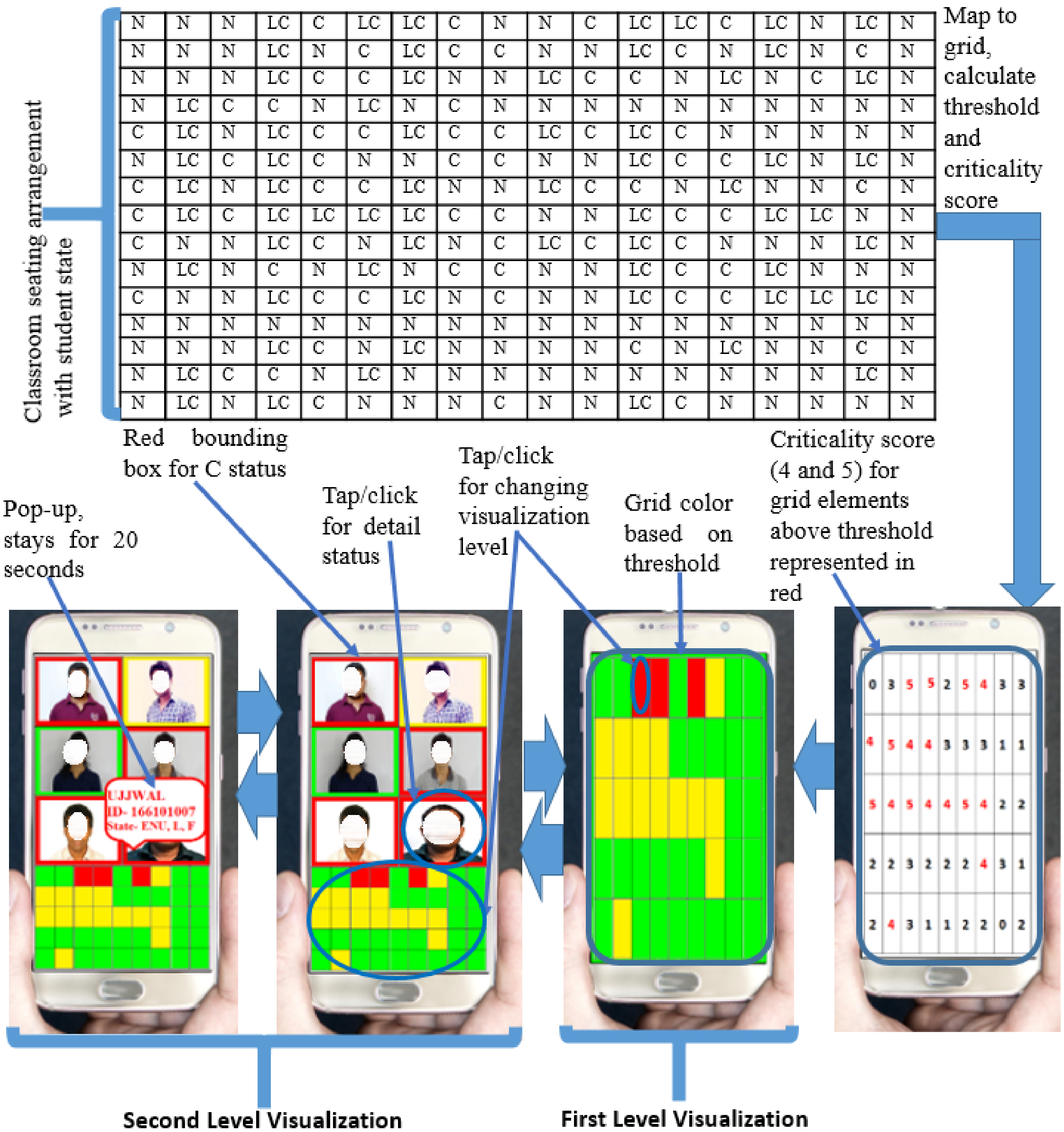


Figure 4.1: Illustration for the two-level visualizer including three states (critical denoted by C, likely to be critical denoted by LC and normal denoted by N). The bottom part of the figure depicts the first level (with grid layout) and second level (with the students' photo in a colored bounding box).

The image is prestored (captured during the registration for the course). The color code used is the same as in the first level with the same significance.

In order to get to the second level, the teacher needs to tap or click on a grid element in the first level. For a touchscreen device, a tap is required. If the visualization is rendered on a desktop screen, mouse click is needed. A further tap/click on the visual representation reveals the details for the students (textual description of the state information). Along with the details, an overview of the entire classroom status is also present in the second level (in a small region of the screen). With a tap/click on this region, the teacher can get back to the first level view. The idea is illustrated in Figure 4.1 (second level visualization part).

Here, we primarily focus on designing a real-time classroom visualizer. The visualizer aims to anticipate the mental and learning states of students in a BYOD classroom using their mobile devices which are very similar to the research work [184]. As this visualizer design is to use the system in real-time (during the class), if the design uses more than three states, there is a chance to take teachers' teaching time to comprehend the students' states. This contribution utilizes three states (C, LC, and N) and develops visualization and intervention techniques using these states as the basis. The key concern is balancing real-time usability with the comprehensiveness of the visualizer with the three states. Here are some key considerations and potential strategies for addressing real-time uses (mentioned in introductions 1, 2, and 3). The design has the following key concepts: trade-offs and optimization of the display of states for real-time use.

- Using fewer states reduces cognitive load for teachers but might oversimplify student states.

- A simpler model might be easier to act upon quickly but could miss without having to go through voluminous records.

- Focus on states that necessitate immediate action, potentially using a three-state model for real-time display.

- Primary view with essential states for quick comprehension and option to drill down into more detailed states when needed.

The proposed visualizer is discussed in detail in the next section.

4.2.2 Proposed (four) Algorithms

The visualizer takes two inputs: the student location and the student state information. In order to get the location information, we consider a classroom to be organized into a rectangular grid. Thus, each student can be located with an integer pair (x, y), with respect to a 2D classroom reference frame. At the beginning of the class, the location of each student is supplied to the visualizer. We further assume that the state information for each student is supplied on a continuous basis (either manually fed by a teaching assistant or automatically captured and transmitted to the visualizer system by an ICT-enabled infrastructure). The continuous supply of information is assumed for dynamic upgrade. The visualizer consists of four separate algorithms: a grid generator, a threshold calculator, the dynamic grid coloring and the second-level visualizer. At first, the visualizer generates a grid layout taking into account the classroom configuration and the screen characteristics. Each grid element represents a cluster of students in the classroom. The algorithm is shown in Algorithm 1.

ALGORITHM 1: Dynamic Grid Generation

Input: Classroom seating arrangement $S_{M\times N}$, where M*N is the matrix dimension, screen size (Sh) and width (Sw) in pixels.

Output: The dynamic grid $G_{R\times C}$ where $R \times C$ is the grid dimension.

`/* Compute the maximum number of rows and columns possible. */`

$RowMax = \left\lfloor \frac{S_h}{100} \right\rfloor$

$ColMax = \left\lfloor \frac{S_w}{100} \right\rfloor$

`/* Compute grid dimension so that the grid elements are ‘‘clickable’’ AND the students are distributed in equal numbers among the grid elements. */`

if *M is not prime* **then**
- `/* Let factor(M) represents the set of the proper factors. */`
- factorize M

else
- factorize M+1

if *N is not prime* **then**
- `/* Let factor(N) represents the set of the proper factors. */`
- factorize N

else
- factorize N+1

if *Maximum value in factor(M) is less than* $RowMax$. **then**
- Set R = the maximum value in factor(M)

if *the maximum value in factor(N) is less than ColMax.* **then**
- Set C = the maximum value in factor(N)

Return R and C as the dimension of the grid.

In the algorithm, we first find the maximum number of rows and columns possible on the display that makes each grid element “clickable”. It is important on a touchscreen device to have the interactive elements (such as the buttons) "clickable" (can be termed as "touchable" in case of touchscreen interaction). The term implies that the interactive elements should have a size larger than the size of our thumb; otherwise, the area would not be properly visible and it would be difficult to touch at the right place. Findings from earlier research works [185, 186] indicate that the minimum touchable area ranges from 10 square mm to 20 square mm (i.e., approximately 36 to 72 pixel in width as well as in height). To be on the safe side, we considered a touchable area to have the height and width of 100 pixels each. Note that if an area is touchable with the finger, it is easily clickable with mouse cursor (in case of desktop screen). Therefore, we divide the screen height and width (in pixels) by 100 each (lines 1-2) to get the maximum number of rows and columns that ensures that each grid element would be "clickable". The maximum numbers, however, serve as an upper limit only. If we directly use the numbers to set the grid dimensions, the resulting grid may have poor perceptual quality due to the presence of a (possibly) large number of rows and columns. In order to optimize the perceptual quality of the output grid, we propose the following (see Algorithm 1).

We first factorize the classroom dimensions and create two lists of the factors: one for the rows and the other for the columns (lines 4-6, 8-10). In each list, we find out the factor that is less than or equals to the corresponding maximum value (e.g., the maximum row value for the factors pertaining to the number of rows in the classroom and the maximum column value for the corresponding column factors) (lines 12-14). These factors are set as the grid dimension and returned as the output of the algorithm (line 15).

The factorization of the classroom dimensions is a novel step required to ensure that the display grid elements contain equal number of students. At the same time, we ensured that the grid elements are "clickable" by choosing only the factors that are less than or equals to the maximum possible rows or columns. When any one or both of the classroom matrix dimension(s) is/are prime number(s), we add one dummy row or column or both to the original number of rows and columns in the classroom, as the case may be. We do so to enable us to factorize the dimensions. The state of the students in the dummy row and column is set to a special state D (or dummy), so that these do not affect the overall criticality computations. Note that the algorithm involve primality testing and factorization. We can use any standard algorithm for these tasks. The algorithm is illustrated with an

ALGORITHM 2: Threshold Calculation

Input: Classroom seating arrangement matrix $C_{M\times N}$; student state matrix $S_{M\times N}$, and the display grid $G_{R\times C}$.
Output: A threshold value (T_h) and the criticality score $GC_{R\times C}$.

```
/* For each grid element, compute a criticality score (by adding up the number of students in
   the C or LC state.  The criticality score is initialized to 0.  Also compute the total
   criticality score for the entire classroom, which is initialized to 0.                    */
```

1 **for** *Eveery element in* $G_{R\times C}$ **do**
2   **for** *Every student in the grid element* **do**
3   **if** *Corresponding entry in* $S_{M\times N}$ *is either C or LC* **then**
4             $Criticalityscore += 1$.
5   Store the criticality score for the grid element in the corresponding entry for GC_{R*C}.
6   Total criticality score (for the entire classroom) += criti-cality score.
7 Compute the average (avgCS), maximum (maxCS) and minimum (minCS) criticality scores for the entire grid (using $GC_{R\times C}$).

```
/* Compute an elevation factor (S_F) to manage the number of critical elements               */
```

8 **if** $avgCS \leq \frac{N}{2}$, *(N is the number of students in each grid element)* **then**
9     $S_F = \frac{maxCS - minCS}{N}$
10 **else**
11     $S_F = \frac{maxCS - avgCS}{N}$
12 $Threshold = (1 + S_F).avgCS$
13 **if** $Threshold < maxCS$ **then**
14   Return Threshold.
15 **else**

```
    /* if the threshold value exceed the maximum criticality score, we will not have any
       critical grid elements to display.  In such cases, we re-compute threshold without any
       elevation of the average criticality score.                                           */
```

16   Find the median (medCS) and mode (modeCS) of the distribution represented by the criticality score values ($GC_{R\times C}$).
17   **if** $avgCS \geq medCSANDavgCS \geq modeCS$ **then**
18         $Threshold = avgCS$.
19   **else if** $medCS > avgCS$ *AND* $medCS > modeCS$ **then**
20         $Threshold = medCS$.
21   **else if** $modeCS > avgCS$ *AND* $modeCS \geq medCS$ **then**
22         $Threshold = modeCS + 1$
23   **else**
24   **if** $avgCS \leq N/2$ **then**
25             $Threshold = +\infty$
26   **else**
27             $Threshold = -\infty$
28   Return Threshold

example in Figure 4.2.

The second algorithm (the threshold generator) computes a threshold value that is used to identify the nature of the grid elements. The algorithm is shown in Algorithm 2. We first compute a criticality score (CS) for each grid element and store it in the corresponding location of a two dimensional matrix GC (line 5). GC has the same dimension as the grid G (i.e., $R \times C$). For example, the CS value of G(1,2) is stored in GC(1,2) [i.e., the CS of the grid element located at the 1st row and the 2nd column is stored in the 1st row and the 2nd column of GC]. The CS value represents the nature of the grid element. The higher

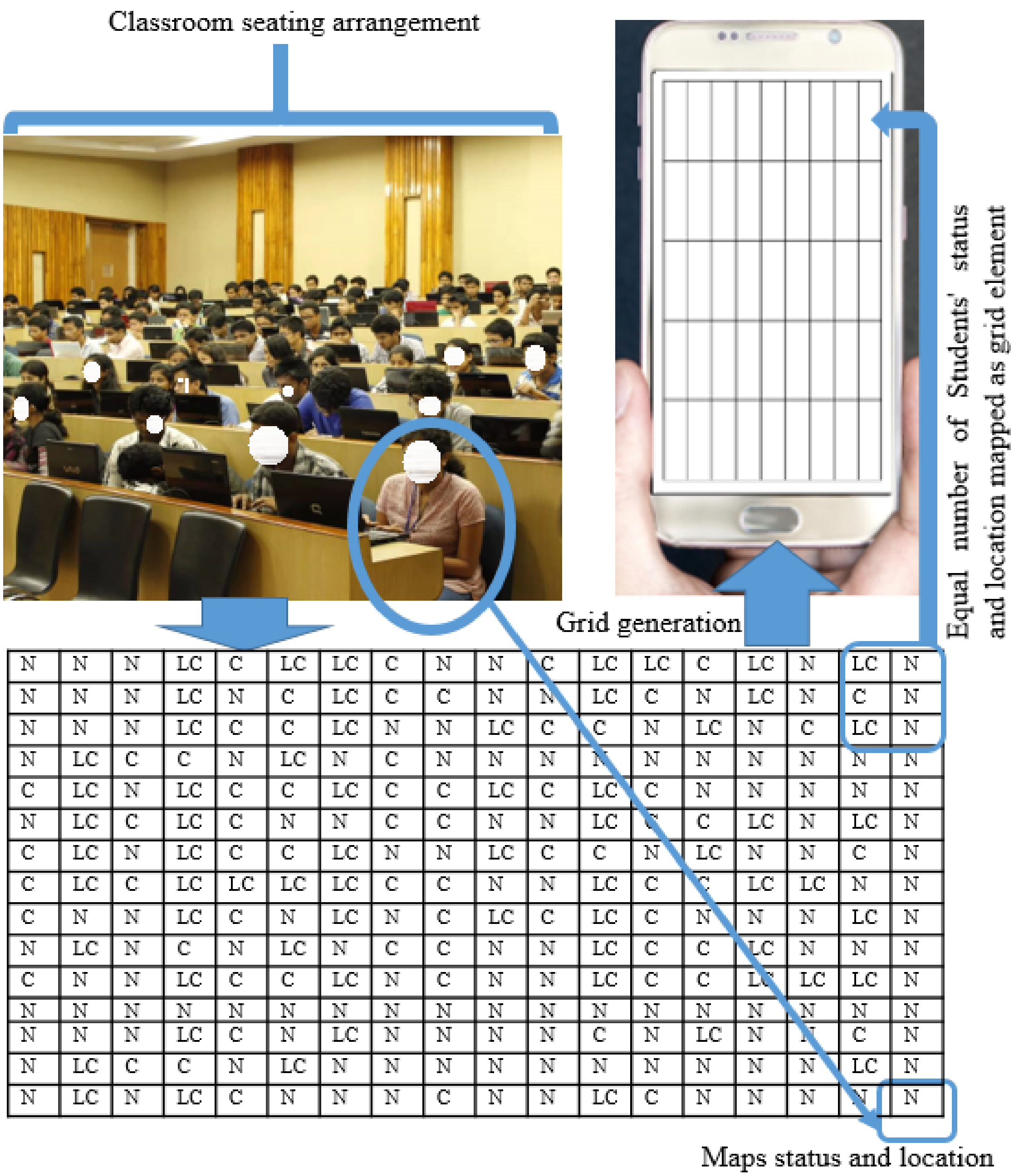


Figure 4.2: Illustration of the grid generation algorithm.

the value, the more critical is the corresponding grid element implying the need for the intervention by the teacher. It may be recalled that each grid element represents a cluster of students in the classroom. Each student is assigned a criticality type based on his/her state: either C, LC or N. In order to compute the CS for a grid element, we compute the total number of students in the element having either C or LC type and then store it (line 4-5). We also compute the total CS for the entire classroom in this step for subsequent use (line 6).

In the next step of the algorithm, we compute the average CS (avgCS), minimum CS (minCS) and the maximum CS values (maxCS) for the display grid (line 7). Note that the CS can have a minimum value of 0 (when every student in the set of students represented by the grid element is of type N) and a maximum value of N, where N is the total number of students represented by a grid element (when every student in the grid element is of type C or LC).

We can set the avgCS as the threshold: any grid element having a CS value above this would be a critical element requiring some intervention of the teacher. In order to understand the implications of using the avgCS as the threshold, we performed an empirical study with thirty six classroom scenarios. The scenarios were generated by varying two factors systematically: classroom seating dimensions (six levels) and student state distribution (six levels). We considered six state distributions. Each distribution was characterized by the percentage of critical students (i.e., having the states C or LC or both) in each grid element (cluster of students). The six distributions were - less than 50%, 50-60%, 60-70%, 70-80%, 80-90%, and above 90%. The six seating arrangements (matrix dimensions) we considered in our study were 9x9, 10x12, 12x10, 13x13, 11x15, and 15x11. For each of the classroom scenarios, we applied the Algorithm 1 to determine the total number of grid elements. Subsequently, we computed the avgCS and determined the number of critical grid elements. The results are shown in Table 4.1 (the third and fourth columns from the left). As can be seen in the Table (fourth column), the use of the avgCS as threshold resulted in a large number of critical grid elements, with the number increasing very fast as the classroom dimension increases. In fact, between 50% and 80% of the grid elements were getting categorized as the critical grid elements in most of the cases, with the choice of the avgCS as the threshold. If such situations are to occur in practice, it may not be possible for the teacher to intervene in all the potential cases due to the limited class time available. Thus, it falls upon the teacher to decide on the students to attend, potentially increasing the cognitive load of the teacher, which may be detrimental to the teaching process. In order to avoid that, we tried to minimize the number of critical grid elements for the teacher. To do so, we first elevated the average CS value by a factor. The factor value is decided based on the relationship between the average CS value and the half of the maximum CS value possible (i.e., N/2). If the average CS value is less than N/2, the factor value is more (line 8) compared to the case where the avgCS is more than N/2 (line 10). We then multiply the avgCS with this factor to get the threshold (line 12). In this way, we elevate the threshold from the avgCS. Any grid element with the CS value higher than the threshold would be marked as critical for the teacher, implying that the teacher attend to those students.

Due to the elevation, it may happen that the elevated threshold overshoots the maximum CS value (i.e., it becomes greater than the maximum). In that case, no grid element can be marked as critical. In order to take care of such situations, we compute the elevated threshold only when it is less than the maximum CS of the grid (line 12). Otherwise, we re-compute the threshold value in a different way (line 13-27). We consider the distribution of the CS values and compute the median and mode of the distribution (if no statistical mode is available, i.e., all values are having the same frequency, we simply take the highest value). On the basis of the relationships between the average, median and mode of the distribution, we set the threshold (lines 17-27) and return it (line 28). The conditions are designed to take care of the facts that the CS values can be positively skewed, negatively skewed or not skewed (i.e., all possible distributions are taken care of that are practical). In Figure 4.3, we illustrate the algorithm with the same example used in Figure 4.2.

As Figure 4.3 shows, just having the display grid with the criticality values is not likely to be of much help to the teacher. The values in itself do not make it easy for the teacher to identify the critical students. Therefore, we propose an algorithm to color the grid, with the assumptions that the coloring would make it easier for the teacher to get a snapshot of the classroom criticality. The algorithm is shown in Algorithm 3. It takes as input the grid with critical scores (i.e., GC that was computed in the second algorithm) and the threshold (the output of the Algorithm 2). In the Algorithm, we re-compute the criticality scores for each interval of visualization by dividing these values with weight values. We

Table 4.1: Case Studies of Different Classroom Scenarios.

Classroom seating arrangement	Student state distribution (% of critical students in each cluster)	Total number of grid elements computed with Algorithm 1	Number of critical grid elements based on above avgCS	Number of critical grid elements with elevated threshold	Elevated threshold overshooting maximum CS	Number of critical grid elements based on CS distributions
9x9	<50	9	4	1	NA	NA
	50-60	9	4	2	NA	NA
	60-70	9	4	2	NA	NA
	70-80	9	5	2	NA	NA
	80-90	9	6	2	NA	NA
	90-100	9	4	4	NA	NA
12x10	<50	30	23	0	Applicable	7
	50-60	30	7	7	NA	NA
	60-70	30	14	7	NA	NA
	70-80	30	17	9	NA	NA
	80-90	30	21	14	NA	NA
	90-100	30	26	22	NA	NA
10x12	<50	30	22	0	Applicable	10
	50-60	30	13	7	NA	NA
	60-70	30	18	7	NA	NA
	70-80	30	15	11	NA	NA
	80-90	30	21	16	NA	NA
	90-100	30	26	19	NA	NA
13x13	<50	49	37	0	Applicable	8
	50-60	49	21	1	NA	NA
	60-70	49	29	11	NA	NA
	70-80	49	19	15	NA	NA
	80-90	49	28	23	NA	NA
	90-100	49	32	28	NA	NA
11x15	<50	30	21	0	Applicable	10
	50-60	30	11	3	NA	NA
	60-70	30	18	4	NA	NA
	70-80	30	14	9	NA	NA
	80-90	30	22	13	NA	NA
	90-100	30	24	15	NA	NA
15x11	<50	30	21	1	NA	NA
	50-60	30	14	3	NA	NA
	60-70	30	17	6	NA	NA
	70-80	30	15	9	NA	NA
	80-90	30	22	11	NA	NA
	90-100	30	25	14	NA	NA

N	N	N	LC	C	LC	LC	C	N	N	C	LC	LC	C	LC	N	LC	N
N	N	N	LC	N	C	LC	C	C	N	N	LC	C	N	LC	N	C	N
N	N	N	LC	C	C	LC	N	N	LC	C	C	N	LC	N	C	LC	N
N	LC	C	C	N	LC	N	C	N	N	N	N	N	N	N	N	N	N
C	LC	N	LC	C	C	LC	C	C	LC	C	LC	C	N	N	N	N	N
N	LC	C	LC	C	N	N	C	C	N	N	LC	C	C	LC	N	LC	N
C	LC	N	LC	C	C	LC	N	N	LC	C	C	N	LC	N	N	C	N
C	LC	C	LC	LC	LC	LC	C	C	N	N	LC	C	C	LC	LC	N	N
C	N	N	LC	C	N	LC	N	C	LC	C	LC	C	N	N	N	LC	N
N	LC	N	C	N	LC	N	C	C	N	N	LC	C	C	LC	N	N	N
C	N	N	LC	C	C	LC	N	C	N	N	LC	C	C	LC	LC	LC	N
N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N
N	N	N	LC	C	N	LC	N	N	N	N	C	N	LC	N	N	C	N
N	LC	C	C	N	LC	N	N	N	N	N	N	N	N	N	N	LC	N
N	LC	N	LC	C	N	N	N	C	N	N	LC	C	N	N	N	N	N

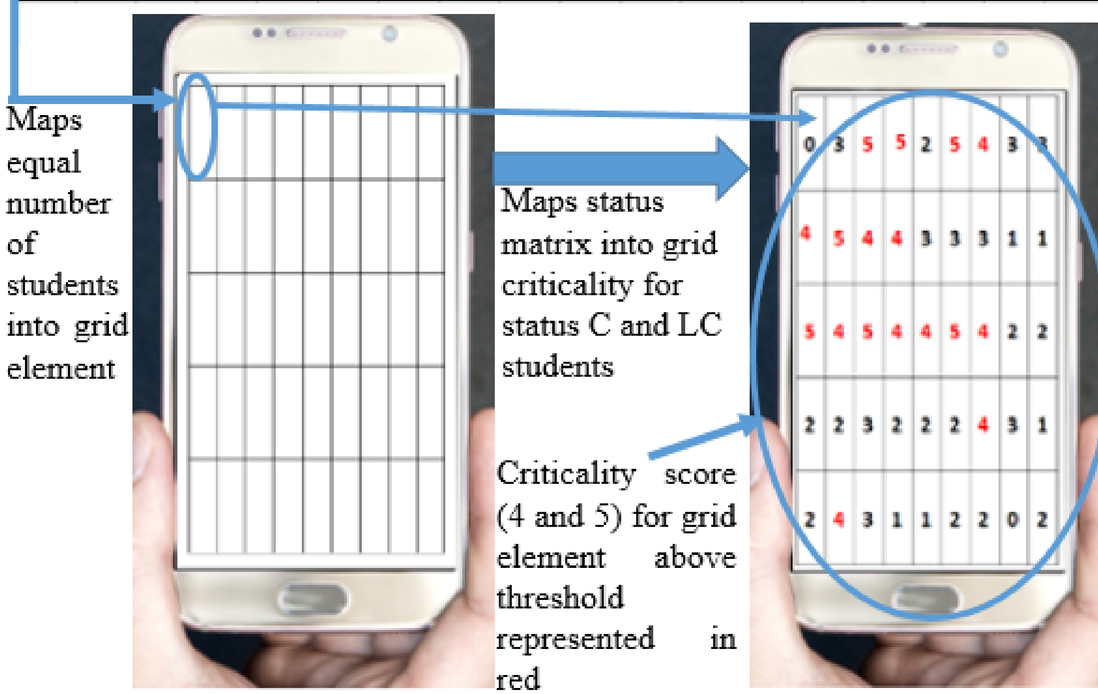


Figure 4.3: Illustration of the algorithm to calculate the critical grid elements and the threshold.

ALGORITHM 3: Grid Coloring

Input: The critical scores ($GC_{R\times C}$) matrix and the threshold.
Output: Colored grid.

`/* In order to assign a color to a grid element, we compute a weighted criticality score. The weight values are stored in a Color Weight matrix (`$CW_{R\times C}$`). At the beginning, the values in this matrix are initialized to one. */`

1 **for** *each time interval* **do**
2   **if** *Number of values in GC above threshold is >3 then* **then**
3   **for** *Each GC value above threshold* **do**
            `/* recalculate the criticality score with weights. */`
4             $GC_{ij} = \frac{GC_{ij}}{CW_{ij}}$
5   Color grid elements having top 3 values in GC as Red.
6   Color the remaining grid elements that are having GC values above the threshold as Yellow.
7   Color the rest of the grid elements as Green.
          `/* Update the weights in `$CW_{R\times C}$`. */`
8   **for** *Each element in* $CW_{R\times C}$ **do**
9   Set value to one if color assigned to corresponding element in the grid is Green.
10   Set value to two if color assigned to corresponding element in the grid is Yellow.
11   Set value to three if color assigned to corresponding element in the grid is Red.
12   **else**
13   Assign the Red color to all the elements with the criticality value above the threshold.
14   Assign the Green color to the remaining grid elements.
15   Render the colored grid on the display.

use a matrix (Color Weight matrix or CW) having the same dimension as that of the grid. Each element in this matrix is used as the weight to re-compute the criticality value of the corresponding grid element as shown in line 4. We use integer values (one, two and three) as weights for the colors green, yellow and red, respectively. Intuitively, if an element is colored red in an interval, the teacher is already aware of the criticality of the element. Therefore, it is futile to highlight the same element with red in the next interval. Instead, it is preferable to highlight other critical elements. That idea is implemented by the criticality score recomputation (line 4) and the assignment of colors on the basis of the new score (lines 2-4). The CW values are updated in lines 9-11 for use in the coloring for the next interval. However, if the grid has three or less number of elements with the CS value above the threshold, we assign the red color to all those values and the green color to the rest (line 14). No element is assigned the yellow color. The grid is rendered on the display with the assigned colors, as illustrated in Figure 4.4.

There are a couple of important points to be noted in the grid coloring algorithm. First of all, we used the three colors (red, yellow and green) to make the display "intuitive". It is expected that the teacher is familiar with these colors as these are commonly found in traffic signals. Therefore, they are likely to learn and remember the meaning of these colors easily. Also, when the number of critical elements are more than three, we have decided to

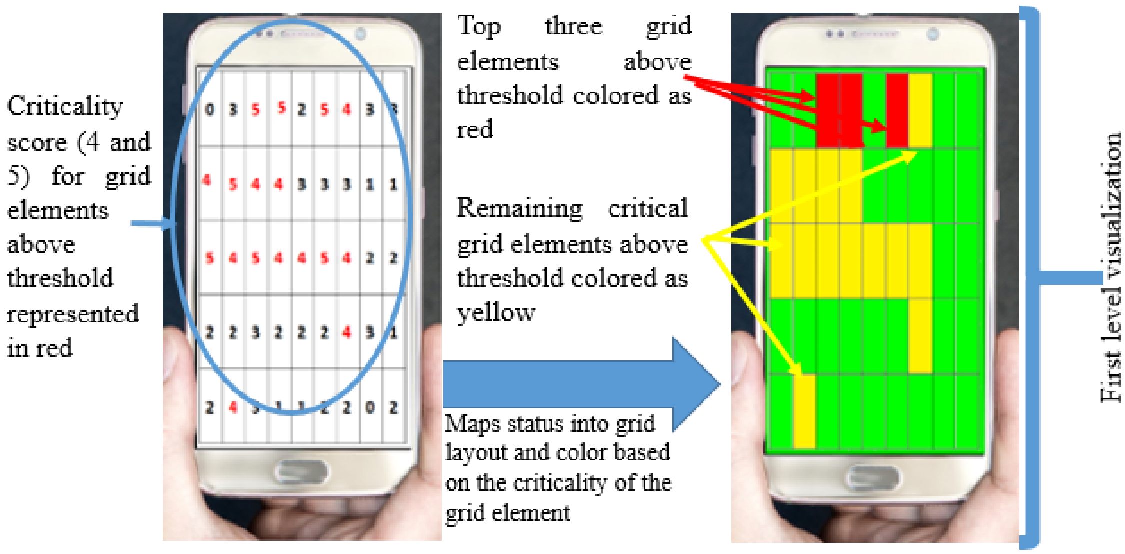


Figure 4.4: Illustration of the grid coloring algorithm.

assign the red color to the top three elements in terms of their criticality score. If we assign the red color to only the element with the top CS value, there might be many yellow colored grid elements, making it difficult for the teacher to decide. Similarly, more number of red colored grid elements may likewise increase the cognitive load of the teacher (to decide which and how many to attend). The value of three seems to be an optimal choice based on our intuition.

The three algorithms constitute the first level of the visualizer. The first level is intended to give the teacher a complete overview of the classroom. However, the teacher cannot get the detailed information about individual students at this level. For that, we designed the second level visualization algorithm shown in Algorithm 4 with illustration in Figure 4.5.

The algorithm is executed once the teacher taps/clicks on a grid element. On tap/click, a new screen appears on the display. There are two components of this display (see Figure 4.5). The upper component contains images of all the students present in the cluster represented by the grid element. The images are pre-stored (during the course registration time). Each image is surrounded by a colored rectangle corresponding to the criticality state (C, LC or N) of the student. On further tap/click on an image, detailed information about the student is displayed (see Figure 4.5). The state information stays on the screen for twenty seconds [187] and then disappears automatically.

We have used images to represent students in the second level. The images occupy

ALGORITHM 4: Second Level Visualizer

Input: Classroom seating arrangement, Student state, colored grid, interaction event (tap/click).
Output: Second level display with details and overview.

```
while tap/click on a grid element in first level do
    Get the location of the element (row and column numbers).
    Get the images of the students at the location using the classroom seating arrangement.
    Get their criticality type using the GC matrix.
    Create a display area covering the upper two-thirds of the screen.
    for Every student at that location do
        if his/her criticality type is C then
            Display his/her image inside a Red rectangle within the two-thirds display area.
        else if his/her criticality type is LC then
            Display his/her image inside a Yellow rectangle within the two-thirds display area.
        else
            Display his/her image inside a Green rectangle within the two-thirds display area.
    Display the colored grid in the lower one-third of the screen.
while interaction made in second level display do
    if tap/click on an image then
        Display the state details of the student in a pop-up display that stays on the screen for twenty
        seconds.
    if tap/click on the colored grid then
        Return to the first level display.
```

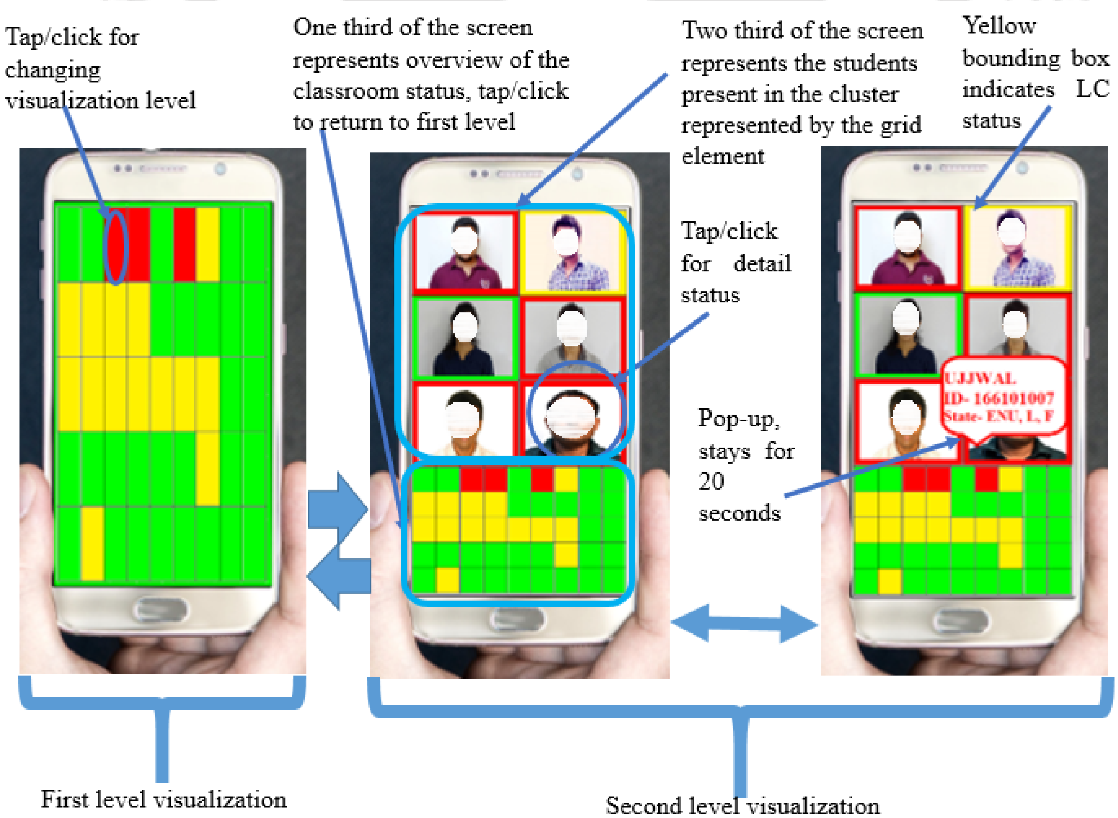


Figure 4.5: Illustration of the second level visualization.

two-third region of the screen. Nowadays, 5.5 inch screens sizes are commonly found on our mobile phones. Hence, one main concern is to determine the number of images that can be accommodated in the two-third region of such a display. We found that the two popular social networking sites, namely the Facebook and the Instagram, use sizes of 128x128 and 110x110 (in pixel squares) respectively, to display profile pictures on smart phones. We propose to use similar sizes to display the student images.

The remaining one-third area of the screen is used to give an overview of the classroom status. It contains the colored grid in a reduced form (see Figure 4.5). Individual elements of this overview grid is not selectable through interaction, however on tap/click on any part of the overview region, the second-level display disappears and the first level is displayed on the whole screen again (i.e., the overview component of the second level serves as a means to return to the first level).

It may be noted that the colored bounding boxes enclosing the images of the students follow the "consistency" principle of interface design. We used the same colors, with the same meanings, as in the case of the colored grid of Algorithm 3.

4.2.3 Empirical Validation

There are mainly three aspects on which the proposed visualizer (or any such teacher awareness system) should be evaluated. The very first measure of evaluation should be the efficiency: does it allow the teachers perform the monitoring tasks efficiently, where we can define efficiency as the time to complete each monitoring task. The task completion time should be as low as possible, to avoid reducing the teaching time in the limited lecture period available (typically about one hour). Otherwise, the teaching process might be affected. The second metric for evaluation should be the user satisfaction of the system. Ideally it should be high, so as to ensure that the teachers find the system acceptable and are willing to use it. Finally and most importantly, we should also evaluate the effect of the system on the learning outcome. The third aspect, however, is difficult to measure since it requires a systematic study over a reasonably long period (say for example, one semester) considering the large classroom sizes. We conducted controlled studies to evaluate mainly the efficiency and the user satisfaction of our proposed design. However, we also performed surveys and interviews on the study participants to understand the likely effect of the proposed visualizer on the learning outcomes.

Setup Used

In order to carry out the experiments, we developed an app for the visualizer. In the app, the input is a classroom configuration matrix and the corresponding state matrix. We assumed a classroom size having fifteen rows and eighteen columns (i.e., the matrix is of size 15x18). The app processes these inputs to produce the visualization following the algorithms. In order to perform the experiments, we randomly assigned states to the students. Figure 4.1 illustrates the visualization of the classroom.

We created a simulated classroom setting to perform the study. In the setting, one participant acted as a "teacher" and between fifteen to twenty participants were the "students". We took proper care to select both the teacher and student participants. Only those with prior teaching experience were enlisted to act as teachers. All the student participants were undergraduate or graduate students. Each "teacher" was asked to take a thirty minute lecture in front of the students. The lecture was taken with the help of a smartboard and projector. The role of the "students" were to keep the teacher engaged during the teaching (by asking questions), to mimic the real-world classroom constraints faced by a teacher. In that way, the interactive classroom scenario was created.

The app was used to collect data from the "teachers" during the teaching. We used the HTC Desire 816 smartphone having 5.5 inches display, 1.5GB RAM and Quad-core 1.6 GHz Cortex-A7 processor. The device had Android version 5.0.2, software number 2.34.720.2, and HTC SDK API level 6.55. Additionally, we video-graphed the entire teaching sessions for later analysis.

Design of Tasks

In order to collect data, we asked the "teacher" participants to perform twelve tasks during their teaching sessions. The tasks are shown in Table 4.2. As we mentioned earlier, we assumed an interval of fifteen minutes to change the color codes of the grid. Thus, there were two such intervals in the thirty-minute lecture delivered by each "teacher". Our tasks were designed to cater to these two intervals. Additionally, we also ensured that all the levels of the visualizer were covered with the tasks. We also conducted a pilot study with

Table 4.2: The list of tasks for functionality and feature testing for first level (FL), second level (SL) and both level (BL) in the visualizer interface.

Task	Task Set for the first window (15 minutes)	Task Significance (visualizer level)
T1	Touch all the critical grid elements.	To confirm the color scheme not/understood (FL)
T2	Tell the approximate percentage of the critical students present in the classroom.	At a glimpse, if it is possible for a teacher to perceive classroom status (FL).
T3	Touch all critical grid elements from the most critical zone in the classroom, out of the four zones - LF (left front), RF (right front), LB (left back), RB (right back).	To check if the teacher can identify the most critical zone/region that requires the teacher's attention (FL).
T4	Touch all normal grid elements from the best normal status zone (LF or RF or LB or RB) in the classroom.	To check if the teacher can identify the least critical zone/region that does not require the teacher's attention (FL).
T5	Identify five critical students in the whole class (by touching the corresponding images).	To check if the color scheme in the second level is not/understood (SL).
T6	Identify all the critical students in the left front (LF) part of the class (by touching the corresponding images).	To check if the teachers can understand the color scheme and the mapping between the real classroom and the grid (BL).
T7	Identify all the critical students in the last row of the class.	To check if the teachers can understand the color scheme and the mapping between the real classroom and the grid (BL).
	Task set for the second window (last 15 minutes)	**Task Significance (visualizer level)**
T8	Mark all the students in the left back (LB) part of the class (by touching the corresponding images).	To check if the teachers can understand the color scheme and the mapping between the real classroom and the grid (BL).
T9	Determine the number of students present in a grid cell.	To check the idea of clustering at a glimpse (BL).
T10	Identify one student who remained critical throughout the lecture (30 minutes).	To check the ease with which a teacher can explore the visualizer to identify a specific student with a specific status (SL).
T11	Identify one student who remained non-critical throughout the session (30 minutes).	To check the ease with which a teacher can explore the visualizer to identify a specific student with a specific status (SL).
T12	Identify all the critical students in the last row of the class.	To check if the teachers can understand the color scheme and the mapping between the real classroom and the grid (SL).

another set of "teachers" (seven in number) to check the appropriateness of the tasks (the wordings and the understanding by the participants) before the tasks were used in the data collection phase.

Participants

We collected data from a total of twenty seven "teacher" participants (twenty male and seven female). All of them were volunteers. They had at least one year teaching experience and all were regular user of smartphone and tablets. The age group of the participants were within 25-41 years, with the average age of 32 years and average teaching experience 4.59 years of undergraduate students of science and engineering (at the college and university level). Among the twenty seven, twenty took part in the experiments (fifteen males and five females). The rest were used to finetune the tasks (wordings and feasibility) of Table 4.2.

Figure 4.6: Controlled experiment session for validating our visualizer.

Experimental Method

Before data collection, each "teacher" participant was introduced to the visualizer app for about fifteen minutes. During this phase, the participants were trained to operate the app and also were given some dummy tasks to perform for familiarization. During the data collection phase, the participants were asked to "take a class". Each participant was asked to prepare power point slides for a thirty minute lecture (one week in advance). They were free to choose a topic of their interest (so that they were confident and comfortable during the lecture delivery). The "student" participants were instructed to ask as many questions as they wished during the lecture delivery. The intention was to keep the "teacher" busy as in a regular classroom and collect data in that state.

During the lecture delivery, each teacher participant was asked to perform the tasks of Table 4.2. The tasks were given to them in printed form, as can be seen from Figure 4.6. The app logged all the touch events along with the time stamps during the execution of each task by each participant. Along with the data logging, we also collected post session ratings for the system from each participant. For the purpose, we designed a questionnaire

Table 4.3: The SUS-based questionnaires used to collect ratings from the participants.

Modified SUS statements (used in the study)
I think that I would like to use this visualizer frequently during the class lecture.
I found the visualizer unnecessarily complex during the class lecture.
I thought the visualizer was easy to use during the class lecture.
I think that I would need the support of a technical person to be able to use this visualizer during the class lecture.
I found the various functions in this visualizer were well-integrated.
I thought there was too much inconsistency in this visualizer.
I would imagine that most people would learn to use this visualizer very quickly.
I found the visualizer very cumbersome to use during the class lecture.
I felt very confident using the visualizer during the class lecture.
I needed to learn a lot of things before I could get going with this visualizer during the class lecture.

based on the SUS [188]. The questionnaire is shown in Table 4.3. A five-point Likert scale was used to rate the visualizer, having the ratings 1 (Strongly disagree), 2 (Disagree), 3 (Neutral: neither agree nor disagree), 4 (Agree), and 5 (Strongly agree).

4.2.4 Results and Analysis

We recorded both quantitative and qualitative data during the experiment. Quantitative data included task completion times, accuracy, and post-session ratings. Qualitative data included the observational data for each participant we recorded manually during the studies as well as the analysis of the recorded videos. When we talk about a real-time classroom visualization system, especially one that makes use of video technology, we must talk about user data privacy. We have taken proper care of the ethical issues, and we have signed a consent form before recording the video data. Additionally, such data also included comments received from the participants about the system.

One measure of system efficiency is the task completion rate (TCR). We computed it using Eq. 4.1, where TCR_{P_i} indicates the rate for the i$^{\text{th}}$ participant. The results are shown in Figure 4.7. Only for two of the participants (2 and 5), the rate is below 50%. The rate varies between about 67% and 100% for the remaining 18 participants with an average accuracy rate of nearly 83%, indicating a high success rate.

$$TCR_{P_i} = \frac{Number\ of\ tasks\ completed\ successfully}{Total\ number\ of\ tasks} \times 100\% \tag{4.1}$$

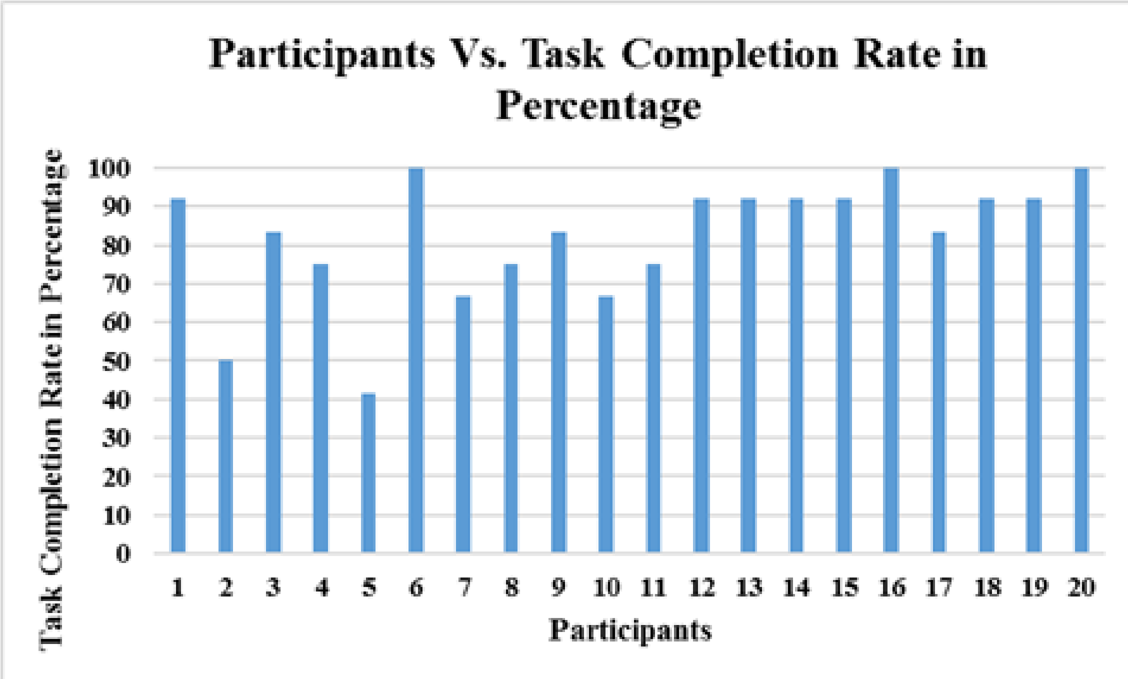


Figure 4.7: Task completion rate for the participants in the experiments.

The high completion rates indicate that the participants found most of the tasks doable in the classroom. The rates, however, do not in themselves indicate anything on the proportion of lecture times a teacher needs to spend on getting aware about the classroom status through the use of the system. Ideally, the teachers should be able to perform the visualization-related tasks taking as little time as possible, so that they get more time to teach. In order to understand this aspect of our visualizer design, we computed the average time (ASCTTi) taken by the participants to perform tasks successfully with Eq. 4.2, where P is the total number of participants, tj is the time taken by the j^{th} participant to complete the task, B is 1 if the participant successfully completed the task and 0 otherwise and N is the total number of participants who successfully completed the task.

Task time is computed based on the time taken by the participant to complete or quit the task. If a task is not completed successfully, then the time is measured until the user quits the task. We used the video recordings to determine the time before quitting. The average successful task completion time for each of the twelve tasks are illustrated in Figure 4.8.

$$ASCT_{T_i} = \frac{\sum_{j=1}^{P} B \times t_j}{N} \tag{4.2}$$

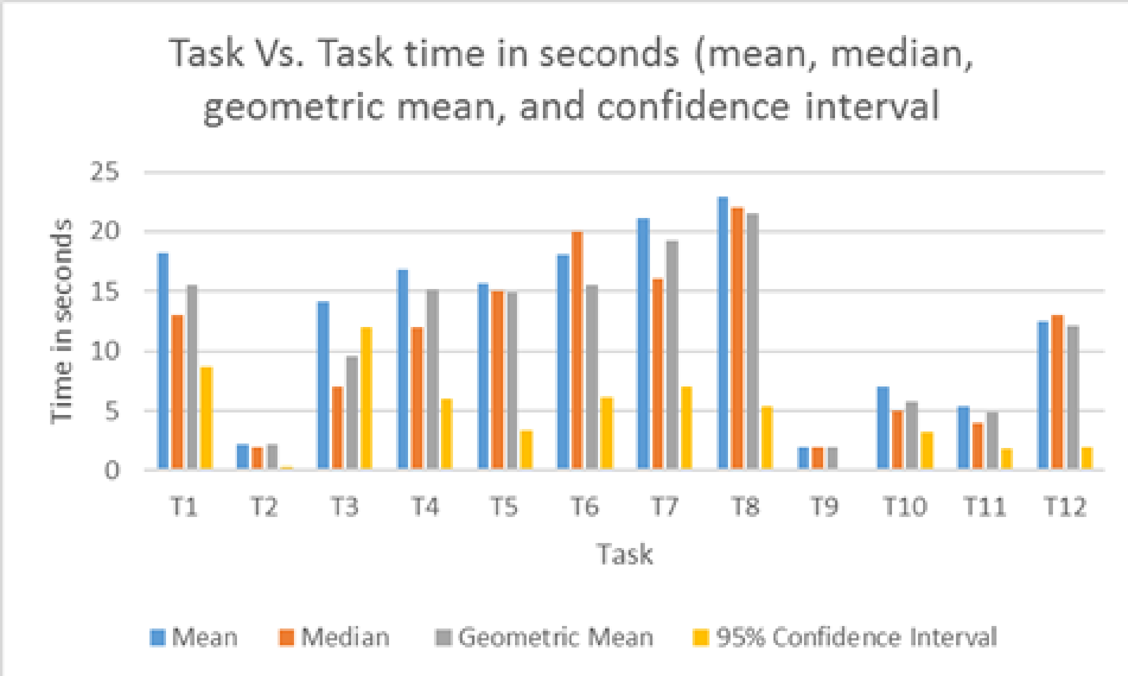


Figure 4.8: Descriptive statistics for task completion times for the twelve tasks.

Figure 4.8 illustrates the descriptive statistics for the task completion times by the participants. It indicates that the tasks T2, T9, T10, and T11, which are likely to be performed frequently in a classroom, can be performed in less than 6 seconds (a reasonably small number considering a one hour lecture). Few other likely to be frequent tasks, namely T3, T4, T5, and T12, can also be completed in about 15 seconds (again, a small number considering the overall lecture duration). The remaining tasks (T1, T6, T7 and T8) are likely to take higher time to complete. However, T1 and T8 are not expected to be performed frequently in an actual class. Thus, the average task completion time (for the remaining ten tasks) was about 10 seconds. This value is certainly not very high with respect to a typical one-hour lecture slot (about 0.3%). We computed other descriptive statistics, namely the median and geometric mean for all the tasks, as illustrated in the figure, to support our argument. Figure 4.8 includes the 95% confidence interval as well. The CI values indicate that the task completion times we computed are likely to represent the actual times required. Thus, the relatively small task completion times for the frequently performed tasks indicate the proposed visualizer can be used by the teacher in a classroom without affecting the lecture delivery time much.

We also compared the task completion times observed in the simulated classroom setting to the task completion times in the absence of any distractions, to understand the performance of the teachers in a real classroom setting. In order to do that, we determined the ideal mean task completion times when participants were not engaged in teaching. We performed a separate study involving the seven participants who did not take part in the actual experiment. We asked them to carry out the tasks but without any "students" present (i.e., they were not interrupted by questions during the execution of the tasks). We took the mean of the times taken by the participants to complete each task as the ideal task completion time. We then compared this time with the observed (mean) task completion time (i.e, the average task completion times we recorded during the experiments). The difference between the mean observed time (M=11.88, SD=8.12, n=12) and the ideal time (M=10.80, SD=7.42, n=12) was found to be statistically not significant [t(22)=2.07, p=0.368]. The results indicate that the design of the proposed visualizer does not affect the task completion times significantly in the classroom setting.

In summary, what we found in our analysis was that the majority of the participants could complete most of the tasks in very less time, as compared to the overall lecture time available. Also, the times they took in the presence of distractions (i.e., the simulated classroom setting) were not significantly different from the times that would have been required in an ideal situation without distraction. These observations point to the efficiency of the proposed visualizer.

In order to measure the user satisfaction of the proposed system, we collected and analyzed the ratings by the participants on the SUS questionnaire, shown in Figure 4.9. As the Figure 4.9 shows, the minimum SUS score is 60. The score varies between about 65 and 90 for 18 out of the 20 participants, with an average score of nearly 75. The score indicates that the user satisfaction of the visualizer is also high. In other words, the teachers are likely to perceive the visualizer as usable and thus, acceptable for use in a classroom.

Along with the above quantitative analysis, we also asked the teacher participants on their overall impression on the system, including its utility in teaching. All the participants agreed that the system is going to be helpful to the teachers. A majority of them (seventeen out of the twenty) found the system to be easy to learn and remember due to the intuitive design strategies (color schemes and interactions). Some of them (three out of the twenty),

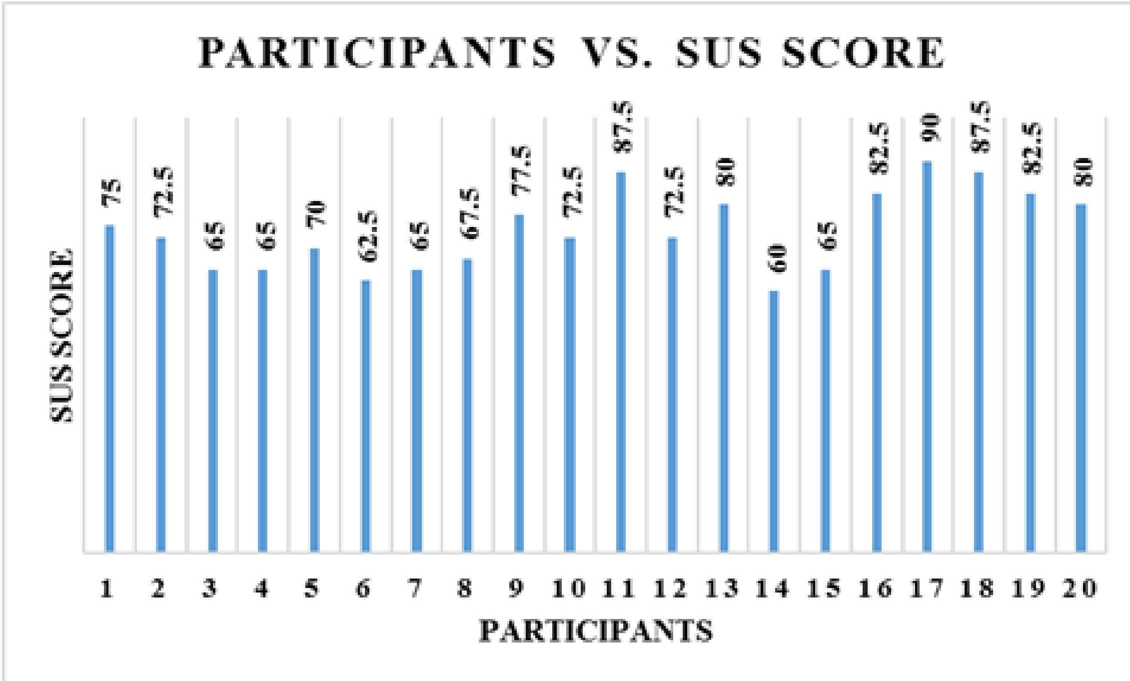


Figure 4.9: The SUS ratings obtained in the experiment.

however, felt that the system might require some time to get familiarized. All of them were very satisfied with the visualizer and opined that the awareness afforded to the teacher by the system would be very helpful to device effective intervention strategy for better learning outcome. There was no unanimity, however, on the best intervention strategy to be adopted. Eighteen participants felt that the intervention may be immediate for those students falling under the red-colored grid elements (most critical) and delayed for the others (the student clusters represented by the yellow color). The delayed intervention should be after the class, so as not to spend further lecture time on intervention only. The participants suggested that the system might have a feature to "remember" all those students for whom delayed intervention is recommended. Only two among the participants felt that all the interventions may be delayed and after the class. The need to have a facility to remember all the cases for intervention was highlighted by those participants as well.

Although the system manages to address most of the challenges associated with large classroom visualization, we found three major shortcomings with the system. In the visualizer, three student states are defined: normal (N), likely to be critical (LC) and critical (C). The last two states indicate the need for a teacher to intervene for improved learning outcome for those students. In the current system, both C and LC states carry the same weight though, making it difficult to discriminate between the two at the overview (first) level. This may affect a teacher's perception of the classroom status. A second problem with the present visualizer is the way it highlights the classroom status. Presently, it paints the top three most critical clusters of students in the red color. It is possible that three adjacent clusters are highlighted. This scheme is actually not very informative since the teacher can be made aware of the criticality of the region of the classroom where all these clusters are located, even if only one of the adjacent clusters is highlighted with red. As a result, other critical sections of the classroom may not get due attention due to this specific highlighting scheme proposed. There is a third and important drawback as well. In the present visualizer, emphasis is given on the optimization of the number of grid elements in the first level only. As a result, the number of clusters for a large classroom remains minimum and visible on the display. However, the cluster sizes (the number of students) increase in that case, making it difficult to accommodate all the students in the same display in the second (details) level. The issue is resolved with the use of scrolling interfaces, putting additional physical and cognitive load on the teacher.

We propose a novel interactive and dynamic visual monitoring aid, the *Manas Chakshu* for large classrooms to overcome these difficulties. We use weighted criticality scores to discriminate between the student states. We also developed algorithms to optimize the display at both the levels and also to highlight critical sections of the classroom more fairly. We performed both theoretical and empirical studies to demonstrate the improvements our proposed system achieved with respect to the state of the art system. In this article, we describe the design and implementation of our proposed system along with the comparative study details and results.

4.3 Discussion

We wanted to design a visualizer that is easy to learn and remember. In order to achieve this objective, we used the "consistent" design principle commonly found in the design of interactive systems [189]. The consistency principle is applied at two levels: external and internal. The external consistency refers to the use of the three colors to visualize the grid in the first level. The colors are commonly used in the traffic signals around the world, with the similar meaning. Therefore, the use of the colors is consistent with our everyday knowledge. The use of the same color code with the same meaning in the bounding boxes enclosing the images of the students in the second level takes care of the internal consistency in the design.

For the visualizer, we also took care of the important human factor of clickability. It depends on the size of our thumb. By taking care of this concern in the first algorithm (Algorithm 1), we tried to ensure that the interaction is error-free and effective. Otherwise, the users are likely to make many errors owing to the so called “fat finger problem” leading to irritations and reduced usability of the visualizer (particularly with touch devices). It is important to note here that the above problems are mostly related to the mobile devices (smart phones and tabs), characterized by small displays. Considerations for such mobile devices, in the design of the visualizer, is important as we wanted to make the visualizer usable with any device. It may be argued that there are typically desktop or laptop computers available in a classroom and hence the need to have the visualizer rendered on a mobile device is not so important. That may be true in many cases. However, it is also quite possible that the teacher may like to roam around the classroom and want to visualize the status during such movements. If the visualizer is rendered only on a desktop/laptop, the movement of the teacher would be restricted. By making our system compatible with the mobile devices, we wanted to address such mobility aspects of classroom teaching as well.

The threshold calculation is also designed to increase the acceptability of the visualizer among the teachers. The idea is to keep the number of critical regions of the classroom that requires immediate intervention by the teacher to a minimum (three at the most). More numbers are likely to create confusion in the teacher’s mind leading to possible disruption in the flow of teaching.

While the above took care of the human side of the system (the users), we also considered the issues that are related to the design of efficient systems. These include the factorization of classroom dimensions, primality testing and the associated corrective measures, the criticality score measure and the consideration of its distribution and so on. The ideas are all unique, nontrivial and used to come up with an optimal system design under the given context.

In our empirical study, we evaluated both these aspects (efficiency and user satisfaction) of the visualizer. The simulated classroom environment we created for our study had between fifteen to twenty student participants, who were instructed to ask as many questions as they wished to the teacher. On an average, we found roughly two questions per student in each session. In other words, there were between thirty to forty questions asked to the "teacher" participants in each teaching session (of thirty minute duration). If we extrapolate this number to a sixty minute lecture period, it comes to between sixty to eighty questions. The number is in fact more than the number of questions typically encountered in a large classroom, as the experience of one of the authors show. This number indicates that the simulated environment could closely represent the actual classroom setting, indicating the validity of the findings beyond the simulated environment.

In the study, we found that the users can use it with high accuracy, as revealed by the TCR measure. The ASCT measure indicates that the visualizer does not require the teacher to take away significant time from teaching to visualize and learn about the classroom status. The measure indicates the efficiency of the proposed visualizer. The SUS scores indicated that the user satisfaction is also likely to be high, indicating higher level of satisfaction with the system. The feedback obtained from the participants also indicate that the teachers are likely to be satisfied and benefited with the system. In fact, earlier studies have revealed that any teaching method that brings satisfaction to the teacher is likely to result in better learning outcome as well [190]. Although we did not directly evaluate the effect of the proposed visualizer on the overall learning outcome, the high SUS score as well as the feedback from the teacher participants indirectly points to the fact that the proposed system is likely to result in higher learning outcome through timely intervention. The intervention strategy should be immediate for the most critical students whereas it can be delayed (post-class) for the other likely to be critical students.

Although the literature on visualization is quite extensive, we did not find any other work that is applicable in the context of large classrooms. The nature of the problem is unique! On the one hand, we have data sets that are not very large but not very small either. The existing approaches, on the other hand, are designed to take care of very large datasets or for small data sets. The large data visualizations may be more cognitively demanding and not suitable for a time constrained environment such as a live classroom.

The small data set visualization techniques are not applicable for visualization of large classrooms on small display areas. Therefore, we believe our proposed approach provides a novel and unique solution to a previously unsolved challenge. It may be noted that the visualizer assumes a two dimensional matrix as an initial classroom configuration. In practice, such configurations occur in many situations other than classrooms as well. For example, the seating arrangements in a movie theater. Our proposed visualizer is expected to work in such situations also (basically, any situation where the input can be provided as a two-dimensional matrix). Thus, although large classrooms are our main target, the proposed system is generic and applicable in non-classroom situations as well.

In spite of the novelty and utility, there are few points of concern. First of all, we assumed that the state information is already available. It is of course very challenging to get the information. For that, we first need to understand what is a “state”. We can consider the mental state of a student (e.g., excited, frustrated, engaged and so on) to be a state. The attendance record of a student can also be construed as a state (attending regularly, irregular, mostly regular and so on). Another potential candidate for defining a state is the learning level (advanced, intermediate, backlogger and so on). There are many other such potential “states” (e.g., level of understanding, classroom activity level). We can define the state of a student as any one or a combination of these “potential states”. It is difficult to capture some of these states such as the mental states, although there are few works in this direction to gather the students’ state information from their mobile usage behavior [191]. Some other states are easier to capture such as the attendance and the level of learning (using scores in classroom tests). Our visualizer does not focus on these challenges. However, this is not a limitation as such since the visualizer can still be used with whatever state information are available (for example, the state of attendance). Also, we assumed a two dimensional matrix data structure as input to the visualizer. Sometime, the classroom seats might not be organized in the form of a matrix. Instead, we might encounter other shapes such as a semicircular seating arrangements commonly found in many lecture galleries. Although we can potentially map such structures to two-dimensional matrices (sometimes by adding dummy rows/columns/both), we plan to study such cases in future as well.

4.4 Summary of the Chapter

We presented the design and validation of an interactive visualizer for large classrooms. The visualizer is intended to aid the classroom instructors for more effective teaching. Moreover, it is designed for relatively small displays as well, making the system useful to the instructors who can use it on a smart phone or tab that they might be carrying. However, it may be noted that the design is generic, making it applicable for situations where the matrix-like seating arrangement can be assumed. It is also to be noted that the algorithms of the visualizer are designed to take care of various human factors with the objective of increasing the system's usability. Many non-trivial optimizations are also made into the visualizer to make it efficient as well, considering the given context. The usability of the visualizer is ascertained through detailed empirical studies.

The details of publication from this contribution are as follows:

Journals

1. Samit Bhattacharya, Viral Bharat Shah, Krishna Kumar, and **Ujjwal Biswas**, "A real-time interactive visualizer for large classroom", ***ACM Transactions on Interactive Intelligent Systems (TiiS)***, 11, no. 1 (2021): 1-26, [Chapter 4]

CHAPTER

5

Manas Chakshu - A Real-time Classroom Monitoring Dashboard

5.1 Introduction

The visualizer discussed in Chapter 1 consists of two levels, implemented as a sequence of four algorithms. In the first (overview) level, the entire classroom status is visualized using a grid structure. An optimum grid size is computed first (first algorithm), keeping in mind the issue of "clickability". Each grid element indicates a cluster of students. A second algorithm was proposed to compute the *criticality* of each cluster for subsequent visualization. Three colors are used to visualize the classroom. Red indicates a *critical* cluster of students that require immediate teacher intervention, yellow denotes a *likely* to be *critical* cluster, which has the potential to turn critical and green indicates a *normal* student cluster. The rendering of the clusters with colors is done with the help of another (third) algorithm. The final (fourth) algorithm is used to obtain the details of each cluster in the second (details) level. In this level, student details (including state information) are displayed in the form of a grid of pre-stored images of the students belonging to particular clusters. The workflow of the algorithms is depicted in Figure 5.1.

Although the system manages to address most of the challenges associated with large classroom visualization, we found three major shortcomings with the system discussed in Chapter 1. In the visualizer, three student states are assumed: normal (N), likely to be critical (LC) and critical (C). The last two states indicate the need for a teacher to intervene for improved learning outcome for those students. In the current system, both C and LC states carry the same weight though, making it difficult to discriminate between the two at

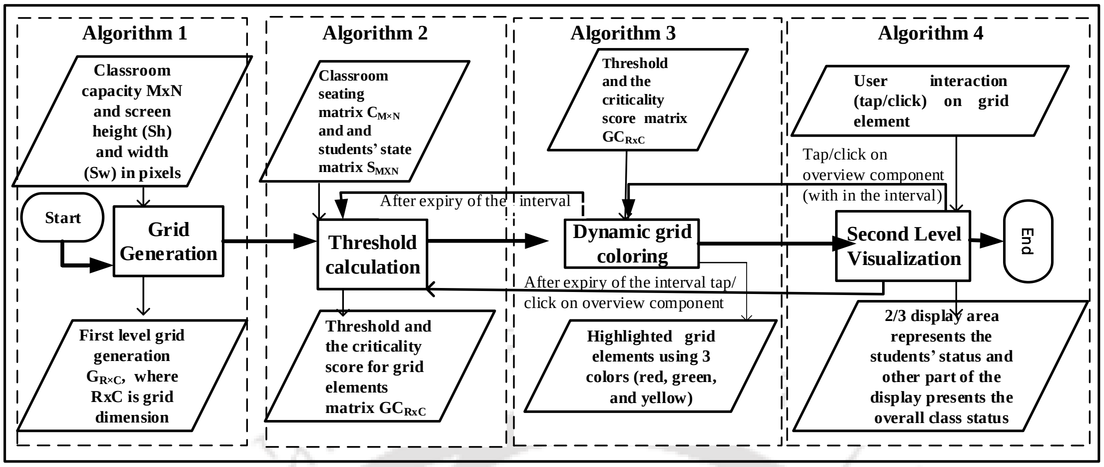


Figure 5.1: Shows the basic idea and the flow of our initial algorithms [1]

the overview (first) level. This may affect a teacher's perception of the classroom status. A second problem with the present visualizer is the way it highlights the classroom status. Presently, it paints the top three most critical clusters of students in the red color. It is possible that three adjacent clusters are highlighted. This scheme is actually not very informative since the teacher can be made aware of the criticality of the region of the classroom where all these clusters are located, even if only one of the adjacent clusters is highlighted with red. As a result, other critical sections of the classroom may not get due attention due to this specific highlighting scheme proposed. There is a third and important drawback as well. In the present visualizer, emphasis is given on the optimization of the number of grid elements in the first level only. As a result, the number of clusters for a large classroom remains minimum and visible on the display. However, the cluster size (the number of students) increase in that case, making it difficult to accommodate all the students in the same display in the second (details) level. The issue is resolved with the use of scrolling interfaces, putting additional physical and cognitive load on the teacher.

We propose a novel interactive and dynamic visual monitoring aid, the *Manas Chakshu* for large classrooms to overcome the above difficulties. We use weighted criticality scores to differentiate between the student states. We also developed algorithms to optimize the display at both the levels and also to highlight critical sections of the classroom more fairly. We performed both theoretical and empirical studies to demonstrate the improvements our proposed system achieved with respect to the initial system design [1]. In this chapter, we describe the design and implementation of our proposed *Manas Chakshu* along with the comparative study details and results.

5.2 Design of Manas Chakshu

In order to overcome state-of-the-art system difficulties, we propose a novel interactive and dynamic visual monitoring aid the "Manas Chakshu" for large classrooms (see Figure 5.2).

5.2.1 Choice of Students State

Like in the present system [1], *Manas Chakshu* requires two inputs: the classroom size and the student state information. We considered the same three states of a student, namely *Critical* or C, *Likely to be Critical* or LC, and *Normal* or N.
We have two objectives: to visualize the status of a classroom as well as the details of the individual student's state. We assume there are three aspects of the students that a teacher is interested to know.

- **Mental state:** If the student is engaged in the classroom activities (asking questions and/or answering questions asked by the teacher or the other students) and if the materials being taught is understandable to the students. With this knowledge, the teacher can easily identify those students who require special attention (those who are not engaged and/or not understanding the lecture).

- **Physical presence:** The teacher might also be interested to know if the students regularly attend the classes or habitual absentees. In the latter case, the teacher might warn the students.

- **Learning state:** This state reveals the performance of the students in various examinations. The state also reveals the progress made by the students. Those who are unable to perform are likely candidates for special care.

We propose to consider four mental states for a student: engaged with the classroom activities and understanding the lecture, not engaged (may be due to shyness and/or laziness) but understanding the concepts being taught, engaged but not understanding and

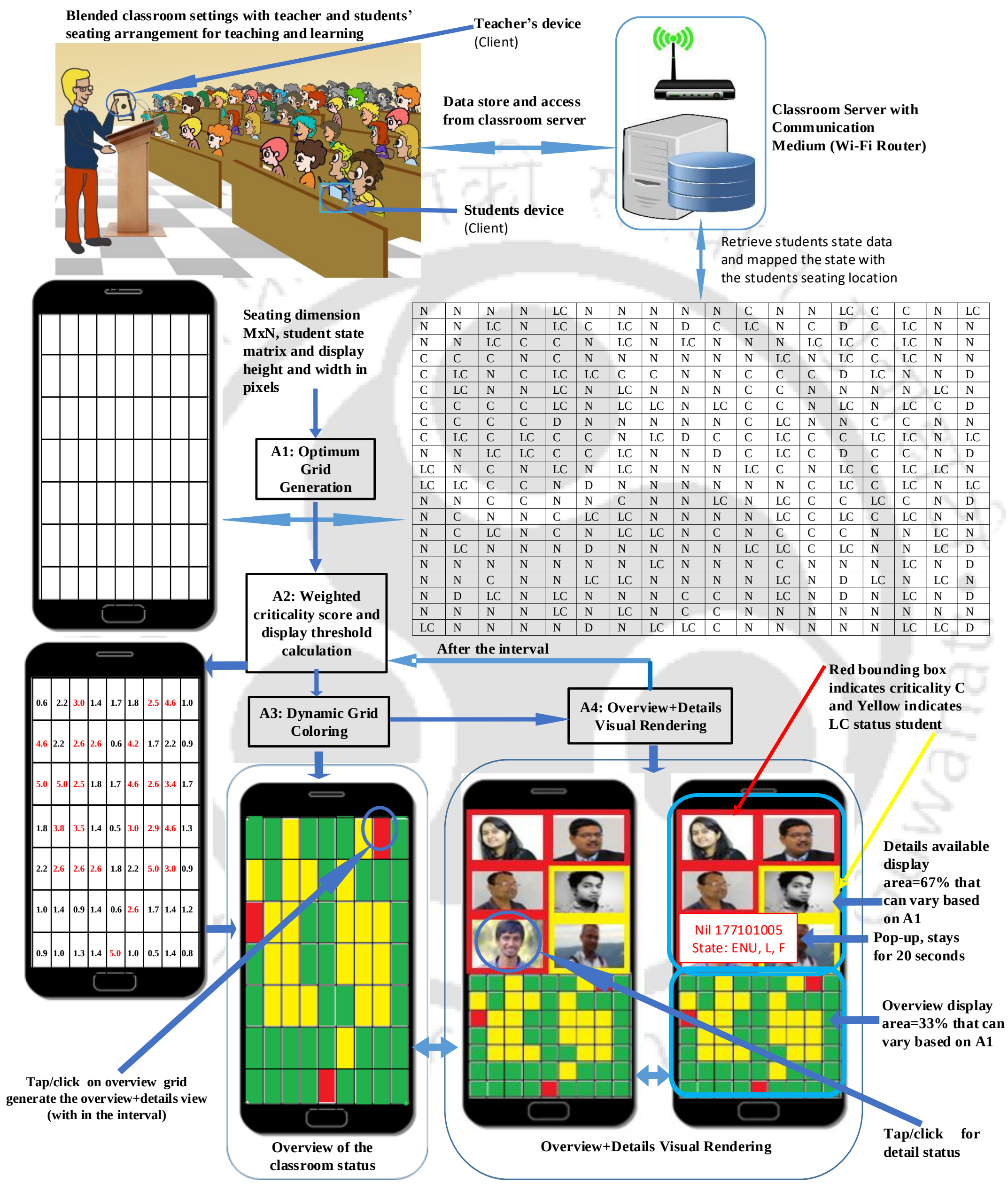


Figure 5.2: Shows the basic blended classroom setting and the flow of algorithms with their outcomes.

Table 5.1: Details of students' states: Criticality, Mental State, Physical Presence (High: Attendance>75%, Medium: 50%<Attendance<75%, Low: Attendance< 50%), and Learning State (Excellent: Score>75%, Good: 60%<Score<75%, Pass: 40%<Score<60%, Fail: Score<40%).

<table>
<tr><th>Criticality</th><th>Mental State</th><th>Physical Presence</th><th>Learning State</th></tr>
<tr><td rowspan="14">Normal (N)</td><td rowspan="8">Engaged and Understanding</td><td rowspan="4">High</td><td>Excellent</td></tr>
<tr><td>Good</td></tr>
<tr><td>Pass</td></tr>
<tr><td>Fail</td></tr>
<tr><td rowspan="2">Medium</td><td>Excellent</td></tr>
<tr><td>Good</td></tr>
<tr><td rowspan="2">Low</td><td>Excellent</td></tr>
<tr><td>Good</td></tr>
<tr><td rowspan="2">Not Engaged but Understanding</td><td rowspan="2">High</td><td>Excellent</td></tr>
<tr><td>Good</td></tr>
<tr><td rowspan="3">Engaged but Not Understanding</td><td rowspan="3">High</td><td>Excellent</td></tr>
<tr><td>Good</td></tr>
<tr><td>Pass</td></tr>
<tr><td>Not Engaged and Not Understanding</td><td>High</td><td>Excellent</td></tr>
<tr><td rowspan="16">Likely to be critical (LC)</td><td rowspan="3">Engaged and Understanding</td><td rowspan="2">Medium</td><td>Pass</td></tr>
<tr><td>Fail</td></tr>
<tr><td>Low</td><td rowspan="2">Pass</td></tr>
<tr><td rowspan="4">Not Engaged but Understanding</td><td>High</td></tr>
<tr><td rowspan="3">Medium</td><td>Excellent</td></tr>
<tr><td>Good</td></tr>
<tr><td>Pass</td></tr>
<tr><td rowspan="7">Engaged but Not Understanding</td><td>High</td><td>Fail</td></tr>
<tr><td rowspan="3">Medium</td><td>Excellent</td></tr>
<tr><td>Good</td></tr>
<tr><td>Pass</td></tr>
<tr><td rowspan="3">Low</td><td>Excellent</td></tr>
<tr><td>Good</td></tr>
<tr><td>Pass</td></tr>
<tr><td rowspan="2">Not Engaged and Not Understanding</td><td rowspan="2">High</td><td>Good</td></tr>
<tr><td>Pass</td></tr>
<tr><td rowspan="18">Critical (C)</td><td>Engaged and Understanding</td><td>Low</td><td rowspan="3">Fail</td></tr>
<tr><td rowspan="6">Not Engaged but Understanding</td><td>High</td></tr>
<tr><td>Medium</td></tr>
<tr><td rowspan="4">Low</td><td>Excellent</td></tr>
<tr><td>Good</td></tr>
<tr><td>Pass</td></tr>
<tr><td>Fail</td></tr>
<tr><td rowspan="2">Engaged but Not Understanding</td><td>Medium</td><td rowspan="3">Fail</td></tr>
<tr><td>Low</td></tr>
<tr><td rowspan="9">Not Engaged and Not Understanding</td><td>High</td></tr>
<tr><td rowspan="4">Medium</td><td>Excellent</td></tr>
<tr><td>Good</td></tr>
<tr><td>Pass</td></tr>
<tr><td>Fail</td></tr>
<tr><td rowspan="4">Low</td><td>Excellent</td></tr>
<tr><td>Good</td></tr>
<tr><td>Pass</td></tr>
<tr><td>Fail</td></tr>
</table>

finally, neither engaged nor understanding. Similarly, for the physical presence, we assume three states: those having 75% or more attendance, those with attendance between 50% and 75%, and finally, those having less than 50% attendance. The learning state depends on both the past performance and the performance in the tests carried out in the class on that day (measured in terms of an overall score). We combine them and define four learning tests: excellent (those scoring more than 75%), good (those with scores between 60% and 75%), average (students having scores between 40% and 60%), and poor (those with scores less than 40%). The states might seem arbitrary. However, these were designed following the teaching experience of one of the authors of this paper.

We combine these states together to obtain the state of a student in a classroom, as shown in Table 5.1. The combination yields a total 48 possible states ($4 \times 3 \times 4 = 48$). In a classroom, a student can be in any one of these 48 states. There can be three types of students. Some are performing well in all the aspects and do not require any intervention by the teacher. We can map such students to the Normal state, as defined in the exiting work. There might be some others for whom the intervention by the teacher is desirable. These are the likely to be critical types (denoted by LC). There can also be students who must be given special attention by the teacher. We call them the critical types (denoted by C). The leftmost column of Table 5.1 indicates these types corresponding to the combination of the state of the students.

5.2.2 Basic Setting and System Diagram

We further assume, as in the current system, that the classroom is represented as a matrix where each cell represents a student position and the state information is already available through an ICT-enabled infrastructure such as the systems reported in [192] and [27]. Our system, which is based on the idea proposed in [3, 176], requires a classroom server, i.e., a local server, a Wi-Fi (communication medium), and a set of client devices, as shown in Figure 5.2. The user (teacher and students) performs classroom teaching-learning activities through the client devices. The local server is responsible for supplying the learning materials and interfaces for classroom interactions. It also takes the role of rich and analytical computations on behalf of the clients, securely stores the students' state information, and supplies it to the users based on the needs and policies designed by the administrators.

The institute may provide the client devices, or students and teachers can bring their own devices (laptops/smartphones) and use them to participate in the teaching-learning process.

The design follow an overview+details visual technique [103]. In the overview level, the classroom is displayed in the form of a rectangular grid. Each grid element represents a group of students. We compute the weighted criticality of each element and color it with red for most critical, yellow for likely to be critical, and green for normal. This way, the teacher gets to know the students to monitor (the critical clusters). In order to get finer details of the students in a cluster, the teacher taps/clicks on the corresponding grid element. This brings on the screen the details view of the classroom. In this level, the teacher gets to see the detailed status of the students belonging to the group. The status information might include the physical presence (attendance), the mental state (not engaged/understand and so on), level of understanding as well as the learning state, subject to the availability of those information (see Table 5.1). An overview for the whole classroom is also present on the display. In order to return to the overview level, the teacher needs to tap/click on the overview region (see Figure 5.2).

The proposed system comprises of four algorithms. In the first algorithm, an optimum grid size is generated for both the levels. In the second algorithm, the first level grid elements are assigned a *criticality* score. In the criticality score calculation, we introduce the novel concept of *weights* for each student's state. On the basis of these scores, the grid is rendered with the specific color coding by the third algorithm. We introduce an intelligent rendering mechanism in the third algorithm. In this rendering, regions that are already highlighted once are not highlighted again in subsequent time intervals. Such a rendering mechanism makes the visualizer *fairer* as the *other critical regions get chance to be highlighted and noticed by the teacher*. The fourth and final algorithm implements the second level visualization. In our proposed system, the second level visualization is implemented with a *dynamic display allocation* strategy so as to make optimum use of the available display space. The four algorithms are explained in the following sections.

5.2.3 Optimum Grid Layout Generation for Both Levels

We propose the Algorithm 5 to generate optimum grid sizes for both the levels. The objective is achieved in four stages, as shown in the algorithm. In the first stage (lines 1-2), we compute the maximum number of rows and columns that the display can support. On a touchscreen, the grid elements should be touchable for better interaction. The interactive components such as buttons should be clickable for non-touchscreen displays. The above term implies that the interactive grid should have a size larger than our thumb's size; otherwise, the area would not be properly visible, and it would be challenging to touch at the right place. Findings from earlier research [185, 193] indicates that the minimum touchable area ranges from 10 square mm to 20 square mm (i.e., approximately 36-72 pixel width and height). In this work, we considered a touchable area of height and width of 100 pixels each (nearest round figure) to be on the safe side. Notably, if an area is touchable with the finger, it is easily clickable with a mouse cursor (on laptop/desktop screen). Therefore, we divide the display height and width by 100 each to get the maximum number of rows and columns that ensure each grid element would be "clickable". In the second stage of the algorithm (lines 3-5), we compute the maximum possible grid size of images in the second level visualization such that the images are recognizable. In order to come up with this computation, we made use of the fact that the two popular social networking sites, namely, Facebook and Instagram, use sizes of 128x128 and 110x110 (in pixel squares), respectively, to display profile pictures on smartphones, as reported in [1]. We used the former to determine the size of each image in the second level display. This computation helps in making optimum use of the display for the second level visualization. The optimum grid size for the first level visualization is computed in the third stage of the algorithm (lines 6-11). Finally, on the basis of the optimized first level, we determine the screen area to be allocated to display the student images in the second level, for optimum utilization of the screen real estate in the fourth stage (lines 12-18). The computed optimum grid size and screen area are returned for use by the subsequent algorithms in line 19.

5.2.4 Weighted Student States and Critical Cluster Computation

Once the optimum grid size for the first level is computed through the Algorithm 5, we compute a *threshold* value for each student cluster (i.e., grid element) to determine the critical clusters for visualization. The steps to achieve the threshold computation are presented in Algorithm 6. The computation is divided into two phases. In the first phase (lines 1-10), we first compute a *weighted* criticality score for each cluster. This score

ALGORITHM 5: Optimum Grid Generation

Input: $M \times N$ - maximum students' seating capacity in a classroom, student state matrix $SS_{M \times N}$, display height D_H, and display width D_W

Output: Display grid size for the first level visualization, student cluster size and the display area coverage in the second level

`/* Compute the maximum number of rows and columns possible on display. */`

Maximum possible rows $= \left\lfloor \frac{D_H}{100} \right\rfloor$

Maximum possible columns $= \left\lfloor \frac{D_W}{100} \right\rfloor$

`/* Determine maximum possible rows and columns in the second level, assuming the available display area initially to be 67% or two-thirds of the total area */`

Compute maximum possible number of "recognizable images" (I_R) on the display: $I_R = \left\lfloor \frac{D_H \times D_W}{128 \times 128} \right\rfloor$

Maximum clickable number of rows (of recognizable images) in second level (R_S) :

$R_S = \frac{\text{available display area} \times D_H}{128}$

Maximum clickable number of columns (of recognizable images) in second level (C_S) :

$C_S = \frac{\text{available display area} \times D_W}{128}$

`/* optimize first level display */`

$Index = 1$;

while $Index \times R_S > M$ *OR* $Index > R_{MAX}$ **do**

  `/* to account for different display orientations, namely landscape and portrait */`

  a. R = Indext; b. Indext++ ;

$Index = 1$;

while $Index \times C_S > N$ *OR* $Index > C_{MAX}$ **do**

  `/* to account for different display orientations, namely landscape and portrait */`

  a. C = Indext; b. Indext++ ;

`/* Optimize second level available display area */`

Compute cluster size $= \left\lfloor \frac{M \times N}{R \times C} \right\rfloor$;

if *cluster size* < 4 **then**

  a. Available display area = 50% of the total area (i.e., half);

else if $4 \leq$ *cluster size* < 10 **then**

  a. Available display area = 67% of the total area (i.e., two third);

else

  a. Available display area = 80% of the total area;

Return R, C, cluster size and the available display area for the second level.

represents the nature of a grid element (i.e., student cluster). The *higher* the value, *more critical* is the corresponding grid element, implying *more urgent* need for the teacher's intervention. In the state-of-the-art approach [1], as we mentioned earlier, there was no way to distinguish between critical clusters and create a *relative order* of the clusters in terms of criticality. However, such ordering is necessary to ensure that the teacher's attention is drawn judiciously to the neediest students, considering the time constraint of fixed classroom teaching periods. In order to address this issue, we propose to have weights for each student state. The weights indicate the relative criticality of the states. In order to compute the weighted criticality score for a cluster, we set weight values as 0.10 for the N (Normal) state, 0.50 for the LC (Likely to be Critical) state, and 0.90 for the Critical (C) state (the actual

ALGORITHM 6: Weighted criticality score and display threshold calculation

Input: Classroom seating matrix $CS_{M\times N}$, student state matrix $SS_{M\times N}$ and display grid matrix $DG_{R\times C}$
Output: Weighted threshold (T_W) value and the weighted criticality score matrix $WCS_{R\times C}$.

/* Compute weighted criticality scores for each student clusters based on weight of the state N=0.1, LC=0.5, C=0.9 of a student and store the values in the matrix. */

1 **for** *every element in* $DG_{R\times C}$ **do**
2   **for** *every student in the grid element* **do**
3   **if** *Corresponding entry in* $SS_{M\times N}$ *is* N **then**
4   criticality score += 0.10
5   **else if** *Corresponding entry in* $SS_{M\times N}$ *is* LC **then**
6   criticality score += 0:50
7   **else if** *Corresponding entry in* $SS_{M\times N}$ *is* C **then**
8   criticality score += 0:90
9 Store the weighted criticality score for the grid element in the corresponding entry for WCS_{R*C}.
10 Total criticality score (for the whole classroom) += criticality score.

/* compute weighted threshold for rendering */

11 Compute average (CS_{avg}), maximum (CS_{max}) and minimum (CS_{min}) weighted criticality score for the whole classroom using WCS_{R*C}

/* compute an elevation factor for management of critical grid elements */

12 **if** $CS_{avg} \leq \dfrac{0.9 \times N}{2}$ *(N = number of students in each cluster)* **then**
13   Elevation Factor $(E_F) = \dfrac{CS_{max} - CS_{min}}{N}$
14 **else**
15     $E_F = \dfrac{CS_{max} - CS_{avg}}{N}$
16 Weighted Threshold (T_W)=$(1 + E_F) \times CS_{avg}$
17 **if** $T_W < CS_{max}$ **then**
18   Return T_W
19 **else**

    /* When T_W exceed the CS_{max}, no critical grid element shall be eligible for display. In that case, we re-compute T_W without elevation to determine critical grid elements. */

20   Find median and mode of the distribution of the score stored in $WCS_{R\times C}$.
21   **if** $CS_{avg} \geq$ *median AND* $CS_{avg} \geq$ *mode* **then**
22         $T_W = CS_{avg}$
23   **else if** *median* $> CS_{avg}$ *AND median>mode* **then**
24         $T_W = median$
25   **else if** *median* $> CS_{avg}$ *AND mode* $\geq$ *median* **then**
26         $T_W = mode + 1$
27   **else**
28   **if** $WCS_{AVG} \leq \dfrac{n}{2}$ **then**
29             $T_W = +\infty$
30   **else**
31             $T_W = +\infty$
32   Return T_W and WCS_{R*C}

calculation of the critical score is shown in Algorithm 6, lines 1–8). Moreover, we use FUMs, such as exam marks and attendance to define student criticality (see Table 5.1).

We performed a simulation study to determine the state weights (Table 5.2). In the study, we experimented with different classroom sizes, pre-defined student state distributions and various weight values. Based on the simulation settings, we computed the number of critical grid elements for each setting following the Algorithm 6. As can be seen from (Table 5.2), we experimented with integer weights including the one used in the state of the art

Table 5.2: Case studies with different weights of the states for various classroom scenarios. Each cell of columns C, D, E, and F contains the number of critical grid elements to be highlighted, improvement in percentage (%) with existing work [1] based on Algorithm 2

A (class-room size)	B (% of C+LC students in class)	C (Weights: C=LC=1, N=0) (as per [1])	D (Weights: C=3, LC=2, N=1)	%	E (Weights: C=9, LC=4, N=1)	%	F (Weights: C=0.9, LC=0.4, N=0.1)	%
13x13=169	< 50	10	10	0	8	33.33	6	16.67
	50-60	1	8		8		8	
	60-70	12	10		9		10	
	70-80	20	20		18		23	
	80-90	23	18		16		16	
	90-100	28	30		30		28	
14x16=224	< 50	16	15	83.33	14	66.67	10	100
	50-60	32	30		30		31	
	60-70	17	12		12		8	
	70-80	14	13		14		10	
	80-90	10	8		6		5	
	90-100	26	26		26		24	
18x16=288	< 50	14	12	0	12	83.33	9	100
	50-60	30	30		28		28	
	60-70	30	30		24		24	
	70-80	14	14		12		13	
	80-90	16	16		16		14	
	90-100	18	20		14		16	
21x17=357	< 50	14	14	50	12	100	10	100
	50-60	10	10		8		8	
	60-70	12	10		10		9	
	70-80	36	32		32		32	
	80-90	32	32		30		28	
	90-100	14	10		12		9	
21x21=441	< 50	10	12	-16.67	10	0	9	100
	50-60	13	14		13		12	
	60-70	24	24		25		22	
	70-80	21	20		21		20	
	80-90	11	8		7		7	
	90-100	10	12		10		8	

approach [1] (columns C-E) and also the fractional weights (column F). The weight values were choses to put maximum emphasis on the C state, followed by the LC state and the least emphasis on the N state.

It may be noted in Table 5.2 that the percentage improvements in the performance of Algorithm 6 is computed in terms of the number of grid elements that the Algorithm identifies as critical for subsequent visualization. It should be as less as possible, to reduce the physical and cognitive load of the teacher. If the number is more, the teacher has to put additional effort to intervene for improved learning outcome. Optimizing the critical clusters, therefore, is essential for improved system performance. Among all the weights chosen, the best performance is obtained with the weights of col F (Table 5.2): C=0.9, LC=0.4, N=0.1. Hence, we have chosen these weights for the student states.

ALGORITHM 7: Dynamic Grid Coloring

```
Input: the weighted criticality score matrix and the threshold
Output: first level of the visualizer (with a colored grid)
/* determine all clusters with the criticality score above threshold */
Sort the criticality score values of all the grid elements in descending order.
Determine the grid elements with score above the threshold.
/* determine 3 non-adjacent clusters to highlight */
if number of elements above threshold > 3 then
    Identify all possible triplets of clusters out of all the clusters with criticality score above threshold.
    for each triplet do
        Compute Euclidian distance between the 3 elements (D):
          D = sum_{i=0}^{2} sqrt((X_{i+1} - X_i)^2 + (Y_{i+1} - Y_i)^2)
    Sort all the distance values.
    Assign red color to the 3 grid elements (triplet) with the highest distance value.
    Assign yellow colors to the remaining elements above the threshold.
    Color all the remaining elements with green.
else
    Assign red color to all the grid elements having value above the threshold
    Assign green color to the remaining grid elements
Render the colored grid on the display
```

In the second phase of the Algorithm 2 (lines 11-31), we compute a *threshold* value of the criticality score to mark a cluster (grid element) as critical or not. We first compute the average, minimum and maximum of the scores for all the clusters. Intuitively, we can set the average of these values as the threshold; any cluster with score above the average can be marked as critical and visualized accordingly. However, this simple approach may lead to a large number of clusters marked as critical. In that case, teacher will be burdened with the need to attend a large number of students, which may not be feasible given the classroom time constraint. In order to avoid this problem, Bhattacharya et al [1] proposed an approach of an *elevated threshold* [1]. We have made use of the same here (lines 12-32). The only difference here is that the values considered are the *weighted* average, *weighted* maximum and the *weighted* minimum values.

5.2.5 Fair Visualization for Improved Awareness

The first two algorithms are designed to produce a matrix of numbers with each number denoting the weighted criticality score of the corresponding student cluster. A threshold value is also computed. Any criticality score value above the threshold represents critical student clusters. These are, however, numbers. We need to visualize these numbers for quick comprehension of the classroom status. That is achieved with the third algorithm (Algorithm 7).

The algorithm 7 takes as input the criticality score matrix and the threshold values computed in the Algorithm 6. It first sorts the criticality scores of the grid elements in descending order (line 1). In the sorted list, if the number of grid elements with score above threshold is less than or equals to 3, we simply assign the red color to all such elements and the green color to the rest (lines 8-10). Otherwise, we perform the steps 4-7. We first compute all the possible triplets of grid elements with values above the threshold. For each of these triplets, we calculate the *total Euclidian distance*, by utilizing the coordinate information of each cluster in the triplet with respect to the grid. These values are then sorted and we choose the one with the maximum distance value. The corresponding clusters (grid elements) in the triplet are assigned the red color. If there are other grid elements with score above the threshold, those are assigned the color yellow. All the remaining grid elements are colored green. In this way, we get the three clusters (grid elements) that are maximally spread in the classroom, thereby ensuring that the teacher's attention is optimally drawn to all sections of the classroom. Finally, the grid is rendered on display with the assigned colors. It may be noted here that we have chosen to utilize the three colors as prescribed by Bhattacharya et al [1]. We have also kept the number of grid elements to be highlighted with the red color (i.e., the most critical elements) as 3 for the same reason as described in [1]. The dynamic nature of the grid coloring is also retained as reported in [5], with the colors changing every fifteen minutes reflecting the change in the state of the students as teaching progresses. We set this value based on the research study indicating that attention level begins to decline between 10 to 15 minutes [194]. However, a teacher can set this value as per his/her convenience also.

5.2.6 Dynamic Second Level Visualization

The first three algorithms create the first level of the proposed system interface. The first level is dedicated to giving the teacher a comprehensive overview of the classroom status. However, the teacher cannot get the detailed knowledge about individual students at this level. For that, we have designed the second level-rendering algorithm shown in Algorithm 8. This algorithm is similar to the one reported in [1] with the only difference being the screen area used to display the student details. In our proposed system, we make use of the dynamic available display area as computed by Algorithm 5 instead of a fixed two-thirds area of the screen. Our proposed scheme is thus adaptable with the cluster size, making more efficient use of the available screen.

ALGORITHM 8: Overview+Details Visual Rendering

```
Input: classroom seating arrangement, first level grid, student states, available display area, and interaction
       event (tap/click).
Output: Overview+Details status on the display
while tap/click on a grid element in the first level do
    Get the location from the grid matrix.
    Get images of the students who are part of the cluster from the classroom seating matrix.
    Get their criticality score from the student state matrix.
    Create a display area covering the available display area as computed in Algorithm 1
    /* M × N classroom size, R × C=first level grid maximum size as computed in
       Algorithm 1                                                                   */
    Create image grid: row number = M/R, column number = N/C.
    for every student in the grid element do
        if corresponding student criticality type is C then
            Render student image with a red bounding box.
        else if corresponding student criticality type is LC then
            Render student image with a yellow bounding box.
        else if corresponding student criticality type is N then then
            Render student image with a green bounding box.
    Display the colored grid in the remaining portion of the screen (overview).
while interaction made on the display do
    if tap/click on an image then
        Display the state details as a pop-up that stays on the display for twenty seconds.
    if tap/click on the overviw then
        Return to the first level display.
```

5.3 Performance Comparison Study

As described in the previous section, we have made many significant and novel changes in the *Manas Chakshu* design. In order to determine the effect of these changes on the performance of the visualizer, we performed a comparative study of our proposed system with the existing system. The details of the study are presented next.

5.3.1 Performance Metric

In order to compare performance, we have defined a metric that captures the overall performance involving both the first (overview) and the second (details) levels. The metric is shown in Eq. 5.1.

$$P = P_{Overview\_level} \times P_{O+D\_level} \tag{5.1}$$

It is computed as a product of two terms: performance at the first level ($P_{Overview\_level}$) and performance at the second level (P_{O+D_level}). The first level performance is computed as in Eq. 2.

$$P_{Overview} = \frac{\text{Maximum possible grid size}}{\text{Maximum possible grid size } + \text{computed grid size}} \tag{5.2}$$

In Eq. 5.2, we compute the performance of Algorithm 5 as a ratio of two terms: *maximum possible grid size* with the constraint that each element should be *clickable* and the *computed grid size* by the Algorithm 1. It is a normalized value ([0,1]) with higher values representing better performance.

In order to compute the second level performance, we propose Eq. 5.3 & 5.4. In these equations, we compute two more ratios related to the row and columns in the second (details) level (the part that displays student images). The ratios are computed based on the *maximum* number of rows and columns possible to display *perceivable* images (computed in Algorithm 5) and the image grid size obtained from the classroom matrix (computed in Algorithm 6).

$$P_{O+D\_level\_row} = \begin{cases} \frac{\text{Max no.of rows allowed in second level}}{\text{No.of rows in each cluster}}, & \text{if } < 1 \\ 1, & \text{otherwise} \end{cases} \tag{5.3}$$

$$P_{O+D\_level\_col} = \begin{cases} \frac{\text{Max no.of col allowed in second level}}{\text{No.of col in each cluster}}, & \text{if } < 1 \\ 1, & \text{otherwise} \end{cases} \tag{5.4}$$

The $P_{O+D\_level\_row}$ (or $P_{O+D\_level\_col}$) can be 1 or more, if the number of rows (or columns) of students in the second level is less than the maximum number of rows (or columns) possible (to have a perceivable student image). In such cases, we do not need the scroll bar in the second level. This is likely to lead to reduced physical and cognitive load to the teacher. Thus, these metrics capture the performance of the second level visualizer in terms of the presence or absence of the scrollbar.

5.3.2 Results

We compared the performance across device platforms (mobile, tablet, and desktop), display resolutions, and different classroom sizes (1×1 to 50×50). We had collected device resolution data of mobile devices for Apple, Samsung, Google, Huawei, Xiaomi and Oneplus; data of tablet devices were collected for Apple, Samsung and Lenovo; data of desktop devices

Table 5.3: Summary of the performance comparison study of our proposed visualizers with the existing method [1] and percentage (%) of improvement.

Device	Screen resolution	Minimum touchable area 63 dp			Minimum touchable area 95 dp			Minimum touchable area 126 dp		
		A	B	%	A	B	%	A	B	%
DESKTOP	1683*2992	0.91	0.99	8.53	0.82	0.99	16.68	0.77	0.97	20.79
DESKTOP	1353*2165	0.86	0.99	12.78	0.76	0.97	20.87	0.69	0.94	25.22
DESKTOP	1097*1950	0.80	0.97	17.22	0.70	0.94	24.14	0.61	0.87	25.76
DESKTOP	1127*1804	0.79	0.97	17.73	0.69	0.93	24.36	0.60	0.86	25.65
DESKTOP	1225*2178	0.85	0.98	13.42	0.73	0.96	22.99	0.67	0.93	26.19
DESKTOP	1100*1956	0.805	0.97	16.94	0.70	0.94	24.14	0.61	0.87	25.76
MOBILE	786*393	0.37	0.49	12.21	0.25	0.32	7.08	0.18	0.23	4.26
MOBILE	881*407	0.387	0.50	11.98	0.26	0.34	7.75	0.18	0.23	4.26
MOBILE	955*429	0.40	0.52	12.49	0.27	0.36	8.7	0.20	0.25	4.66
MOBILE	640*360	0.22	0.28	5.56	0.12	0.14	2.12	0.08	0.09	0.87
MOBILE	846*412	0.38	0.50	11.98	0.25	0.32	7.08	0.18	0.23	4.26
MOBILE	720*360	0.24	0.29	5.28	0.13	0.16	2.26	0.08	0.09	0.87
MOBILE	994*447	0.45	0.59	14.47	0.29	0.39	10.01	0.22	0.27	5.71
MOBILE	912*410	0.39	0.51	12.13	0.26	0.34	7.75	0.20	0.25	4.66
MOBILE	667*375	0.22	0.28	5.56	0.13	0.16	2.26	0.08	0.09	0.87
MOBILE	736*414	0.33	0.42	9.09	0.21	0.26	4.85	0.14	0.17	2.68
MOBILE	812*375	0.26	0.34	7.41	0.16	0.20	3.54	0.11	0.12	1.59
MOBILE	896*414	0.39	0.51	12.13	0.26	0.34	7.75	0.20	0.25	4.66
TABLET	1053*1684	0.77	0.96	19.7	0.68	0.93	24.64	0.60	0.85	25.26
TABLET	1241*1655	0.82	0.97	15.52	0.72	0.94	22.06	0.64	0.90	25.73
TABLET	994*1494	0.76	0.95	19.68	0.63	0.90	27.1	0.55	0.79	23.24
TABLET	857*1428	0.71	0.93	22.29	0.58	0.82	24.44	0.47	0.67	19.97
TABLET	981*1309	0.74	0.94	20.24	0.62	0.88	26.66	0.55	0.77	22.21
TABLET	677*1083	0.55	0.76	21.08	0.44	0.60	16.17	0.34	0.46	11.93

were collected for Asus, Lenovo, Xiaomi, Apple, HP and Dell. We visited the websites of the manufacturers to collect the data. Next, we mapped the resolutions to dip (device independent pixel) based on the standard conversion rules [1]. Also, one of the objectives of the visualizer is to have a large enough grid size so that the elements are *distinguishable* and *clickable/touchable*. According to the previous findings, the minimum touchable area should be between 10 - 20 square mm [185, 193]. In our study, we have considered three values: the lower limit of 10 square mm, the upper limit of 20 square mm, and the average of the two or 15 squire mm as a minimum touchable area. These areas were converted to dip resolutions as well following standard conversion rules [2], which gave us 63 dp, 95 dp, and 126 dp for 10, 15, and 20 mm square touchable display areas, respectively.

We run both the algorithms for all the combinations of minimum touchable area, resolution of the display and classroom sizes. We calculated the performance metric for each of these cases. For each screen resolution on each device platform, we executed the algorithms for all the class dimensions. Therefore, for each screen resolution there will be

[1] https://developer.android.com/training/multiscreen/screendensities
[2] https://developer.android.com/training/multiscreen/screendensities

2500 different combinations (from 1x1 to 50x50) and the corresponding performance values. We took average of all these 2500 results. Theses average results for each device platform and resolution are shown in Table 5.3. In the Table 5.3, A denotes the initial system [1] performance and B represents the performance of our proposed system Manas Chakshu. We have also shown the % improvement in performance of our system over the existing system alongside.

Table 5.3 shows that our proposed visualizer outperforms the existing system in all test scenarios (device platform, resolution and class sizes) for the three touchable area measures. With the touchable area as 63 dp, we found that the performance of the new design is significantly better than the existing design in 90.92% of the cases. In the remaining cases, it performed as good as the existing system. When we set the touchable area to 95 dp, our proposed design performs better in 89.72% of all the cases. The performance improvement reduces a bit further to 86.72% of all the cases when the touchable area was set to 126 dp. Overall, our proposed system was found to have performed significantly better in 89.12% of the cases compared to the existing classroom visualizer [1].

5.4 Empirical Usability Study

Although the performance study clearly indicated significant improvement over the existing system, it was meant to test the performance of only the screen-area optimization scheme. In addition to the optimization, we have also introduced two changes to improve the user (teacher) experience. These are, (a) weighted state concept to more refined identification of critical clusters, and (b) critical cluster visualization. There was no direct way to check the system performance with respect to these changes except empirical usability testing. We carried out such a study, which is described next.

5.4.1 Setup

In the study, there were two distinct stages. In the first stage, we collected task performance data from a group of teachers in a simulated classroom environment. In the second stage, we collected perceived usability data from the teacher participants on the basis of a set of questionnaires.

The setup for the simulated classroom study was the same as the one reported in [1]. It was comprised of two Android applications developed to render the existing work [1] (App A, contribution reported in Chapter 4) and the proposed (App B) visualizers on a smartphone screen and a group of teachers and students. We used a Sony Xperia C3 smartphone with a 5.5-inch display, 8GB of ROM, 1GB of RAM, and a 1.2 GHz quad-core processor to render the visualizer (for an imaginary classroom of size 15×18). The device had Android version 5.1.1. In the simulated classroom setting, one participant acted as a "teacher". The teaching was done in the presence of between 15 - 20 students. We took proper care to select both the teacher and student participants. Only those who had prior teaching experience were considered as teachers. All the student participants were Undergraduate (UG) or postgraduate (PG) students. Each teacher took half an hour lecture in front of the students. The lectures were conducted with the help of a smartboard and projector. Students were instructed to the teacher engaged during the teaching (by asking questions), to mimic the real-world large classroom constraints faced by a teacher.

In order to capture the task performance, we used the same set of twelve tasks as reported in [1]. All task performance data were logged by our app for later analysis. Along with the data logging, we also collected post-session ratings from each participant. The ratings were collected with a questionnaire having three components: questionnaire for teacher satisfaction (TSQ), perceived efficiency (PEQ), and perceived learnability (PLQ). The questionnaire was based on the Computer System Usability Questionnaire (CSUQ) [195], Questionnaire for User Interface Satisfaction (QUIS) [196], Usefulness, Satisfaction, and Ease of use (USE) [197], and Perceived Usefulness and Ease of Use (PUEU) [198]. The questionnaire is shown in Table 5.4. A five-point Likert scale was used to record ratings, with values 1 (strongly disagree), 2 (disagree), 3 (neutral: neither agree nor disagree), 4 (agree), and 5 (strongly agree).

5.4.2 Participants Details

We have collected data from 26 participants (19 males and 7 females). Each had at least two years of teaching experience, and all were regular users of smartphones and tablets. The participants' age group was within 29-41 years, with an average age of 32.96 years and teaching experience of 5.37 years.

Table 5.4: Details of questionnaire used to collect ratings from the teacher participants and ratings (mean, standard deviation (SD), and interpretation) in terms of user perceptions about the system use.

Construct	Item No.	Questionnaire statements	Teachers' rating score (n=26)		
			Mean	SD	Interpretation
Teachers satisfaction questionnaire (TSQ)	TSQ1	Overall, I am satisfied with how easy it is to use this visualizer during a class lecture.	3.96	0.53	agree
	TSQ2	It is simple to use this visualizer.	4.62	0.5	strongly agree
	TSQ3	I can effectively complete my work using this visualizer.	3.81	0.49	agree
	TSQ4	I am able to complete my work quickly using this visualizer.	3.77	0.76	agree
	TSQ5	I am able to efficiently complete my work using this visualizer.	3.73	0.6	agree
	TSQ6	I feel comfortable using this visualizer.	3.96	0.66	agree
	TSQ7	It was easy to learn to use this visualizer during a class lecture.	3.88	0.52	agree
	TSQ8	I believe I became productive quickly using this visualizer.	3.73	0.72	agree
	TSQ9	I feel I need to have it in my classroom lecture.	4.58	0.5	strongly agree
	TSQ10	I would recommend it to my colleague.	4.54	0.51	strongly agree
Perceived efficiency questionnaire (PEQ)	PEQ1	I find it easy to get students' states using visualization approach.	3.88	0.71	agree
	PEQ2	Interacting with the visualization tool does not require a lot of mental effort.	4.53	0.5	strongly agree
	PEQ3	I find visualization approach is easy to handle.	4.03	0.66	agree
	PEQ4	Do you feel it will add your workload in a classroom?	3.88	0.77	agree
	PEQ5	Do you feel it will take additional time to know your students' status in a classroom?	2.96	0.53	agree
Perceived learnability questionnaire (PLQ)	PLQ1	Learning to operate the visualizer is not difficult.	4.38	0.49	agree
	PLQ2	Remembering color schemes and interaction is not difficult.	4.57	0.5	strongly agree
	PLQ3	Performing tasks is straightforward.	3.88	0.52	agree
	PLQ4	I can quickly become skillful with the visualizer.	3.57	0.5	agree
	PLQ5	My interaction with the visualizer would be clear and understandable.	3.73	0.72	agree

5.4.3 Experimental Procedure

We performed one between-group study. One group of thirteen teachers (10 males and 3 females) performed the tasks with App A. The other group (of the remaining 13 teachers with 9 males and 4 females) performed the tasks with our proposed visualizer (App B). We followed the same procedure to collect the task performance data as in [1].

5.4.4 Results and Observations

As reported in Chapter 4, a useful measure to compare task performance is the mean task completion time [1]. We used the logged task performance data to compute that for each task (see Figure 5.3). It may be observed in the figure that the mean tasks completion times are less with our proposed visualizer as compared to the existing system. Overall, our proposed visualizer the *Manas Chakshu* achieved 27.96% less task completion time on average. We also performed a t-Test to determine the statistical significance of the results. The group mean difference was found to be significant [$t(11)=5.097$, $p(0.0003)<0.05$]. The results

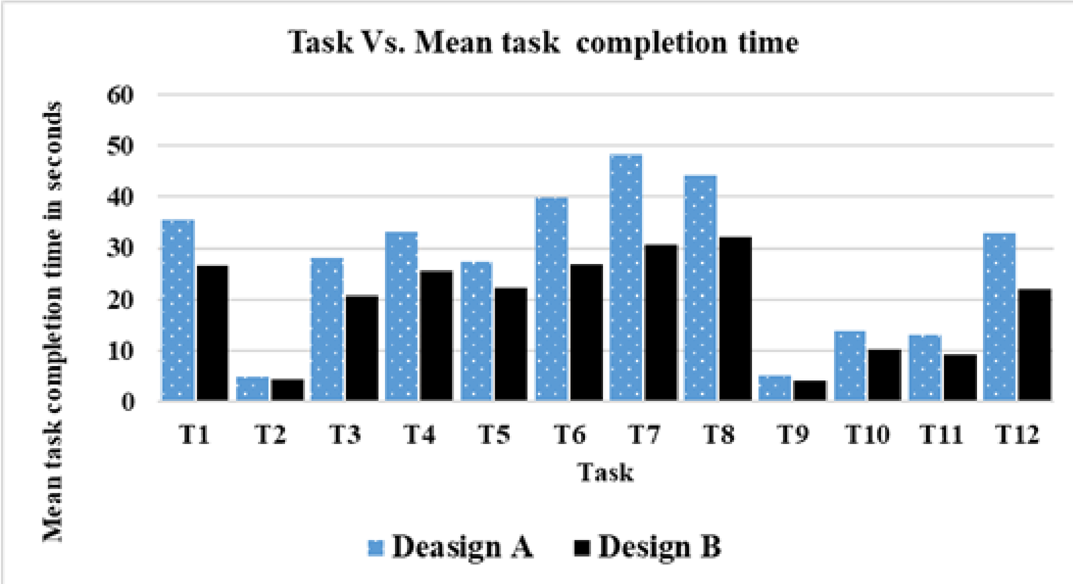


Figure 5.3: Performance in terms of mean task completion time for the existing visualizer (Design A) and "Manas Chakshu" (Design B)

indicate that the proposed *Manas Chakshu* outperforms the existing visualizer in terms of the task completion time. The Cronbach's alpha values of TSQ, PEQ, and PLQ were found to be 0.8123, 0.7574, and 0.7724, respectively, indicating high reliability (>0.6, [6]). The rating scores (mean, standard deviation (SD), and interpretation) are shown in Table 5.4. The maximum mean rating score for TSQ is 4.62 (for TSQ2) with SD=0.5 interpreted as strongly agree, and similarly, we got high scores for TSQ9 and TSQ10. The high score values indicate that the system is simple, and users want to have it in the classroom and willing to recommend it for further use with high acceptance. The minimum score is 3.73 (for TSQ5 and 8), which is not bad, but they agreed and accepted. The remaining scores were close to 4, which is also a higher score. The mean values for PEQ were on the higher side too, except probably PEQ5. *These values indicate a reasonably high degree of perceived efficiency.* In PLQ, the scores vary between 4.57 - 3.73, which indicates perceived learnability is high. In summary, the results suggest that the perceived usability in terms of teachers' satisfaction, efficiency, and learnability ratings of the proposed system is highly acceptable.

5.5 Discussion

The proposed monitoring aid is designed to equip a teacher in a classroom to monitor the students. It does so without explicit awareness of the classroom students. The design is similar to having an invisible eye, which can see things without being seen - the minds' eye. Hence, the name that means the same in Sanskrit.

Our proposed design is built on the idea espoused in [1]. We assume the state data (Table 5.1) to be available. The students' mental states are challenging to gather [3], even though attendance and learning levels are simpler to determine. We kept the basic design elements intact as in the existing system. These include the use of a two-level visualizer, three colors for visualization of the classroom status as well as the student details (image bounding box) and split-screen approach in the second level of visualization. This is done to ensure that the perceived usability and system acceptability are not affected. At the same time, we introduced significant and non-trivial changes in the way the system works.

One of the significant changes we brought in the design is the optimization of the classroom status visualization at both the overview (first) and details (second) levels. Unlike in the existing approach, we computed the first-level grid size based on the maximum possible grid size at the second level. In doing so, we ensured that the first level grid size remains "clickable/touchable", the student images in the second level are "perceivable" and finally, screen-area available to display the student images with details is maximized to eliminate the need for scroll-bars. The second significant change we introduce is the way the critical student clusters are determined and visualized. We introduced the idea of "weighted" criticality score to *improve* the classification of student clusters as critical or non-critical. Once those are identified, we ensured that the clusters are suitably highlighted so as to draw the teacher's attention to the classroom regions where it is due, with the help of the "distance maximization" method. Our performance comparison and empirical user studies show that the changes managed to improve the performance of the visualizer significantly, without adversely affective the perceived usability.

In order to test the performance of Manas Chakshu, we proposed a performance metric and computed the scores for the existing design and our proposed design. The approach revealed the extent of improvement our proposed system achieves vis-a-vis the exiting design. In order to test the effect of these changes on the system usability, we relied on the methodology used in [1] including the setup and experimental procedures. Along with that, we also collected feedback through questionnaires, which we designed for the purpose. Although these tests can be relied upon to conclude about the significance of our proposed approach, we feel a longitudinal study in a real-classroom setting is required to come to a final conclusion about the system performance and its impact on the teaching-learning outcome. We intend to do that in future. One limitation is that there is a need to implement a full-fledged system that should be able to capture student states. Automatic capturing of such states in an ICT-enabled classroom infrastructure can be of great help in realizing the goal. Few promising works have been reported in the literature in this direction, such as Tikadar et al [3]. Our other future goal is to integrate those works with our proposed visualizer, Manas Chakshu to come up with an integrated blended-learning system classroom teaching for studies as well as practical use.

5.6 Summary of the Chapter

This research work presented the design and validation of a novel teaching aid, the "Manas Chakshu". It is meant to let a teacher visualize the current status of a classroom as well as individual student's state. The proposed aid is a significant improvement over an existing classroom visualization tool. The improvements pertain to the optimization of screen-area usage, more refined differentiation methods of critical students, and an improved classroom status awareness scheme. Our studies (both theoretical and empirical) show that our proposed system significantly improves system performance without affecting usability.

This contribution has been published in a Q1 journal. The details are as follows:

Journals

1. Samit Bhattacharya, **Ujjwal Biswas**, Shubham Damkondwar, and Bhupender Yadav, "Real-time ICT-based Interactive Learning Analytics to Facilitate Blended Classrooms", ***Education and Information Technologies***, URL: https://doi.org/10.1007/s10639-023-12327-x [Chapter 5]

Chapter 6

Real-time Classroom Notification System

Designing peripheral notifications to support teaching-learning is progressively increasing. To address the challenges of real-time notification, we propose a novel *real-time multimodal peripheral notification system* for supporting teachers and students in a student-centered blended classroom. The proposed system takes advantage of peripherals (such as smartphones and wearable bands) to avoid issues with real-time notification. Furthermore, it reduces additional cognitive load and notification fatigue to perceive status during class. The technique helps to minimize notification fatigue and motivate students to be attentive during lectures. It consists of a performance prediction and classifications to automatically send notifications based on intervention strategies (e.g., timing, message content, and modality). The challenges addressed are identified through user interviews and interactions (teachers and students). We investigated users' opinions on the current notification with interactive sessions. Using UCD method, we went through many trials to finalize the notification method and feedback contents. The approach has helped to refine the design over twelve weeks (eight weeks of the interactive session, including four weeks of trial and error method before the final version). In summary our major contributions are as follows.

- The proposed system design includes performance prediction, classifying academic performance of the students, real-time learning and/or engagement states. Based on some intelligent intervention strategies, the statistics related to students' performance automatically send feedbacks to the end users.
- The dynamic feedback timings are based on historic feedback statistics, choice of peripheral devices, and feedback modalities. We propose two real-time feedback

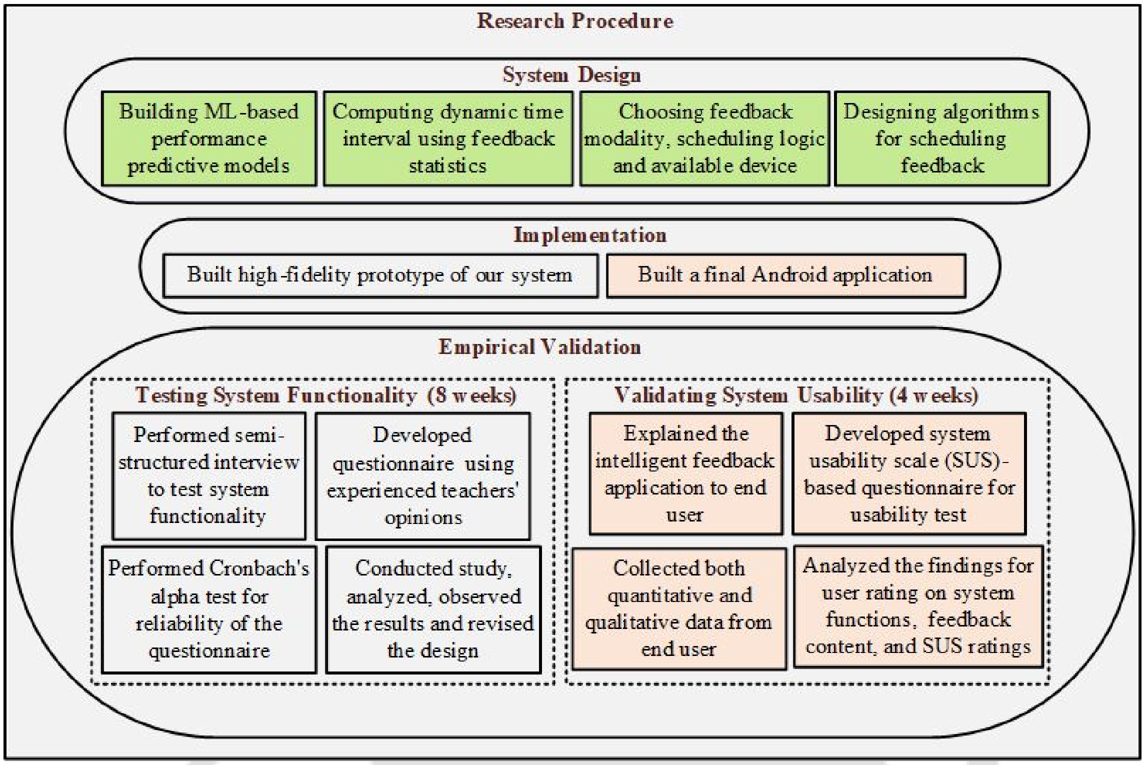


Figure 6.1: Illustrates the User-Centered Design (UCD) for building and validating the system.

scheduling algorithms based on feedback timing, device selection, and modalities to optimize user fatigue.

- We went through many trials to finalize the feedback method with usable contents. The design process has helped to understand user demands, their priorities, and refine the design accordingly.

- The challenges addressed are identified through intensive interviews and interactions with the teachers and students. The entire process takes around eight weeks of interactive sessions and functionality testing with users before the final design of the proposed system.

The above contributions help in perceiving weaknesses [12], seamless teacher-student interaction [176], monitoring students performances [1], providing timely feedback to student [8].

6.1 Design of the Notification System

In order to address the research gap, we propose a novel *real-time multimodal notification system* for blended classrooms. We follow an UCD method to design the system [199]. The research procedure to design the system is shown in Figure 6.1. There are three phases in our research procedure. The phases are system design, implementation, and empirical validation. The *design phase* consists of four key subgoals to develop *intelligent feedback system.* The subgoals are 1) building ML-based student performance predictive model, 2) computing time interval based on feedback statistics, 3) choosing feedback modality based on logic and availability of device, and 4) designing algorithms to achieve the design goals (see Figure 6.1 top part). The *implementation* is the second phase of our research procedure. The entire process is based on building high-fidelity prototype and Android application of the proposed system (see Fig 6.1 middle part). The final phase of research procedure is *empirical validation*. It has two core parts - *testing system functionality and validating system usability* (see Figure 6.1 bottom part). *Testing system functionality* using prototype of the system helps us to refine the final design. It involves interactive meetings with users (teacher and students) for about eight weeks before the proposed final design is built. *Validating system usability* helps in performing user study for testing and validating the system interface using the Android application. This phase is based on four key components and takes approximately four weeks. Further details regarding *empirical validation* is discussed in section 6.2.

6.1.1 Overview of the System

The basic infrastructure required for our classroom feedback system is similar to the blended classroom systems reported in [12, 176]. Students use headphones to hear the live stream voice of a teacher. The design of our system follows a client-server architecture. It needs a classroom server and a collection of teacher and student client devices, including a communication medium such as WiFi. The classroom server securely stores student data and performs complex calculations such as analytical computations for generating real-time feedback (see Figure 6.2 part C).

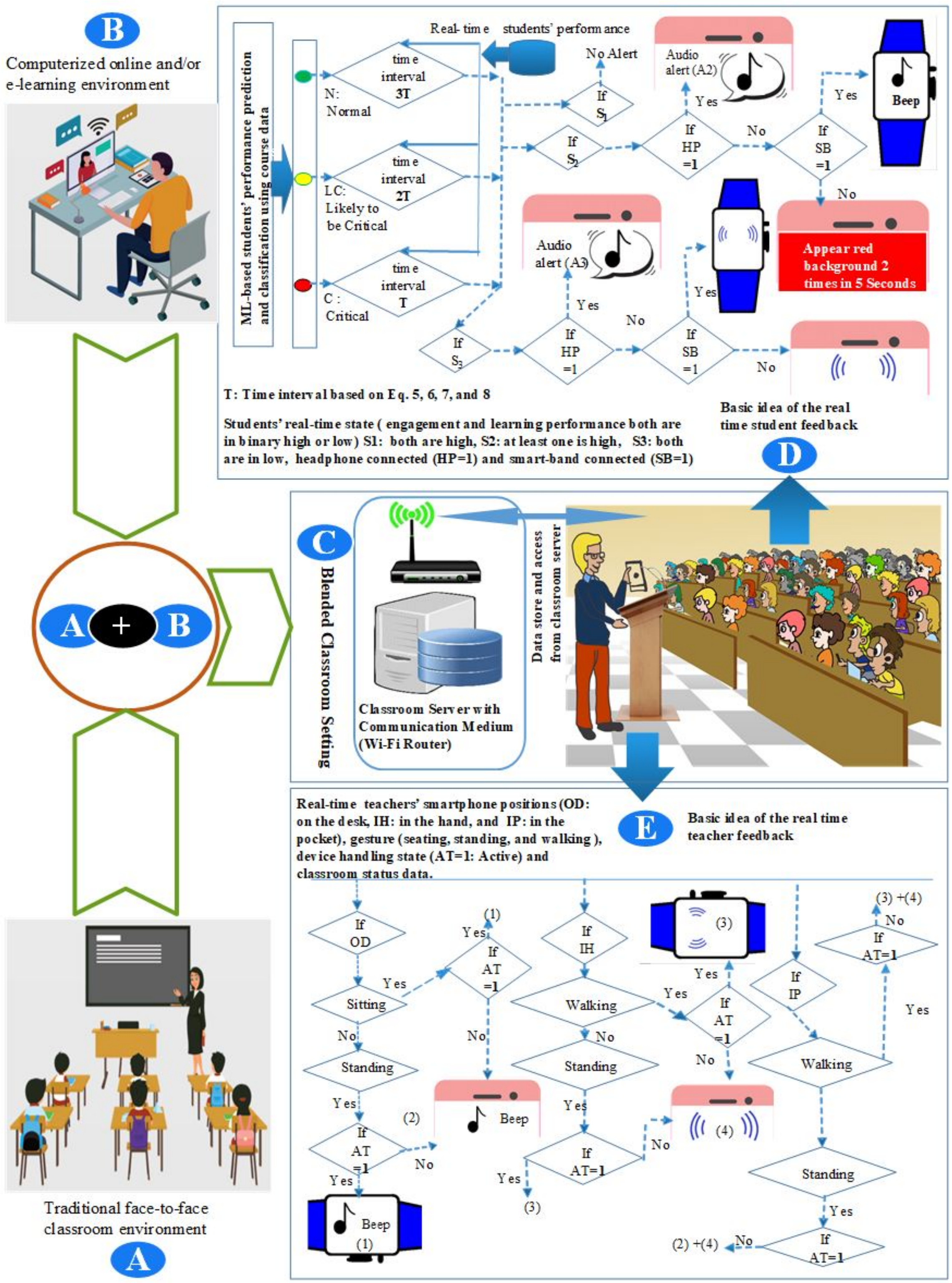


Figure 6.2: Illustration of the notification systems: basic logic flow for optimization of multimodal notifications for students during lecture session (top right) and the idea of teacher's notification (bottom right).

Basic System Settings

The system allows sending feedback to students and teachers on two types of devices using classroom server and WiFi. A smartphone or tablet serves as the main device, whereas a smart watch/bracelet is kept as an additional secondary device. The system dynamically chooses primary or secondary devices to give feedback to in-class students and teachers. The basic logic flow for real-time feedback are shown in Figure 6.2 (part D and E). For students, the audio alert is sent only when the headphone is connected (see in Figure 6.2, part D top right) which ensures no disturbance to other students present in the class. We assume student engagement and learning performance states are available using the concepts of state identification reported in the work [3]. We also assume that it is possible to identify posture of the teachers as well as the position of their smart phones. It could be done using the sensors of their smart phones. Sensors like accelerometer, gyroscope, magnetometer, and touch sensors are common embedded sensors in a smartphone [184] and it is possible to detect the postures such as sitting, standing, walking, and running using smartphones' accelerometer sensor [200]. In our work, we assume three types of postures of the teachers namely, 1) sitting, 2) standing, and 3) walking, which can be detected using smartphone sensor while delivering lecture. The combination of posture and smartphone positions (i.e., on the desk, in hand, and in the pocket) help to select the real-time feedback modality for teacher (see Figure 6.2 part E).

Predictive Models for Student Performance

We use ML model for predicting and classifying students academic performance. Academic performances help in real-time decision-making and notifying in-class students. Our system uses three state classifications of students. The states are similar to the real-time classroom visualizer reported in [1]. The states are C, LC, and N. We refer some students as being of the N-type because they consistently do well and require little assistance. For certain students i.e., LC-types the intervention might be desirable. Students who need special attention may also exist, known as C-types. These states help to ensure that students get the optimum number of notifications to reduce fatigue.

The proposed predictive models used suitable classifiers to predict students' performance during the ongoing course [30]. Our approach helped to conform the predictive model building using suitable classifiers and available assessment data. We use seven state-of-the-art machine learning models (based on our survey discussed in chapter 3) to verify and build the student state predictive model. The predictive models are *SVM, NB, DT, ANN, kNN, RF, LR* [30, 201].

We use course assessment metrics (such as attendance, class test performance, and quizzes) to predict students' performance and classify them based on performances during the ongoing course. It helps to conform predictive model building using the convenient classifiers. The system predicts states using data from the students assessments for the course. To validate our ML-based prediction and classification model, we collected data from five experienced teachers from the Department of Computer Science and Engineering, IIT Guwahati. Data are collected for 4 laboratory and 8 theory courses for 1358 students. The model was trained and evaluated using the cross-validation approach. We used a train and test split, in which we trained our model on 80% of our data and kept the remaining 20% to test it (e.g., 80:20 split). In this study, we have used data from one theory course and one laboratory course.

$$Precision = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \tag{6.1}$$

$$Recall = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \tag{6.2}$$

$$F1Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{6.3}$$

$$Accuracy = \frac{\text{True Positive} + \text{True Negative}}{\text{True Positive} + \text{False Positive} + \text{False Negative}} \tag{6.4}$$

We used precision, recall, F1 score, and accuracy [202, 203, 204] to adapt ML algorithms for the predictive model. Precision is used to calculate the probability of a positive test result (see Eq. 6.1). High precision values imply the input data are accurately classified students with a high probability. Precision indicates the fraction of students who performed poorly in classroom. Our goal is to predict students' performance with high precision value. High precision indicates that the probability of accurately predicting the states related to students' performance is high. For example, if the state of the student is N, the model with a high precision has a greater chance of predicting the state as N type. The number of true positives of the actual course predicted by the model is measured by recall [205, 206]. We

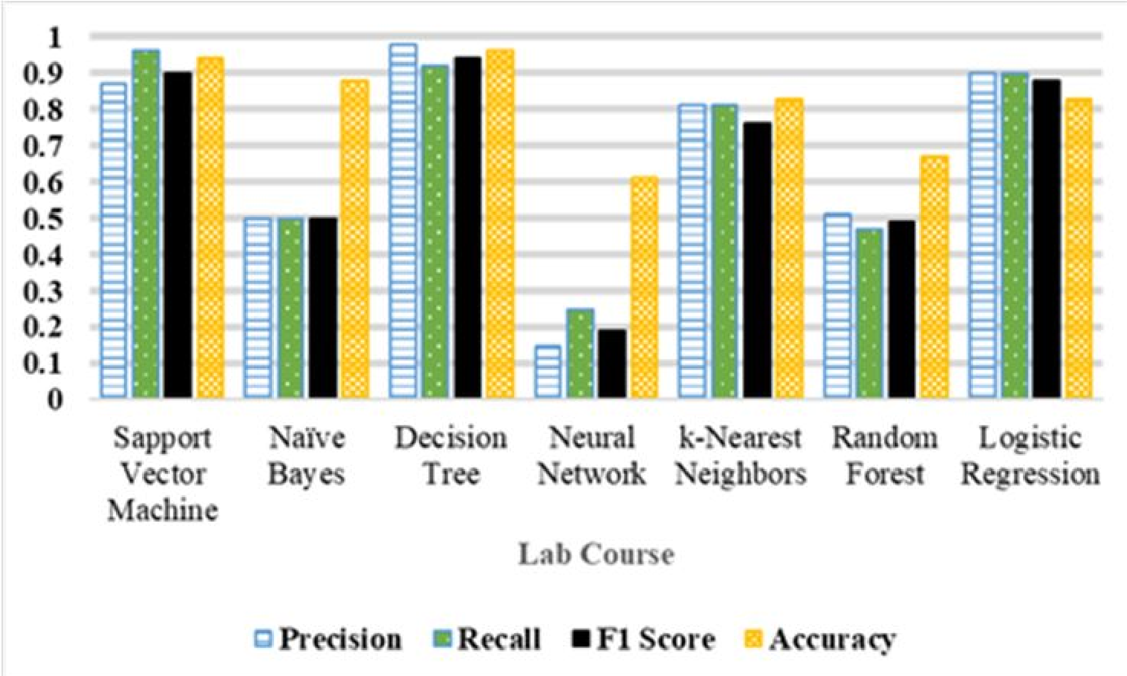


Figure 6.3: Performance of machine learning algorithms in predicting students' academic performance for Lab course.

calculated the recall measure (see Eq. 6.2), the percentage of all students in the data set who are critical and were correctly classified by the classifiers. The present study model's recall (see Eq. 6.3) can be deduced as higher recall scores indicate better classifier performance. Recall and precision work together to determine how effectively an algorithm performs. We used the accuracy metrics to evaluate state classification model accuracy and applicability (see Eq. 6.4). Fig. 6.3 & 6.4 show the comparative results of our studies for proposing an ML-based predictive model and classification. In our study, we have observed that the highest 88-100 percent accuracy is attained by *decision trees, support vector machines, and naive bayes* classifiers. We have used decision tree based model to achieve high-performance prediction and classification of students' states.

Interval Time (T) for Real-time Feedback

Our real-time in-class feedback of students depend on the dynamic time interval T. The interval T will decide the frequencies of the feedback. For example if we provide 12 maximum feedback in an hour class to a student. In this case the value of T should be 5 minutes. The design goal of the automated and dynamically suggested interval T is to enhance

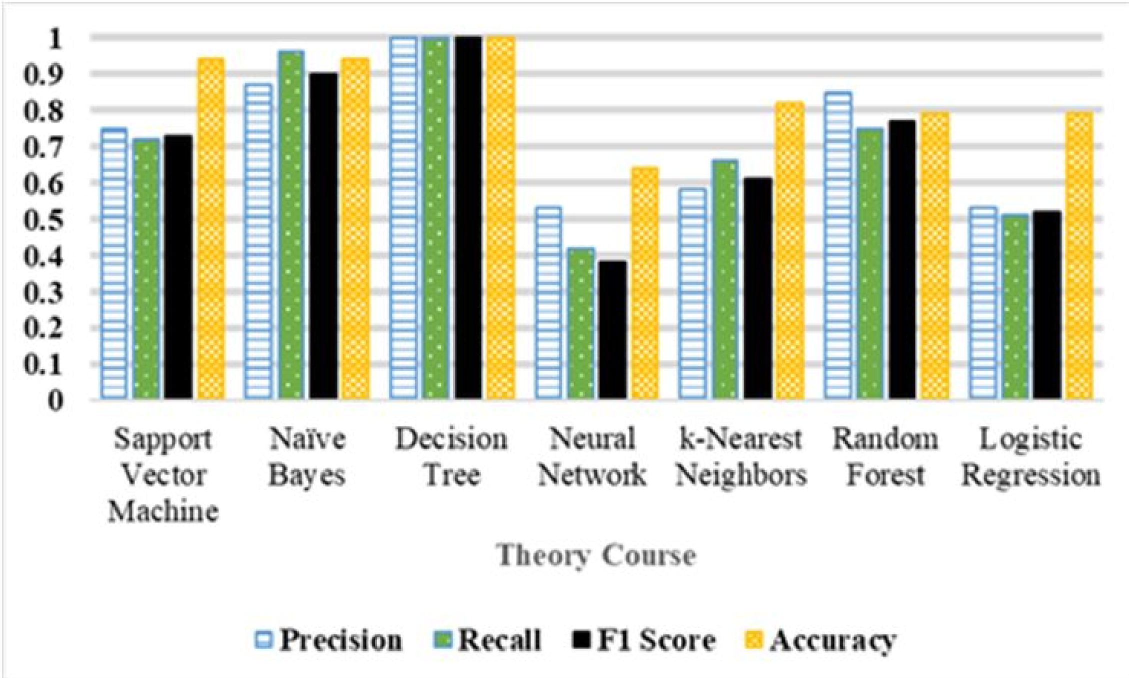


Figure 6.4: Performance of machine learning algorithms in predicting students' academic performance for Theory course.

the in-class teaching-learning experience and minimize feedback fatigue. It is required to optimize the number of feedback to students during lecture delivery, thereby minimizing fatigue. Minimizing fatigue helps to improve system usage satisfaction. Earlier research has revealed that any teaching method that brings satisfaction to the students or teacher is likely to result in better learning experiences and outcomes as well [1].

We use the feedback score (F_S) and instantaneous score (I_S) to calculate T for real-time alerts. Initially, the interval time T_0 is fixed (i.e., 5 minutes) for the start of the class. However, teachers can change the time T_0 based on their classroom handling experience. It may also vary automatically depending on the time T based on equations (see Eq. 6.5 to 6.8); hence it is called a dynamic time interval.

Eq. 6.5 helps to calculate the feedback score (F_S). It is the average number of feedback per interval up to the last class, i.e., $(n-1)$. We assume classes are as $\{1, 2, 3..., n-1, n\}$, where n indicates the n$^{\text{th}}$ live class. The numerator of Eq. 6.5 calculates the total number of feedback up to (n-1) class. The denominator calculates total feedback intervals up to (n-1) class. Here, we consider a live class having $\{1, 2, 3..., i-1, i\}$ feedback intervals. Eq. 6.6 helps to calculate instantaneous score (I_S) for the n$^{\text{th}}$ live class up to the expired interval. It is the average number of feedback per interval up to the ith interval. We compute feedback factor (F_{fact}) using Eq. 6.7. It helps to increase or decrease the next feedback interval T_{i+1}. The number of feedbacks theoretically increases for smaller values of T. However, frequent feedbacks may lead to high fatigue in the students. In contrast, increasing the value of T reduces number of feedback counts. Our intuition behind these dynamic time intervals is to reduce the number of feedback when most of the students are engaged by increasing the interval T, during lecture. The value T_{i+1} helps to get the next feedback interval for nth live class (see Eq. 6.8). The T_i is the ith feedback interval and the (F_{fact}) calculated using Eq. 6.7 from the feedback statistics. The (F_{fact}) helps to increase the interval T_{i+1} if the value is positive; otherwise, it decreases the interval.

In every expiry of the interval T system will check for a students states e.g., C, LC, and N in the classroom (see Figure 6.2., part D) and send feedback.

$$\text{Feedback score } (F_S) = \frac{\text{Total no. of feedbacks sent since last class}}{\text{Total no. of feedback intervals expired since last class}} \tag{6.5}$$

$$\text{Instantaneous score } (I_S) = \frac{\text{Total no. of feedbacks sent in a live class}}{\text{Total feedback intervals expired in a live class}} \tag{6.6}$$

$$\text{Feedback factor } (F_{fact}) = \frac{F_S - I_S}{F_S} \tag{6.7}$$

$$T_{i+1} = T_i \times (1 + F_{fact}) \tag{6.8}$$

The visual feedbacks are potentially better for understanding real-time circumstances. The feedback containing visual content with information are termed as multimodal feedback which are important for perceiving the content in real-time [106]. In our system, each feedback has a time interval, feedback content, and feedback modality. The audio and visual combinations in modalities can impact user acceptability and usability [109]. Therefore, we consider four feedback modalities in designing the system. The audio alert has gained popularity in different fields, such as hospital [107], atomic power plants [108], aviation [109], and vehicle drivers [110] applications. The visual colors, shapes, and text alerts improve the user experience using smartphones and wearables [106].

We use text, audio, vibration, and screen flash modalities for building Android application for the proposed system. Figure 6.2 (part D & E) shows detail logic flow for scheduling feedback with modalities. Student real-time feedback depends on three parameters, the predicted state of the student, real-time engagement, and availability of the peripheral

ALGORITHM 9: Students' Feedback Scheduling

Input: All available states of students (N:normal, LC: likely to be critical, C:critical) including real time engagement, learning performances, and smartphone sensory data.

Output: Send feedback for the students whom it is aplicable.

```
/* Organize and reformat the data to request and generate the feedback during class.
   */
for Each start of the class session do
    for Every registred student in the course do
        processCoursePerformanceData()
        deviceType=smartphone
        F_M=selectFeedbackModality()
        F_C=mapFeedbackContent()
        if Login flag true AND F_M is not empty AND F_C is not empty. then
            scheduleFeedback()
for Each expairy of the time interval do
    for Every student in the classroom do
        processRealTimePerformanceState()
        selectPeripheralDevice()
        F_M=selectFeedbackModality()
        F_C=mapFeedbackContent()
        if F_M is not empty AND F_C is not empty. then
            scheduleFeedback()
for At the end of the class do
    for Every student in the classroom do
        processCoursePerformanceData()
        processFutureData()
        deviceType=smartphone
        F_M=selectFeedbackModality()
        F_C=mapFeedbackContent()
        if F_M is not empty AND F_C is not empty. then
            scheduleFeedback()
```

devices (headphones and smart band). For critical state students, it checks real-time state based on that send audio and vibration feedback. Similarly, for S2 state student system provide screen flash and beep for faster effect on feedback. Similarly, for teachers' real-time feedback, it depends on smartphone position, teachers' device handling data, and classroom students' performance status. There are two modalities of real-time feedback vibration and beep sound. When teachers' primary device is in use, the system will select a secondary device, i.e., a smart band. Based on teachers' posture, modality of the feedback will be decided. In the worst case, the system will select sound alert to user as it may disturb students.

Algorithms for Scheduling Feedback

The design of the system collectively presents real-time scheduling algorithms for in-class feedback to improve teaching-learning activity. The overall algorithm consists of four princi-

ALGORITHM 10: Teacher's Feedback Scheduling

```
Input: All available states of students (N:normal, LC: likely to be critical, C:critical) including real time
       engagement, learning performances, and smartphone sensory data.
Output: Send feedback to teacher when it is aplicable.
   /* Organize and reformat the data to request and generate the feedback during class.   */
1  for Each start of the class session do
2      for Every registred student in the course do
3          processCoursePerformanceData()
4          deviceType=smartphone
5          F_M=selectFeedbackModality()
6          F_C=mapFeedbackContent()
7          if Teachers' login flag true AND F_M is not empty AND F_C is not empty. then
8              scheduleFeedback()
9  for Each time interval during class do
10     for Every student in the classroom do
11         processRealTimePerformanceState()
12         selectPeripheralDevice()
13         selectSmartphonePosition()
14         processTeachersGesture()
15         F_M=selectFeedbackModality()
16         F_C=mapFeedbackContent()
17         if F_M is not empty AND F_C is not empty. then
18             scheduleFeedback()
19 for At the end of the session do
20     for Every student in the classroom do
21         processCoursePerformanceData()
22         processFutureCourseData()
23         deviceType=smartphone
24         F_M=selectFeedbackModality()
25         F_C=mapFeedbackContent()
26         if F_M is not empty AND F_C is not empty. then
27             scheduleFeedback()
```

pal concepts: selection of feedback content, device to be used (peripheral or smartphone), modalities (e.g., text, audio, screen flash, and vibration), and intelligent feedback timing (e.g., when to schedule feedback). Algorithm 9 is proposed to handle students' feedback. Algorithm 10 is used for scheduling and managing feedback to teachers.

Algorithm 9, describes how our system generates the list of feedback for students. This list of feedback is based on three timings. The timings are at the start, during, and end of the class lecture. "Start" means when students join the class by logging in to the in-class server using available WiFi. The procedure processAcademicPerformanc checks the performance, and if any abnormal issues are found for a particular student or list of students, it initiates sending feedback (see line 3). The selectFeedbackModality procedure helps to select the feedback modality. The mapFeedbackContent procedure processes and maps suitable feedback content for a particular student. The scheduleFeedback procedure schedules feedback based on modality and content. “During” class means giving feedback to students in a live class. The procedure processRealTimeState checks an individual student’s real-time state in a live class. If abnormal states are identified, generate requests for feedback. The logic flow, device selection, choice of the modality, and feedback content are shown in Figure 6.2 part D (the list of procedures involved is mentioned in lines 9 to 16). “End” of the class means when students log out from the in-class server and are about to leave the class. The system generates the list of feedback for students based on the procedure mentioned in lines 17 to 28. The partitioning of the feedback into three timings, i.e., the start, during, and end of the class, reduces feedback fatigue during lectures.

Like Algorithm 9, Algorithm 10 describes the TeachersFeedbackSheduling procedure. At the start of the class, the list of the procedures shown in lines 1 to 8 helps to generate feedback based on students’ overall course performance. The functionality and the logic flow of the list of procedures for real-time feedback (see lines 9 to 18) are shown in Figure 6.2 part E. At the end of the class, when teachers are about to leave by logging out from the in-class server, our system generates feedback based on the statistics of students’ course performances and future course data. The list of all procedures is given in lines 19 to 27.

The algorithms are intended to give real-time feedback to students and teachers about their performance and engagement in the teaching-learning process. Most importantly, when and how to generate and provide feedback to minimize the cognitive burden on comprehension of performance status and state. Our design supports deploying novel techniques and technologies in blended classroom settings such that neither users nor the flow of the teaching-learning is disturbed. We went through many studies to finalize validate the design. Details of our empirical studies are discussed in the next section.

6.2 Empirical Validation

The empirical validation have two phases. They are testing system functionality and validating system usability. The functionality testing is based on in lab study, prototype design, and pilot study. We carried out six user studies to validate and confirm the system design. A total of 87 participants (34 teachers and 53 students) participated in our empirical validation. All the participants are PG or research scholars in the Department of Computer Science and Engineering, IIT Guwahati, Assam, India.

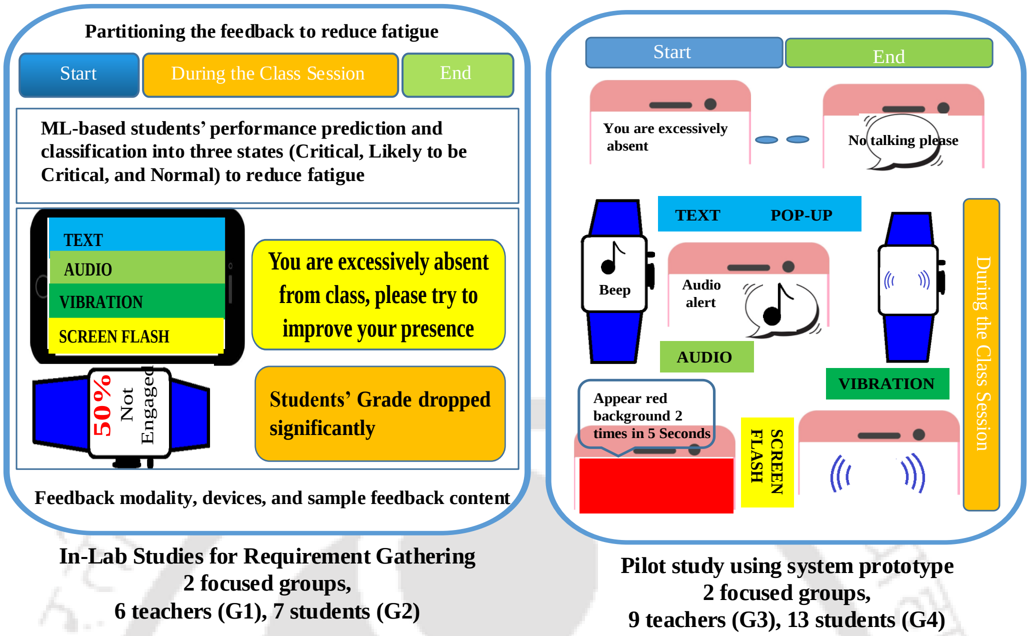


Figure 6.5: Illustrates basic idea and system prototype for in-Lab and pilot study.

6.2.1 In-Lab Studies for Requirement Gathering

In the initial stage, we conducted two focused group studies. The G1 consists of six teachers (four male and two female), and in G2, seven students (five male and two female). All teachers have experience of about 5 to 14 years of teaching and delivering a lecture in a hall containing more than 100 students. Notably, G1 teachers have at least seven years of smartphone and a year of smart band usage experience. The teachers' age group was 30 to 42 years (an average of 33.67 years). The G2 students have at least five years of interface design experience, seven years of smartphone usage experience, and more than one year of smart band usage experience. The students' age group was 24-33, with an average of 28.43 years.

Procedure

We performed a semi-structured interview process. We start with a short introduction, and signing the consent form takes about 10 to 15 minutes, including addressing their queries about the system's functions. All the discussion audios are recorded to improve system design and post-analysis of the feedback. We use a color-printed copy on all different systems features (see Figure 6.5 left part).

We requested users to provide their opinion on a printed copy of the questionnaires in a 5-Point Likert Scale about the system functions, including additional advice (see Table 6.1). We collect ratings for analysis and validation of functional requirements and their usefulness in real-time classroom use. Each participant spent about 40 to 50 minutes of their valuable time in completing the entire session.

Findings

The focus groups G1 and G2 studies show that the acceptance of smartphone and wearable technologies in classroom alerting and feedback is important. G1 users rated the system functions with more than 75% (9 out of 12) cases with mean ratings between 4.17 to 4.67 and remaining between 3.50 to 3.67 (see Table 6.1, 3rd column from the left). Also, for G2 participants, we received an issue where user mean ratings are below 4 (3.87) (see Table 6.1, 4th column from the left). All teachers and students were satisfied with the novel idea and technologies to utilize real-time in-class teaching-learning.

We have observed four main research challenges to answer based on teachers and students reported opinion. The actual user requirements are to answer (a)-(d) for improving the acceptability of the system are mentioned in Table 6.2 left column. We also received some valuable inside about the system functions to answer. The design should support the *correlation of students' academic performance aspects, learner-centric (instead of teacher-centric), and provide user-friendly platforms.*

6.2.2 Prototype Design and Pilot Study

We addressed the research challenges (a)-(d) in designing the system interface to make it usable in a real-time blended classroom based on user feedback. The details are given in Table 6.2 right two columns. We conducted a paper-based mockup session (see Figure 6.5 right part) to evaluate the system design based on the above goals, user preferences, and requirements identified in the initial studies. Each participant took between 50 and 55 minutes to finish the whole session.

Table 6.1: Statements for functionality and feature testing for users perception about the proposed system interface based on user rating.

Teachers' perception statements about the system	Students' perceptions statements about the system	In-lab study		Pilot study	
		T (G1) (n=6)	S (G2) (n=7)	T (G3) (n=9)	S (G4) (n=13)
		$X\pm$ SD	$X\pm$ SD	$X\pm$ SD	$X\pm$ SD
Do you feel partitioning alert and awareness contents into three intervals (starting, during, and end) of the class session reduce teachers' alert fatigue?	Do you feel partitioning alert and awareness contents into three intervals (starting, during, and end) of the class session reduce students' alert fatigue?	4.67 ± 0.52	4.43 ± 0.53	4.78 ± 0.44	4.23 ± 0.93
Do you think the alert and awareness contents to teachers using a combination of smartphone and smart-band during the lecture delivery reduce teachers' alert fatigue instead of using smartphones only?	Do you think the alert and awareness contents to students using a combination of smartphone and smart-band during the lecture delivery reduce alert fatigue instead of using smartphones only?	4.67 ± 0.52	4.43 ± 1.13	4.00 ± 0.50	4.31 ± 0.95
Do you think the alert and awareness to teachers using a combination of smartphone and smart-band during the lecture delivery reduces users' technological distractions in lecture flow instead of using a smartphone only?	Do you think the alert and awareness to students using a combination of smartphone and smart-band during the lecture delivery reduces users' technological distractions in learning flow instead of using a smartphone only?	3.67 ± 1.03	4.14 ± 1.07	4.22 ± 0.44	4.08 ± 1.04
What is your opinion about students' characterization based on their performance metric, and delaying alert for relatively good students will reduce alert fatigue?	What is your opinion about students' characterization based on their performance metric, and delaying alert for relatively good students will reduce alert fatigue?	3.50 ±0.84	4.29 ±0.49	4.00 ±0.87	4.08 ±0.86
What is your opinion concerning the delaying alert T to 3T time interval that will reduce alert fatigue for relatively good students?	What is your opinion concerning the delaying alert T to 3T time interval that will reduce alert fatigue for relatively good students?	4.17 ±0.75	3.86 ±1.07	4.33 ±0.71	4.38 ±0.65
What is your view about the characterization of students based on their performance metric and delaying alert for relatively good students will optimize technological destruction?	What is your view about the characterization of students based on their performance metric and delaying alert for relatively good students will optimize technological destruction?	3.50 ±0.84	4.14 ±0.69	4.11 ±0.78	4.31 ±0.63
What is your view concerning the delaying alert T to 3T time interval that will reduce technological destruction for relatively good students?	What is your view concerning the delaying alert T to 3T time interval that will reduce technological destruction for relatively good students?	4.33 ±0.52	4.29 ±0.76	4.11 ±0.60	4.38 ±0.51
What is your perception regarding the delaying alert time interval T=fixed (maybe 5 minutes) to reduce real-time alert fatigue?	What is your perception regarding the delaying alert time interval T=fixed (5 minutes) to reduce real-time alert fatigue?	4.67 ±0.52	4.00 ±0.82	3.78 ±1.09	3.62 ±0.96
The various functions for notification are well integrated for real-time large classroom use.	The various functions for notification are well integrated for real-time large classroom use.	4.33 ±0.52	4.14 ±1.07	4.22 ±0.67	4.38 ±0.50
The various functions for notification are necessary for real-time large classroom use.	The various functions for notification are necessary for real-time large classroom use.	4.33 ±0.52	4.43 ±0.53	4.33 ±0.50	4.15 ±0.80
I would like to use this notification in my classroom teaching.	I would like to receive this alert and awareness content in my classroom for further assistance and better learning.	4.67 ±0.52	4.00 ±0.82	4.56 ±0.53	4.23 ±0.83
I feel the system will help in customizing the lecture.	I feel the system will help to avoid future difficulties.	4.67 ±0.52	4.14 ±0.90	4.56 ±0.53	4.07 ±0.95
Additionally, if needed some functionalities or features in system design please mention those.					

Table 6.2: Details of the system requirements based on in-Lab studies, our solutions, and overall remarks to address the requirements.

Requirements based on in-Lab studies	Our Solutions	Over all remarks
(a) what will be the appropriate notification timing to intervene in regulating the teachers' and students' behaviors to improve in-class engagement and interaction?	We propose the design consideration of dynamic timing to get back students and teachers into teaching-learning with minimizing the interruption.	The system automatically determines actual timing for teachers using interaction data and embedded sensory data (e.g., screen lock) of smartphone for the teacher. The timing of students' notification depends on the classification of students states to reduce fatigue (see in Figure 6.2 top part). Also, proposed timing (start, during, and end of the class session) of notification will reduce human user cognitive load in their busy schedule.
(b) what will be the suitable frequency of notification for avoiding students fatigue?	The classification of students into performance state is to optimize the number of notification. The system will vary time intervals for relatively poor performer to good students i.e., critical student to normal for real-time notification (see in Figure 6.2 top part). The T, 2T, and 3T are time in minute use to reduce the number of notification for relatively good students (here *normal* students).	The real time notification count is not constant. The teacher can change the T value according to their classroom handling experience. However, our initial notification both from teacher and student confirm that notification count 12 - 4 is acceptable. If we decrease the T value, theoretically, it will increase the problem of fatigue. When we increase the T, then still, there is a chance of missing the positive effect of the real-time notification.
(c) how to select the teacher's primary and peripheral devices to avoid technology distractions?	The system selects primary or secondary devices dynamically in real-time notification to teachers. Our design selects a device to notify the teacher in their periphery of attention to minimizing lecture flow disturbance. The dynamic device selection ensures that the teacher's primary task, the lecture delivery not hampered (see in Figure 6.2 bottom part).	We use two types of input data to select the teacher's peripheral device. The input data are primary device screen on/off system information and tap/touch stroke sensory data. When the primary device screen is not locked, the system checks the touch stock. While the primary device screen is not locked for the period and a touch stroke detected notification is sent to the peripheral. The touch stock detection within the time means the teacher is using the primary device for teaching-learning. In this case selection of peripheral devices can reduce the teacher's disturbance.
(d) what are the notification contents and the modalities of alerts and awareness to render on users' devices to minimize classroom distractions?	We group classroom notification, keeping in mind the suitable contents and modalities. The data gathering module captures and stores course performance data. The data is formatted and reorganized as per the timing, content, and modalities (see Figure 6.2) to schedule notification by the system.	The prediction module can provide real-time information about the students real-time state. The states and the update about new classroom activities will initiate new notification generation requests. We consider text, audio, vibration, pop-up, and screen flash notification modalities.

Results and Observations

In the prototype design and pilot study, we invited two groups of participants. Six men and three women comprise the nine teachers in group three (G3). The 13-student group is the other G4 (nine males and four females). The teachers' age group was within 29-40 years, with an average age of 33 years, teaching experience of 6.56 years, and smartphone usage experience of 7.89 years. The students' age group was 25-34 years, with an average age of 28.77 years, interface design experience of 6.69 years, and smartphone usage of 7.39 years.

We asked both teachers and students to rate and comment on a printed copy of the

Table 6.3: Open-ended statements for users (teachers and students) perceptions about the system for qualitative analysis.

Item No.	Teachers' open-ended questionnaire (TOQ)	Item No.	Students' open-ended questionnaire (SOQ)
TOQ1	Do you agree that the 16 alert and awareness mentioned above are useful for classroom teaching?	SOQ1	Do you agree that the 16 Alert and awareness mentioned above are useful for classroom teaching learning?
TOQ2	Do you agree that the 16 alert and awareness timing are useful for classroom teaching?	SOQ2	Do you agree that the 16 alert and awareness timing are useful for classroom teaching learning?
TOQ3	Do you agree that the 16 alert and awareness and their timing are helpful to enhance your teaching?	SOQ3	Do you agree that the 16 alert and awareness including their timing are helpful to enhance your learning?
TOQ4	Do you agree that the three real-time (during class) peripheral alert is useful for classroom teaching?	SOQ4	Do you agree that the four intervals t to 3t time interval (fail category students to outstanding students) varies for real-time alert is useful for classroom teaching learning?
TOQ5	Do you agree that the three real-time (during class) peripheral alert will reduce class flow disturbance?	SOQ5	Do you agree that the four intervals t to 3t time interval (fail category students to outstanding students) varies for real-time alert will reduce class flow disturbance?
TOQ6	Do you agree that the three real-time (during class) peripheral alert will reduce alert fatigue?	SOQ6	Do you agree that the four intervals t to 4t time interval (fail category students to outstanding students) varies for real-time alert will reduce alert fatigue?
TOQ7	Do you agree that the alert messages are sufficient for real-time classroom use?	SOQ7	Do you agree that the time interval t=5 minute is sufficient for real-time alert to reduce alert fatigue?
		SOQ8	Do you agree that the alert and awareness messages are sufficient for real-time classroom use?
Additionally, if you want to add some functionalities or features in alert and awareness feedback design, please mention those:			

questionnaire. The functions described in Table 6.1 are tested using the same questionnaires. We also use the sample notification content to get the user a rating on a 5-point Likert scale based on timing, importance, and modalities. Furthermore, we also include the seven yes/no construct items for teachers (TOQ: teachers open-ended question) and eight for student participants (SOQ: students open-ended question), including the opinion mentioned in the table (see Table 6.3). We collected ratings for analysis and validation of functional requirements and their usefulness using yes/no with explicit remarks for real-time classroom use.

G3 users rated the system functions in more than 75% (9 out of 12) cases, with mean ratings ranging from 4.17 to 4.67 and remaining between 3.50 to 3.67 (see Table 6.1, 3rd column from the left). Also, for G4 participants, we received an issue where user mean ratings are below 4 (3.87) (see Table 6.1, 4^{th} column from the left). All teachers and students were satisfied with the novel idea and technology for real-time in-class teaching and learning.

Most of the participants agreed on the system design features in the TOQ statements.

In TOQ6, 100% (9 out of 9) users reported that the intelligent peripheral alert features would reduce alert fatigue. In TOQ2, 88.89% (8 out of 9) users agreed that the list of alert and awareness features is helpful for in-class use. For other remaining feature sets (TOQ statements), 80.67% users decided that the list of features is also crucial for real-time classroom use.

Most of the participants agreed on the system design features on SOQ statements. In SOQ1 to SOQ4 and SOQ6, 92.30% (12 out of 13) users decided that the intelligent features are helpful in classroom teaching and learning. In SOQ5, 84.62% (11 out of 13) users agreed that the time gap t to 3t alert scheme is helpful for in-class use. For other reaming feature sets (SOQ7 and SOQ8 statements), 61.54% of users agreed that the list of alert and awareness features is also essential.

The quantitative analysis consists of the 16 notification contents in which the participants' level of satisfaction with the construct statement is shown in the table (see Table 6.4). The mean rating for teachers varies from a maximum of 4.67 to a minimum of 3.58, with an average mean of 4.22. These average mean values indicate that all the teachers' participants strongly agree that the contents are necessary. Similarly, the mean rating for students varies from a maximum of 4.39 to a minimum of 3.54, with an average mean of 4.08. These average mean values indicate that all student participants strongly agree that the contents are necessary and suitable for real-time use.

However, some users (3 teachers and three students) mentioned that they "need a clearer idea about the alert scheduling, "need real-time state identification", "need clear motivation of using notification modalities", and "how to manage dynamic notification time interval?

6.2.3 User Studies for Validating System Usability

System usability should be another evaluation metric. It should ideally be high to ensure that the users find the system acceptable and are eager to use it. The final and most crucial evaluation should be on the system's effect on the learning outcome. However, it is not easy to quantify because it necessitates a thorough study over a long period of time (at least one semester). We conducted controlled experiments to assess the efficacy and usability of our suggested design.

Table 6.4: The summary of the alert and awareness timings and contents with modalities for proposed system interface with user rating and interpretation (IP).

Content Delivery Timing	Alert and awareness Content Example for Teacher	Alert and awareness Content Example for Students	Teacher' Rating				Students' Ratings			
			Experienced		Normal		Experienced		Normal	
			$\bar{X}\pm$SD	Interp-retation	$\bar{X}\pm$SD	IP	$\bar{X}\pm$SD	IP	$\bar{X}\pm$SD	IP
Staring of Class Session	More than 50% of students performed below average in last (quizzes/exam)	You failed in the last test (quizzes/exam), please try to improve	4.33 ± 0.62	Agree	4.30 ± 0.62	Agree	4.08 ± 0.73	Agree	4.25 ± 0.66	Agree
	Number of students failed in last test out of total students	You are excessively absent from class, please try to improve your presence	4.33 ± 0.62	Agree	4.22 ± 0.66	Agree	3.92 ± 0.82	Agree	4.25 ± 0.62	Agree
	List of students excessively absent from class	You missed last surprise assessment for your absence	4.75 ± 0.43	Agree	4.70 ± 0.55	Strongly Agree	4.69 ± 0.60	Strongly Agree	4.58 ± 0.66	Agree
	List of students missed last assessment for absence	You submitted incomplete assignment, please try to avoid it	4.33 ± 0.85	Agree	4.26 ± 0.90	Agree	4.31 ± 0.82	Agree	4.15 ± 0.96	Agree
	List of students submitted incomplete assignment	Very poor performance in assignments/homework, please try to improve it	4.42 ± 0.64	Agree	4.48 ± 0.58	Agree	4.38 ± 0.62	Agree	4.48 ± 0.50	Agree
	List of students' poor performance on writing assignments	Build confidence in completing assignments	4.00 ± 0.71	Agree	3.91 ± 0.65	Agree	4.00 ± 0.68	Agree	3.85 ± 0.76	Agree
	List of students faces difficulty in completing assignments	You are constantly late in a class, please try to avoid it	4.50 ± 0.65	Agree	4.34 ± 0.63	Agree	4.38 ± 0.62	Agree	4.30 ± 0.68	Agree
	List of students lacking basic communicational skills	Please improve your basic communicational skills	4.50 ± 0.50	Agree	4.52 ± 0.58	Agree	4.54 ± 0.63	Agree	4.53 ± 0.55	Agree
During the Class Session	Percentage of students not engaged in learning	You are not engaged in learning, please be with class lecture	4.58 ± 0.64	Agree	4.65 ± 0.63	Strongly Agree	4.69 ± 0.61	Strongly Agree	4.55 ± 0.71	Agree
	Percentage of students not under standing	You are not under standing the concepts, please try to be active	4.58 ± 0.64	Agree	4.65 ± 0.56	Strongly Agree	4.54 ± 0.63	Agree	4.58 ± 0.67	Agree
	Percentage of students absent from class work or discussion	Your participation in class work/discussion is very poor, please involve	4.67 ± 0.47	Strongly Agree	4.65 ± 0.47	Strongly Agree	4.46 ± 0.84	Agree	4.58 ± 0.49	Strongly Agree
	50% students not engaged in learning (Peripheral)	No talking please	4.58 ± 0.64	Agree	4.52 ± 0.65	Agree	4.62 ± 0.49	Strongly Agree	4.55 ± 0.63	Agree
	40% students not under standing (Peripheral)	Performed below average in quizzes/exams	4.50 ± 0.50	Agree	4.43 ± 0.50	Agree	4.46 ± 0.50	Agree	4.53 ± 0.50	Strongly Agree
	60% students absent from class work or discussion (Peripheral)	Your Grade dropped significantly be careful	4.50 ± 0.50	Agree	4.57 ± 0.50	Strongly Agree	4.54 ± 0.63	Agree	4.48 ± 0.59	Agree
At the End of the Class Session	Students' Grade dropped significantly	Your absence rate is higher than an average students test	4.50 ± 0.64	Agree	4.39 ± 0.82	Agree	4.54 ± 0.75	Agree	4.23 ± 0.85	Agree
	Higher absence rate than an average in quizzes/class test/surprise test	Next assignment or home-work submission dead line	4.50 ± 0.64	Agree	4.48 ± 0.65	Agree	4.54 ± 0.50	Strongly Agree	4.43 ± 0.63	Agree

Setup Used

We built a final Android application (app) for the system discussed in section 6.1 to do the usability study. The predicted states and the related performance are the inputs for the app. The program processes these inputs, using the algorithms to build the intelligent

Table 6.5: Modified SUS-based questionnaire used to collect usability ratings on our intelligent feedback system.

Modified SUS-based statements
I think that I would like to use this intelligent feedback system frequently.
I found the intelligent feedback system unnecessarily complex.
I thought the system interfaces was easy to use.
I think that I would need the support of a technical person to be able to use this system.
I found the various functions in this system were well-integrated.
I thought there was too much inconsistency in this feedback system.
I would imagine that most people would learn to use this system interfaces very quickly.
I found the feedback system very cumbersome to use.
I felt very confident using the feedback system.
I needed to learn a lot of things before I could get going with this intelligent system.

feedback system. We assigned the states to the students at random to conduct the usability study. The visual representation of the intelligent feedback system is shown in Figure 6.2.

Participants

In the final phase, the teachers group (G5, 14 male and 5 female) and in the students' group (G6, 26 males and 7 females) were participated. The teachers' age group was 28-37 years, with an average age of 32.56 years, teaching experience 3.2 years. The students' age group was 21-28 years, with an average age of 25.36 years.

Experimental Method

Each participant was taught the intelligent feedback app, it takes roughly fifteen minutes before data collection. During this phase, the participants received instructions on how to use the app and some practice assignments.

The post-session ratings of the system by each participant were also collected to complete this study. We used SUS based questionnaire for testing usability of the proposed system [188]. Table 6.5 shows the modified SUS questionnaire. We used five-point Likert scale with the following ratings: 1-Strongly disagree, 2-disagree, 3-neutral: neither agree nor disagree, 4-agree, and 5-strongly agree. However, to determine the possible impact of our system on the learning outcomes, we conducted surveys to confirm it. We also validated the functions and the importance of the feedback content. The same questionnaire (see Table 6.3) and the contents (see Table 6.4) were used to gather user ratings similar to initial study (see section 4.1).

To create a background for discussion, we demonstrated all different schemes for both smartphones and peripheral notification (see Figure 6.2). These visual representations of notification are chosen based on diverse feature sets, including timing, content, type, and visual appeal. Each visual representation of notification content delivered to participants device (see Table 6.4). The opinion gathering, rating collection, and verbal feedback has taken approximately an hour in the context of real-time in-class notification design (see Figure 6.2) similar to the pilot study.

6.3 Results and Analysis

During this study, we collected both quantitative and qualitative data. The post-session SUS ratings, rating on system functions, and rating on feedback contentment are the quantitative data. The qualitative data included observational data for each participant, which the author manually documented during the study. Furthermore, such data includes comments received from participants about the usability of the system and infers whether the system will improve the learning outcomes.

We gathered and analyzed participant ratings on the SUS questionnaire to assess user satisfaction with the proposed system, as shown in Figure 6.6. As seen in Figure 6.6, the minimum SUS score is 60 for students and 65 for teacher participants. A score of 60 means "ok" based on benchmarks [2]. The average SUS score for the teacher is approximately 76. The average SUS score for the students is around 74. The score is relatively high, and according to the benchmark, the score is good. For four of the 11 participants, the score ranges between 80 and 87.5, with an average of approximately 83.13. The score shows that user satisfaction is high while using an intelligent feedback system. In other words, teachers and students are more likely to consider the intelligent feedback system usable and appropriate for classroom use. Similar to the initial study, high acceptance of the system functions and the useful contents of the feedback (see results in Table 6.1 & 6.4 of 5^{th} and 6^{th} columns from the left). Based on the teachers' rating the minimum mean rating on features is 3.86 which is not bad but acceptable (see Table 6.1, 5^{th} column from the left). All other ratings for teachers are more than five out of five which means users highly accept the system's features. For students, the mean ratings are between 3.6 to 4.38 which are almost similar to the teachers' ratings (see Table 6.1, last column from the left). Therefore, the end-users have expressed appreciation for the proposed system's intelligent features. In

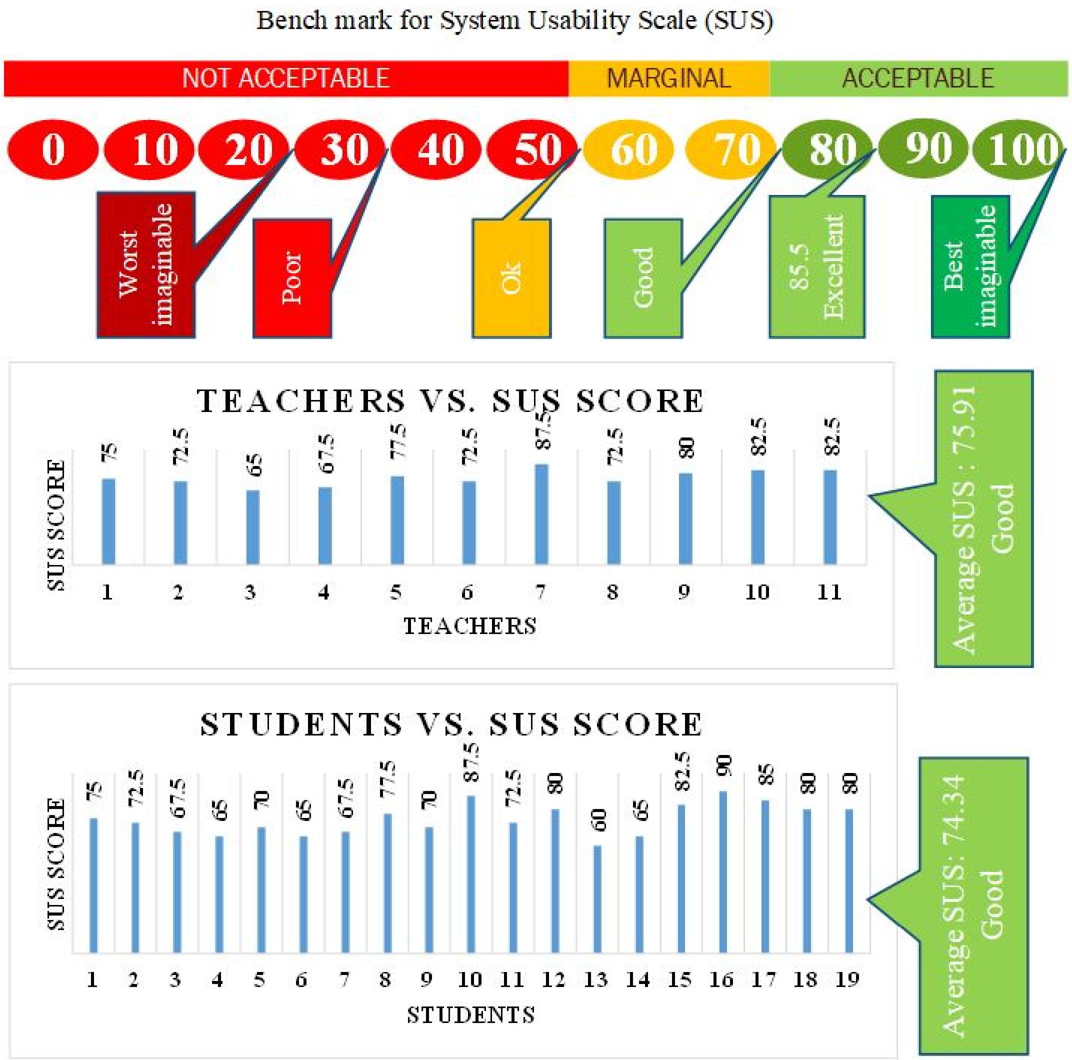


Figure 6.6: The details of SUS ratings' bench mark [2] and ratings obtained in our usability study.

the case of feedback content, the minimum mean ratings for teachers and students are 3.91 and 3.85 (see Table 6.4, last two columns from the left). Similarly, the maximum ratings are 4.70 and 4.58. The results show that most of the feedback content is important for the intelligent real-time feedback system.

In addition to the quantitative analysis stated above, we asked the teacher and student participants about their general impression of the system, including its utility in the classroom. Most of the teachers (seven out of eleven) considered the system easy to learn and remember due to the intuitive design strategies (modality and peripheral interactions). Yet, some of them (two out of eleven) thought the intelligent feedback system would take some time to get used to the system. They were all happy with the intelligent feedback system design and agreed that the system's feedback would be highly beneficial in developing effective intervention methods for improved learning outcomes. Fifteen out of nineteen students said that the assistance should be immediate for students during the class (the most crucial) and delayed for the other category of feedback (start and end of the class). The delayed feedback should take place after the class to avoid wasting more teaching-learning time on intervention. Participants advised that the system should include a feature called "modality of feedback" that may help in real-time assistance. Two participants believed that feedback should be postponed until after the lesson. Participants also emphasized the necessity of having the facility to recall all feedback cases for action.

6.4 Discussion

This section discusses the key design goals and the user validation of the proposed system for use in a real-time blended classroom. The system design is the outcome of a three-step iterative UCD method (see Figure 6.1). It uses students' course performance state prediction with classification, dynamic feedback timing, and choice of peripheral devices selection with multimodal feedback content to make the system design unique and intelligent.

The identification of student academic performance states is challenging for real-time use [1]. Extensive research have been done to predict states in this direction [30]. We utilized the ML-based prediction and classification model in our system design to avoid student feedback fatigue for real-time learning environment. We got an accuracy of approximately 96%-100% using an academic dataset and suggested valuable predictors by *decision trees* classifiers (see Figure 6.3 & 6.4). This system helps teachers and students get timely feedback on their learning performance and engagement to improve learning outcomes.

The design goal behind the dynamic time interval is to optimize the number of feedback. Our system increased the interval, i.e., T to 3T, when students were in a critical state to a normal state (see Figure 6.2., part D). The dynamic timing T (see Eq. 6.4) is calculated using the feedback factor (see Eq. 6.3), depending on the course feedback statistics. Eq. 6.1 and Eq. 6.2 help to calculate T based on historical and live class feedback statistics. Eq. 6.1 calculates the number of feedback messages sent per interval based on the historic feedback statistics. Eq. 6.2 computes the instantaneous score based on feedback scheduled for the present interval in the live class. The idea of using feedback statistics is unique and novel. Based on our user study, participants agreed that delaying feedback time intervals for comparatively good students helped to reduce real-time feedback fatigue (see Table 6.1).

Majority of the experienced teachers agreed that the design principle of peripheral feedback to teachers reduces lecture flow disturbances (see Table 6.1). There are chances of disturbing the teaching-learning flow by giving feedback on users' smartphones. Therefore, only smartphone feedback is non-persistent. The persistence of feedback based on real-time users' peripheral device selection and the modality helps to improve usability and prevent fatigue. The participants found that the proposed intelligent feedback system is useful for real-time in-class teaching and learning (see Table 6.1 and Figure 6.6). Interestingly, 100% of the 100% teachers agreed that the real-time peripheral feedback should reduce user fatigue, and over 90% of the teachers agreed that the *intelligent feedback* system could reduce lecture flow disturbance. Furthermore, students and teachers appreciated the idea of classifying students' performances to reduce the number of real-time in-class feedback. Students, however, appreciated the *intelligent notification* system design, as evidenced by their positive comments and high usability ratings (see Table 6.1 and Figure 6.6).

All the participants (teachers and students) appreciated the system features. We get higher ratings from students and teachers in three key system design directions: usefulness, usability, and reduced disturbance in lecture flow including feedback fatigue (see Table 6.1).

We also compared the experienced (G1 and G2) and normal users' (G3 and G4) ratings while using the system in the context of classroom use. We took the mean ratings reported by the experienced and normal participants (not experienced). We performed t-Test on the users perception ratings for the intelligent feedback interface. Table 6.6 shows the details of the research hypothesis including null and alternative hypothesis. In our research hypothesis testing, we compared the ratings with the mean ratings for the two groups. The difference between the mean observed for normal teachers (G3) ratings (M=4.47, SD=0.172, n=16) and the experienced (G1) ratings (M=4.44, SD=0.204, n=16) was found to be statistically not significant [t(30)=2.045, p=0.336]. Similarly, for experienced students (G2) and normal students (G4) ratings (M=4.41, SD=0.172, n=16) and the experienced ratings (M=4.39, SD=0.204, n=16) were found to be statistically not significant [t(30)=2.042, p=0.384]. Therefore, the utility and usefulness of the system design are valuable for all categories of users. Similarly, experienced students' mean ratings vary between 4.69 and 3.92. The users also agreed that the 12 feedback contents were useful. On the other hand, users strongly agreed that the other four feedback contents are also extremely useful. The regular student users' mean scores ranged between 4.58 and 3.85 (agreed with 14 contents are useful and remaining two are extremely useful). These mean values and interpretations indicate that all teachers and students agreed that the contents were useful and necessary (see Table 6.1).

Table 6.6: Details of the research hypothesis including null and alternative hypothesis to perform t-Test for users' perception on uses of feedback interface.

User	Hypothesis (null/alternative)	P-value	Significance difference
Teacher	**Null hypothesis** H_1 : The mean ratings reported by the experienced teachers is the same as the mean ratings reported by the normal teachers (not experienced). **Alternative hypothesis** H_1 : The mean ratings reported by the experienced teachers is different as the mean ratings reported by the normal teachers (not experienced).	p=0.336	statistically not significant, therefore, null hypothesis holds and the alternative hypothesis is rejected
Student	**Null hypothesis** H_2 : The mean ratings reported by the experienced students is the same as the mean ratings reported by the normal students (not experienced). **Alternative hypothesis** H_2 : The mean ratings reported by the experienced students is different as the mean ratings reported by the normal students (not experienced).	p=0.384	statistically not significant, therefore, null hypothesis holds and the alternative hypothesis is rejected

The statistical test results (see Table 6.6) indicate that the design of the proposed system does not significantly affect the experienced user's rating in the classroom setting for both teacher and student reported in Table 6.1. These statistical test results and feedback analysis indicate high user satisfaction with the proposed system design. Earlier studies have shown that any teaching tool that brings satisfaction to the teachers and students is likely to result in better learning outcomes [1].

We performed the user study with a relatively small number of students (n=52) and teachers (n=30), so generalizability to the broader academic population of real-time classroom usage is restricted. Albert et al. (2013) [207] reported that system testing with a small group could identify the majority of usability issues. Moreover, testing with a few experienced users (at least five) for interactive system studies is usually recommended [207].

Therefore, we hope that generalizability will not be an issue in designing the novel *intelligent notification* system. Furthermore, the ubiquitous portable devices, such as smartphones and wearable peripherals, utilized for in-class feedback simplify the users' ability to comprehend and understand.

According to the SUS ratings (see Figure 6.6), usability is also high, indicating higher satisfaction with the system. The participant response also suggests that the students and teachers will likely benefit from the system. Past research has shown that any teaching strategy that makes students and teachers happy will also provide higher learning outcomes [1]. The high SUS score and the feedback from the end user indirectly indicate that the proposed system is likely to produce higher learning outcomes through timely feedback, even though we did not directly assess the impact of the proposed *intelligent real-time feedback* system on the overall learning outcome.

6.5 Summary of the Chapter

This chapter has reported peripheral notification design to facilitate in-class teaching-learning and empirical validation of the system. We suggested the three predicted states. However, that might be challenging for universities, particularly those with small student records. We utilize the classification of three states [1] and peripheral selection in our real-time notification system to avoid alert fatigue in real-time face-to-face teaching-learning, which is novel and unique. Teachers and students confirm that the system is crucial for better learning outcomes. The idea is novel and valuable based on user feedback (see Table 6.1).

The results show that teacher and students participants preferred the system design (see Table 6.1). The user found the tool helpful for real-time classroom teaching-learning. All teacher participants agreed that multimodal peripheral feedback would reduce alert fatigue. Moreover, participants believe that one crucial design goal, lecture flow disturbance, can be optimized using users' peripheral selection. The teachers prefer characterizing and classifying students into performance states to optimize the number of alerts during the lecture. On the other hand, student participants also appreciated and gave positive comments on the tool's uses. Users also agreed that only smartphone alert content is non-persistent, as there are more chances of disturbing the teachers' lecture flow. The persistence of alerting based on the teacher's peripheral alert adds to improve usability and helps to ensure alert fatigue established through the empirical study.

We obtained positive comments from participants in three directions usefulness, reduced alert fatigue, and disturbance in lecture flow (see Table 6.1). Experience users advised that combining more explicit alerts and feedback contents would be more helpful.

The details of publications from this contribution are as follows.

Conferences

1. **Ujjwal Biswas** and Samit Bhattacharya, "Multimodal Peripheral Alert to Improve Teaching-Learning for Blended Classroom", ***In ICT Analysis and Applications: Proceedings of ICT4SD 2022***, pp. 703-713, Singapore: Springer Nature Singapore, [Chapter 6]

Journals

1. **Ujjwal Biswas** and Samit Bhattacharya, "ML-based Intelligent Real-time Feedback System for Blended Classroom", Springer, ***Education and Information Technologies (2023).*** https://link.springer.com/article/10.1007/s10639-023-11949-5 [Chapter 6]

Journal Under Review

1. **Ujjwal Biswas** and Samit Bhattacharya, "AI-enabled Multimodal Peripheral Notification System for Student-centered Blended Classroom", ***IEEE Transactions on Artificial Intelligence***, [Chapter 6]

Chapter 7

Conclusion and Future Work

We have proposed an intelligent real-time classroom visualization and notification system. We made three key contributions to achieve our ultimate goal to integrate both the visualizer and notification system into a blended classroom environment. We have identified important performance metrics to characterize students based on potential academic performance metrics for real-time classroom monitoring. We have performed a critical literature review and determined metrics with their categories using most recent terminology. This chapter concludes the thesis with descriptions of incorporating classroom visualization techniques with peripheral notification for in-class use. The following section and subsections depict the summary of the thesis, along with a discussion on the limitations, and scope for future work.

7.1 Summary of the Thesis

The primary goal of our thesis work is to propose a real-time classroom monitoring and notification system for blended classroom settings. The system can automatically determine students' states and assist teachers in monitoring students in real time. Students' states in terms of learning progress are determined by their academic performance metrics. The real-time classroom monitoring necessitates the use of unique visualization techniques. We proposed four classroom visualization algorithms. Because existing classroom visualization methods did not appear to be easily adaptable in the current real-time classroom context,

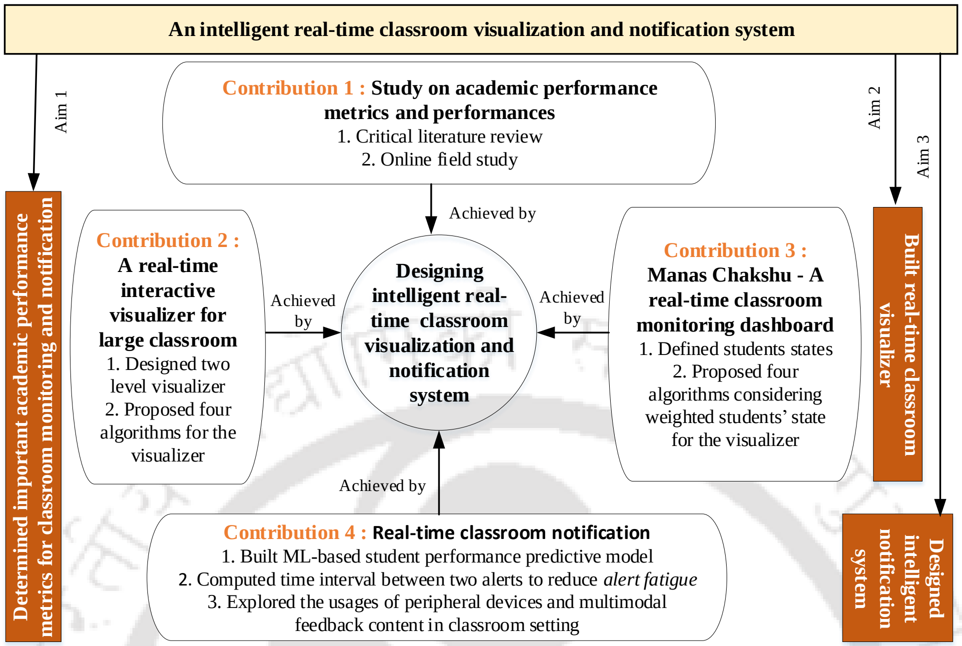


Figure 7.1: Summary of the thesis with research aims.

we created four new algorithms. The first three algorithms help to render the overview of the present classroom performance status. The fourth algorithm shows individual students' learning performances and their detailed states. We have further enhanced the real-time classroom visualization techniques to make the visualizer usable. The modified techniques help to optimize screen-area usage, provide a more refined determination of critical students, and an improved classroom status awareness scheme. Finally, we designed the notification system to improve real-time teaching and leaning process in a blended classroom.

This research explores the commonly available peripheral devices (smartphones, smart bands, and headphones) for real-time classroom monitoring and notification. The summary of the thesis including research aims are shown in Figure 7.1. The figure depicts each contribution and how the aims of the thesis are achieved to enhance the learning outcomes in a blended classroom.

7.1.1 Study on academic performance metrics and performances

This research determines *academic performance metrics*, *frequently used metrics*, *relative importance* and ML models to predict student performances based on the critical literature review and field study. Additionally, we test the applicability and usage of academic metrics to predict academic performance.

We observe that the prior approaches use various *academic performance metrics* without covering the teachers' actual recorded data and their opinions. This study identifies an optimized number of *academic performance metrics* termed as *frequently used metrics*. We reported the state-of-the-art *academic performance metrics*, *frequently used metrics* and *relative importance* to link with the metrics chosen by teachers through the critical literature survey and the field study. The field study covers large geographical locations and diverse populations to find the *frequently used metrics*. The *relative importance* values and the confidence interval for the *frequently used metrics* help in showing the usage importance and their variations. The t-Test shows no significant differences in their *relative importance* values based on the various categories of HEIs with the overall *relative importance* of the *frequently used metrics*. Therefore, we hope that the suggested *relative importance* of the *frequently used metrics* can help to predict performances with higher accuracy in the higher education systems. The high-level tags for *frequently used metrics* and *relative importance* will help in choosing metrics to quantify student performance for intelligent tutoring systems in a blended learning environment. We observe seven ML models, namely, SVM, ANN, KNN, NB, DT, LR, and RF models are very important in predicting academic performances. However, DT, SVM, and NB models outperform in predicting academic performances using suggested academic metrics.

We expect our research will benefit many interdisciplinary researchers, intelligent tutoring systems, educational data mining, and learning analytics. Particularly, the broad familiarity of the *academic performance metrics* will help to choose suitable metrics and reuse findings in the ML models to predict academic performance routinely in a blended learning environment.

7.1.2 Real-time interactive visualizer for large classrooms

We presented the design and validation of an interactive visualizer for large classrooms. The visualizer is intended to aid the classroom instructors for more effective teaching. Moreover, the system is helpful for teachers since they may use smartphones or tablets that they may be carrying because it is also designed for relatively small displays. However, it may be noted that the design is generic, making it applicable for situations where the matrix-like 2D seating arrangement can be assumed. It is also to be noted that the algorithms of the visualizer are designed to take care of various human factors with the objective of increasing the system usability. Considering the given context, many non-trivial optimizations are also incorporated into the visualizer to make it efficient as well. The usability of the visualizer is ascertained through detailed empirical studies.

7.1.3 Manas Chakshu

In this research work, we presented the design and validation of a novel LA tool, the *Manas Chakshu*. It is designed to let teachers see their classroom status and how individual students in the class are doing at any given moment. The proposed visualizer achieved a significant improvement over existing classroom visualization techniques. The improvements concern the effective use of display screens, a more precise identification of students who are at risk, and an improved mechanism for keeping track of classroom conditions. Our studies (both theoretical and empirical) show that our proposed system significantly improves system performance without affecting usability.

7.1.4 Real-time notification system

This research presented the design of an *intelligent real-time feedback* system for in-class use. This system design addressed the challenges of managing suitable feedback timing, choice of feedback content, and feedback modality to optimize user fatigue. The peripheral device selection for the users helped to improve the system usability and to maintain lecture flow. The idea is unique and not addressed in the state-of-the-art techniques. Studies show that users are interested in using it regularly in real-time classrooms. Teachers agreed that the system would enhance teaching efficiency by timely knowing the difficulties of students in a classroom routinely. Teachers who participated in the studies believed that systematic student feedback would raise the standard of care in a real-time classroom. Positive student feedback demonstrates that our system can regularly help to correct the students when they know their performances. The higher SUS score also shows that users will get chances to rectify themselves when they know their weaknesses timely.

We hope the reported findings and *intelligent real-time feedback* design considerations will inspire learning technology researchers in digital feedback for classroom use. In addition, researchers will be encouraged to deal with research challenges and hurdles when designing the real-time feedback system.

7.2 Limitation

Despite its novelty and usability, there are a few concerns and limitations to our intelligent real-time classroom visualizer and notification system design. One primary concern is the need to define the concept of “state” and determine the key academic performance indicators that should be monitored and notified. We assume that feedback information is already available. Obtaining the data is, of course, difficult and is an emerging branch of research [3, 27]. A student’s state, such as engagement state might be considered as a performance state. A student’s attendance record can also be seen as a state (attending regularly, irregularly, mostly regularly and so on) [1]. The learning performance is another possibility for defining a state (advanced, intermediate, backlogged and so on). There are numerous additional potential “states” (e.g., level of understanding, level of classroom activity) [176, 177]. A student’s state can be defined as any one or a mix of these “possible states”. Although, there are a few efforts made in this area to obtain the students’ state information from their mobile usage behavior [3, 176], it is difficult to capture some of these states, such as the “mental states” [184]. The states, such as attendance and level of learning, are more easily captured (using scores in classroom tests). Our *intelligent visualizer and notification system* does not pay attention to the issues of capturing the mental state. However, this is not a limitation because the *intelligent visualizer and notification system* can be used with whatever state information is provided (for example, the state of attendance, engagement, and learning performances).

The limitation of our notification system is in determining the alert contents. Just by using the data from their mobile sensors, it is challenging to compute some of the alert contents, such as identifying students talking in a class and their level of comprehension of the concepts delivered in the classroom [184]. Some other contents are more straightforward to compute, such as the attendance, the quiz and the class test performances. Our notification system design is not focused to address these challenges. This is not a limitation though, as our system continues to utilize any feedback content that is available.

The other limitation is that we assumed a teacher's *posture, such as sitting, walking, and standing* as the available input to the system. Nowadays, it is possible to capture these *posture* using an accelerometer sensor embedded in a smartphone [200]. This sensor records acceleration data along the three axes (x, y, and z) at each sample instant. These sensory data help to identify the human posture such as sitting, standing, and walking. In a given time interval, the deviation of sensory values is less for standing and large for walking when compared with the sensory values recorded for sitting posture [200]. In our initial phase of the system design, we performed a pilot study and experienced a similar observation on posture identification. Therefore, it is possible to identify these postures to address this limitation.

7.3 Scope for Future Work

The contributions made in this thesis can be used to advance the field of blended learning environments. Our research has addressed various aspects and challenges of this domain. However, it is important to acknowledge that there is still ample room for further exploration and improvement. Moving forward, we propose several potential research directions that are worth pursuing. The following is a list of such future research directions:

1. In this thesis, we use predictive modeling for students' academic performances for the classroom notification system. However, predictive modeling of students' states can also be implemented for the classroom visualizer.

2. The proposed visualizer is implemented for commonly available rectangular 2D classroom sitting arrangement. This system can be adapted to work with other seating arrangements of the classroom. An updated system is required to check for the applicability of the system to visualize non-rectangular seating configurations as well (such as semicircular sitting arrangement).

3. In this thesis, we collected data from our Department of Computer Science and Engineering, IIT Guwahati, built the predictive models, tested them, and used DT model to predict students' performance states. Further research can be done to gather *frequently used metrics* and test the suitability of applying them with a focus on the relative importance of the metrics to predict the academic performances of students.

4. Our notification system assumed the teacher's *posture* for selecting modality of the real-time feedback to reduce lecture flow disturbances. There is a possibility to extend our research to identify and predict the *posture* of the teacher automatically and integrate it into our system to further reduce the real-time feedback fatigue.

5. Individual visualizer and notification modules that we presented can improve learning outcomes in blended classroom environments. However, it can be extended to work with an integrated visualization and notification module for in-class use.

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List of Publications

Publications from Thesis Work:

Journals

1. Samit Bhattacharya, Viral Bharat Shah, Krishna Kumar, and **Ujjwal Biswas**, "A real-time interactive visualizer for large classroom", ***ACM Transactions on Interactive Intelligent Systems (TiiS)***, 11, no. 1 (2021): 1-26, [Chapter 4]

2. Samit Bhattacharya, **Ujjwal Biswas**, Shubham Damkondwar, and Bhupender Yadav, "Real-time ICT-based Interactive Learning Analytics to Facilitate Blended Classrooms", ***Education and Information Technologies***, URL: https://doi.org/10.1007/s10639-023-12327-x [Chapter 5]

3. **Ujjwal Biswas** and Samit Bhattacharya, "ML-based Intelligent Real-time Feedback System for Blended Classroom", Springer, ***Education and Information Technologies (2023).*** https://link.springer.com/article/10.1007/s10639-023-11949-5 [Chapter 6]

Conferences

1. **Ujjwal Biswas** and Samit Bhattacharya, "Multimodal Peripheral Alert to Improve Teaching-Learning for Blended Classroom", ***In ICT Analysis and Applications: Proceedings of ICT4SD 2022***, pp. 703-713, Singapore: Springer Nature Singapore, [Chapter 6]

Journals Under Review

1. **Ujjwal Biswas** and Samit Bhattacharya, "Usage of Academic Metrics to Predict Student Performance in Blended Learning Environment", ***IEEE Transactions on Learning Technologies***, Revised and resubmitted [Chapter 3]

2. **Ujjwal Biswas** and Samit Bhattacharya, "AI-enabled predictive modeling of student performance using teacher choice of metrics", ***International Journal of Artificial Intelligence in Education (IJAIED)***, [Chapter 3]

3. **Ujjwal Biswas** and Samit Bhattacharya, "AI-enabled Multimodal Peripheral Notification System for Student-centered Blended Classroom", ***IEEE Transactions on Artificial Intelligence***, [Chapter 6]

Doctoral Committee

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Professor and Head of the Department
Department of Computer Science and Engineering
Indian Institute of Technology Guwahati

Research Advisor: Dr. Samit Bhattacharya
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Members: Prof. Manas Kamal Bhuyan
Professor
Department of Electronics and Electrical Engineering
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Vitae

Ujjwal Biswas joined the Ph.D. programme in the Department of Computer Science and Engineering at Indian Institute of Technology (IIT) Guwahati, India in July 2016. In IIT Guwahati, he was affiliated with the User-Centric Computing and Networking (UCNET) Lab of the Department of Computer Science and Engineering. He received his Master of Technology (M.Tech.) in the Department of Computer Science and Engineering from National Institute of Technical Teachers' Training and Research (NITTTR) Kolkata, India, in 2010 and graduated with a B.Tech. degree in Information Technology, from BPPIMT (under W.B.U.T) in 2006. Before joining his Ph.D., he worked as a software developer for about two years at the Govt. of West Bengal, WBAT, Bikash Bhawan, 3rd Floor, East Block, Salt Lake, Kolkata-700091, for support and the project, supervised by the National Informatics Center (NIC), India, Vidyut Bhawan Gr. Floor, Block DJ, Sector II, Salt Lake City, Kolkata. In addition, Mr. Biswas had about six years of teaching experience in three different colleges, including the Visiting Faculty of the Department of Computer Science and Engineering, National Institute of Technology (NIT) Durgapur. He qualified for UGC NET three times in Computer Science and Applications in 2012, 2013, and 2014. Also, qualified for West Bengal SET in Computer Science and Applications in 2015 and GATE 2008 with an all-India rank of 846. After graduation, he worked in the software industry for two years as a senior software faculty trainer for C, C++, Java, VB, advanced Java, and internal projects. His research interests include Human-computer interaction (HCI), Learning technology, Machine learning, Mobile HCI, and user-centric computing.

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Appendix

A

Appendix

A.1 Consent Form

The consent form used in the controlled experiments for my thesis is shown one by one in the figures. It is vital to notice that the precise name of the experiment differed between each study, although all the other fields on the form stayed the same. To ensure ethical data collection, participation in these trials was only permitted after receiving informed consent from both the subjects and the researchers involved, indicating their agreement to all of the terms mentioned in the consent form.

Request for Survey Response

MR. UJJWAL BISWAS <ujjwalbiswas@iitg.ac.in>

Tue 03-11-2020 18:04

To:pallavi.kiranfhu@kiit.ac.in <pallavi.kiranfhu@kiit.ac.in>

Respected Dr. Pallavi Kiran Madam,

GREETINGS OF THE DAY!

I hope you and your family are doing well and safe in this pandemic time.

I am Ujjwal Biswas, pursuing Doctoral Research in Computer Science and Engineering (CSE), Indian Institute of Technology Guwahati, under the supervision of Dr. Samit Bhattacharya. My research is to address the issues of a large classroom, particularly interested in devolving in-class student activity and performance monitoring systems to improve learning outcomes.

You may know, in a large classroom (more than 100 students), managing the class smoothly requires high-end effort (mental and physical). During a lecture, the challenging tasks are to understand students (e.g., visualize whether they understand the concepts), giving feedback, motivating, and warning to engage them in active participation in teaching-learning. To address these issues, we need an actual marking/grading scheme used by teachers in Higher Education Institutions (HEIs).

The objective of this research study is "to examine how a teacher uses different performance metrics used for classifying and finalizing final grade," especially IITs, IIITs, NITs, NITTTR, IISCs, IISERs, and other distinguished institutions all over India. It will help me to develop a generalized model for monitoring in a real-time classroom system.

In this interest, I am requesting you to kindly participate in this online research survey by sparing five (5) Minutes of your valuable time to fill up a set of questionnaires. Your kind reply and data will be helpful for my doctoral research work.

Figure A.1: Details for online survey request and consent.

We would be grateful if you could please forward/circulate the survey request to your community/faculty colleagues or close contacts.

To participate in my research survey, please click on the URL below:

https://docs.google.com/forms/d/e/1FAIpQLSfuluqrhyE-WwO0Vl2i64O0adwtJXzEAkWl4FfM1ywkHMiuhw/viewform?usp=sf_link

I assure you that all data will be used solely for my doctoral research to maintain anonymity and confidentiality.

If you have any additional queries or would like to get more information about the research, please contact me or visit our website, the link of which is given below.
https://www.iitg.ac.in/cseweb/uccn/

We are thankful for your wholehearted willingness and cooperation in participating and giving your valuable time.

Thanks and Regards'

Ujjwal Biswas
Research Scholar

Department of Computer Science & Engineering
Indian Institute of Technology Guwahati
Guwahati - 781039, Assam, India
B. Tech in Information Technology (2006) WBUT, B. P. Poddar Institute of Management And Technology
M. Tech in CSE (2010) NITTTR, Kolkata, West Bengal, under MHRD Govt. of India
UGC-NET- Computer Science and Applications-June (2012)
UGC-NET- Computer Science and Applications-December (2013)
UGC-NET- Computer Science and Applications-December (2014)
West Bengal-SET-Computer Science and Applications-December (2015)
Contact Number: 9435685177|9836822001
Email: ibiswas.ujjwal@gmail.com | ujjwalbiswas@iitg.ac.in
For more details, click on the link https://www.iitg.ac.in/cseweb/uccn/people.php

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Figure A.2: The URL and the details of the research and researcher.

Consent Form for Participation in a Research Study UCNET

Name of the research: *Students' interview for usefulness and effectiveness of the smart warning design for real-time large classroom use.*

Experiment(s) conducted at: *Indian Institute of Technology Guwahati, Assam, India.*

I, the undersigned, confirm that

1. I willingly agree to participate in the research study.
2. I understand that I can withdraw at any time without giving reasons and that I will not be penalized for withdrawing, nor will I be questioned on why I have withdrawn.
3. The use of the data in research, publications, sharing, and archiving has been explained to me.
4. I allow to record/capture video/audio/image while participating, and I understand that those can be used solely for research purposes, maintaining the anonymity.

I have read this consent form and have been allowed to ask questions. I, along with the Researcher, agree to sign with date in this informed consent form. I give my consent to participate in this study.

Participant:

SIKHA DEKA	Sikha Deka	28-12-2019
Name of Participant	Signature	Date

Researcher:

UJJWAL BISWAS	UBs	28/12/2019
Name of Researcher(s)	Signature	Date

Figure A.3: Details of the teachers' consent form for visualizer

Please answer all the questions, just put a tick mark on the best alternative

Name: TATHAGATA BAKSH ***Age:*** 32 ***(years) Gender:*** M ***Teaching Experience :*** 5 ½ ***(years)***

1 SUQ1. I think that I would like to use this visualizer frequently during class lecture
[1] Strongly Disagree [2] Disagree [3] Neutral (Neither agree nor disagree) [4] Agree [5] Strongly Agree

3 SUQ 2. I found the visualizer unnecessarily complex during class lecture
[1] Strongly Disagree [2] Disagree [3] Neutral (Neither agree nor disagree) [4] Agree [5] Strongly Agree

4 SUQ 3. I thought the visualizer was easy to use during class lecture
[1] Strongly Disagree [2] Disagree [3] Neutral (Neither agree nor disagree) [4] Agree [5] Strongly Agree

2 SUQ 4. I think that I would need the support of a technical person to be able to use this visualizer during class lecture
[1] Strongly Disagree [2] Disagree [3] Neutral (Neither agree nor disagree) [4] Agree [5] Strongly Agree

3 SUQ 5. I found the various functions in this visualizer were well integrated
[1] Strongly Disagree [2] Disagree [3] Neutral (Neither agree nor disagree) [4] Agree [5] Strongly Agree

3 SUQ 6. I thought there was too much inconsistency in this visualizer
[1] Strongly Disagree [2] Disagree [3] Neutral (Neither agree nor disagree) [4] Agree [5] Strongly Agree

4 SUQ 7. I would imagine that most people would learn to use this visualizer very quickly
[1] Strongly Disagree [2] Disagree [3] Neutral (Neither agree nor disagree) [4] Agree [5] Strongly Agree

3 SUQ 8. I found the visualizer very cumbersome to use during class lecture
[1] Strongly Disagree [2] Disagree [3] Neutral (Neither agree nor disagree) [4] Agree [5] Strongly Agree

4 SUQ 9. I felt very confident using the visualizer during class lecture
[1] Strongly Disagree [2] Disagree [3] Neutral (Neither agree nor disagree) [4] Agree [5] Strongly Agree

4 SUQ 10. I needed to learn a lot of things before I could get going with this visualizer during class lecture
[1] Strongly Disagree [2] Disagree [3] Neutral (Neither agree nor disagree) [4] Agree [5] Strongly Agree

4 TSQ 1. Overall, I am satisfied with how easy it is to use this visualizer during class lecture.
[1] Strongly Disagree [2] Disagree [3] Neutral (Neither agree nor disagree) [4] Agree [5] Strongly Agree

5 TSQ 2. It is simple to use this visualizer.
[1] Strongly Disagree [2] Disagree [3] Neutral (Neither agree nor disagree) [4] Agree [5] Strongly Agree

4 TSQ 3. I can effectively complete my work using this visualizer.
[1] Strongly Disagree [2] Disagree [3] Neutral (Neither agree nor disagree) [4] Agree [5] Strongly Agree

2 TSQ 4. I am able to complete my work quickly using this visualizer.
[1] Strongly Disagree [2] Disagree [3] Neutral (Neither agree nor disagree) [4] Agree [5] Strongly Agree

Figure A.4: Details of the teachers' consent form and user ratings for Manash Chakshu

UCNET

Consent Form for Data Collection in a Research Study

Name of the research: Smart *Warning System for Classroom Use*

Research Study at: *UCCN Lab, Department of CSE, IIT Guwahati, Guwahati, Assam, India*

We proposed "Smart Warning System" for the 21st century smart classroom system. The warning system is a real-time feedback-driven. The system will notify students when they are at risk, not engaged in learning, and not participating in real-time classroom discussions. The system will take care of the concern to minimize the fatigue and disturbances in lecture flow due to the warning. However, it always notifies the students of the attention and involvement level of the student during the lecture. The feedback warning/notification helps the students to evaluate themselves and motivate them to change his/her learning attitude towards engaging in the classroom teaching learning. We illustrate the basic idea of my Smart Warning System in the given figure (see Figure 1).

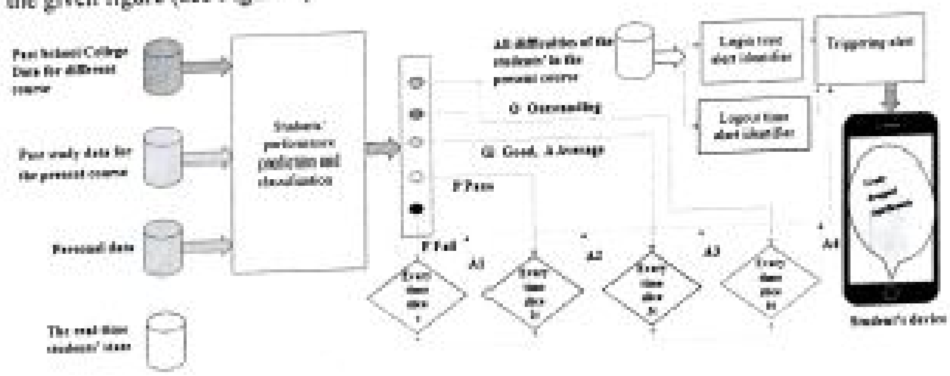


Figure 1: illustration of smart warning.

To confirm our design, we follow systematic steps to iterate and conduct a formative study. We begin by looking at all the possible past course data for CSE students in the various course (B.Tech, M.Tech. and Ph.D.) marks and final grade to identify which one would be useful to determine performance prediction and classification. Initially, we feed the data to different machine learning pre-built frameworks and determine the prediction accuracy for testing on the training data as well as new data. This state prediction should be fed back to the server, which accordingly schedules the warning/notifications.

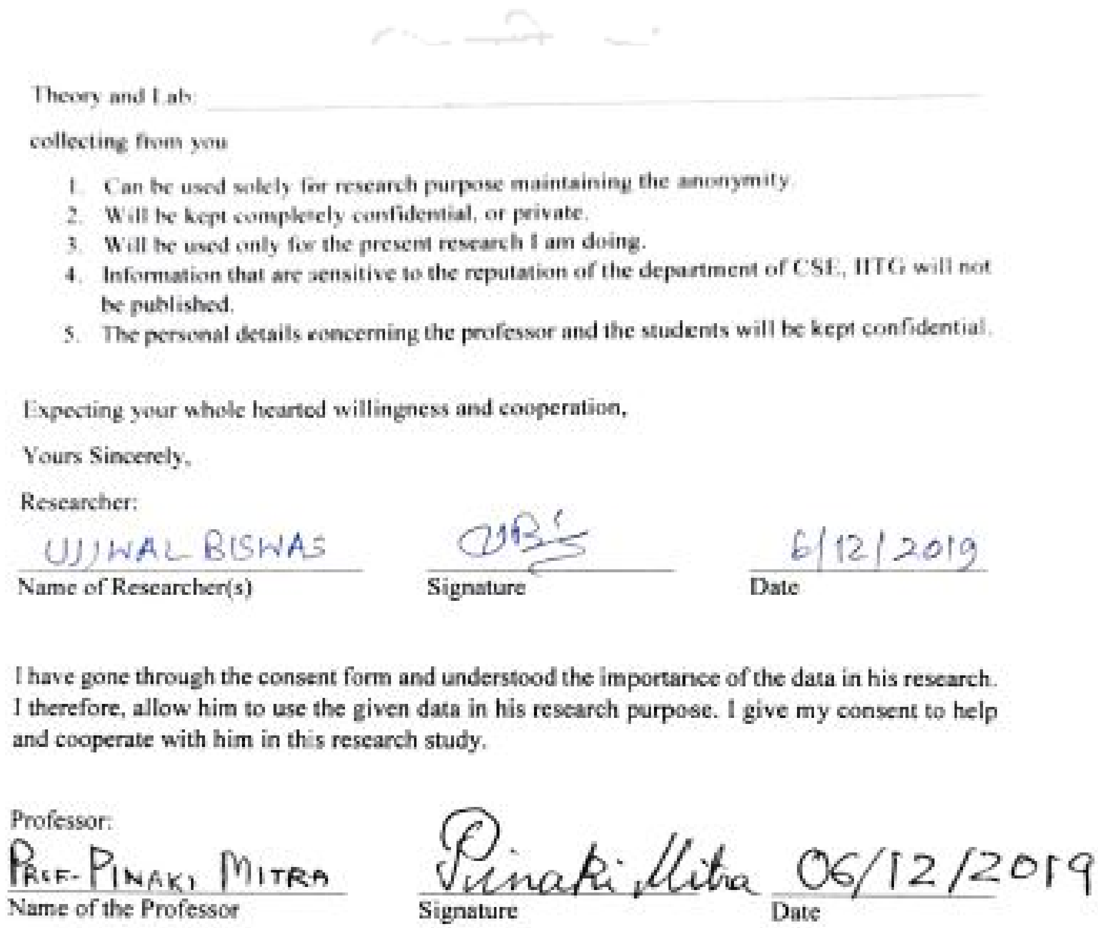
To do so, we need students' historical data in any course (theory, lab, and both). We are collecting students' marks, including final grade in the form of various components (attendance, quiz, assignment, project, mid sem., end sem., and so on).

I, the undersigned, confirm that the data for the following course/courses

Theory: CS461 Computer Graphics, CS350M Computer Systems

Lab: CS462 Computer Graphics Lab

Figure A.5: Request later for data collection for notification system



Theory and Lab: ______________________

collecting from you

1. Can be used solely for research purpose maintaining the anonymity.
2. Will be kept completely confidential, or private.
3. Will be used only for the present research I am doing.
4. Information that are sensitive to the reputation of the department of CSE, IITG will not be published.
5. The personal details concerning the professor and the students will be kept confidential.

Expecting your whole hearted willingness and cooperation,

Yours Sincerely,

Researcher:

UJJWAL BISWAS		6/12/2019
Name of Researcher(s)	Signature	Date

I have gone through the consent form and understood the importance of the data in his research. I therefore, allow him to use the given data in his research purpose. I give my consent to help and cooperate with him in this research study.

Professor:

PROF- PINAKI MITRA	Pinaki Mitra	06/12/2019
Name of the Professor	Signature	Date

Figure A.6: Details of the teachers' consent form for notification system