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Improving Didactic Teaching and Learning Outcomes: A Framework for Sensor based Approach in Education

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Learner monitoring is key to personalized education. Technology can be used extensively to capture and improve learning and didactic teaching outcomes. The paper examines pioneering application cases of sensors and management systems, learning, content, and awareness; for delivery, supervision, assessment, and social interaction; and to measure, monitor, and offer real-time learning outcomes. Educational intelligence, emerging as a prominent trend in student data and management systems, empowers data-driven decision-making, planning, and forecasting within the educational landscape. Our work provides a 3-step framework for inferential analysis on heterogeneous datasets.

Keywords: Sensing Technologies, Educational Intelligence, Business Analytics, Learning Management System, Teaching Effectiveness, Learning Outcomes.

1. Introduction

Learning Management Systems (LMS) or e-learning portals are virtual classroom spaces designed to facilitate online learning. It allows learners to understand and learn, reread, pause, or run through concepts as needed. Learners who consider online classes as edutainment often create new learning goals for themselves on a regular basis. In other words, an interactive online learning course usually deploy a variety of interaction and participation techniques to improve “inclusion, personalization, and intelligence” instead of reenacting an actual lecture or class, video capabilities. As e-learning makes greater inroads into the education system, the emergence of blended learning model, with live classes, doubt clearance sessions, and test-preparation routines is anticipated. The inherent openness of this medium presents obstacles in quality learning using online platforms. These necessities close supervision, analysis and assessment of learning outcomes over the tenure of a course to improve user interaction and interest towards any concept.

Learner monitoring is fundamental for providing customized learning experience. Common approaches for measuring and capturing learning outcomes usually employs a generic feedback pipeline, rating metrics or a standard questionnaire irrespective of the course. Feedback gives the practitioner and learner proof of current understanding and skill advancement.

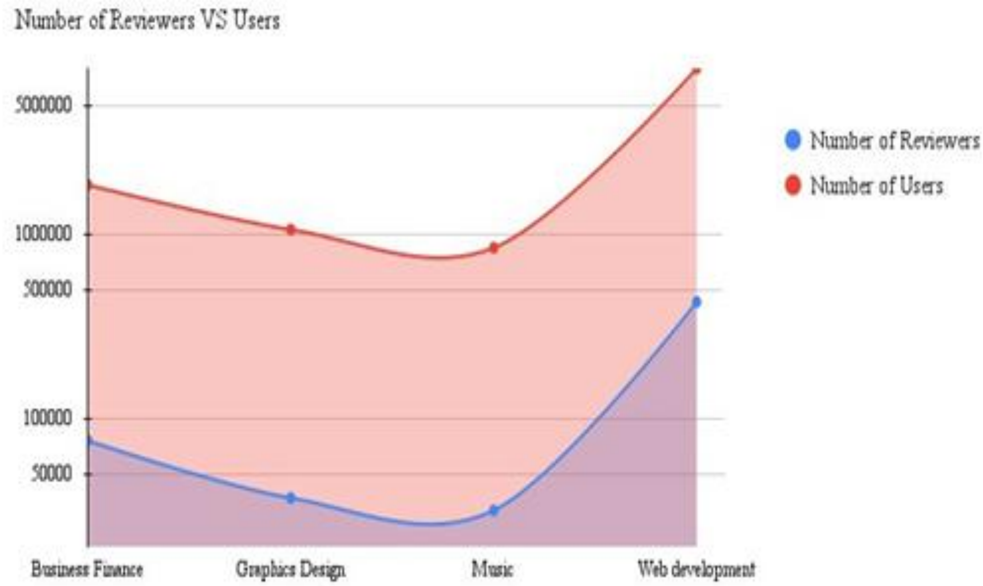

Fig.1.UdemyCourseDetails

The practitioner might choose the following phases to plan in the learning programme by knowing the learner’s progress and degree of achievement. Feedback can come in a variety of formats, including verbal, written, casual, formal, descriptive, and evaluative, as well as peer and self-assessed. One of the best teaching and learning techniques, feedback has a quick influence on student learning. Specific and continuous feedback is of high quality. The feedback from the expert to the student is most important: A practitioner’s useful criticism: They emphasize the caliber of the student’s procedures and/or work products, encourages and tests the learner to advance their knowledge and abilities does not reward, commend, or personalize recognizes the student’s accomplishments and points out any areas where they may have fallen short. Also, it has a direct connection to the success criteria and learning intents. Practitioners can receiveinsightful feedback regarding the level of learner understanding and their practice by care-fully observing how students complete learning exercises and listening to their responses to questions. This data facilitates introspection and offers methods for helping students advance their learning more successfully. In most e-learning systems, data incompleteness due to non-response to rating and reviews is much prevalent. Learner monitoring is fundamental for providing customized learning experience. Some of the most widely used methods for measuring and capturing learning.

Outcomes usually employ a generic feedback pipeline, rating metrics or a standard questionnaire irrespective of the course. In most e-learning systems, data incompleteness due to non-response to rating and reviews is much prevalent and the number of users who provide rating is much lesser than the total enrolled users (see Figure 7). It is noticeable that the reviewers and users vary significantly. This leads to data incompleteness and improper user judgement of a course of choice. It is noticeable that the reviewers and users vary significantly. This leads to data incompleteness and improper user judgement of a course of choice. There can be many reasons for this, some of which may include, (i) surveys not asking the right or clear questions (ii) questionnaires taking too much time to complete (iii) lack of standard metrics/basis of rating (iv)users not wanting to project themselves negatively. Hence, these methods prove inadequate or inaccurate in case of capturing the actual data needed for improvement.

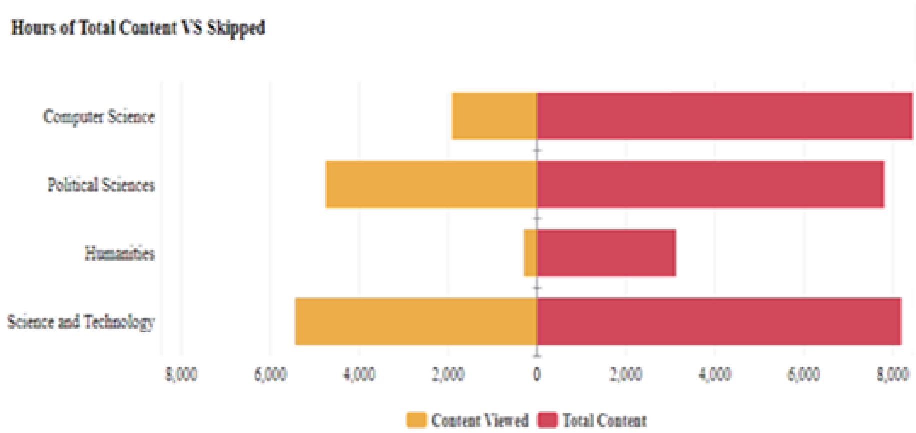

Fig.2.Harvard-coursecontentviewed

Formative assessment provides learners with information that allows them to improve their performance and learning. In our study we carefully analyzed how sensor-based platforms have been used to improve fact-based decision making, planning, and forecasting the learning, since formative assessment includes student assessment and high quality feedback which should be given as soon as possible after submission; be relevant to the task and the pre-defined assessment criteria; and should help the student to understand how to improve his/her work (not just highlighting strengths and weaknesses). However, the required effort for this type of assessment easily leads to a work overload for teachers forcing them to give merely summative instead of formative feedback. Implementing formative assessment with more human work force is currently not a feasible solution, therefore in this review we explored whether sensor-based platforms can contribute to it.

2. Classification of Framework

The paper uses three classification steps to enhance teaching and learning using sensors:

- Methods to Measure Learning Outcomes using Sensors.
- Analyzing teaching effectiveness using Educational Intelligence (three main aspects of EI are: analytical, creative, and practical.)
- The Integration of multiple sources in real-time data.
- Business Intelligence for process improvement or predictive analytics for student success interventions.

This is larger than any single departments or data source's collection of information. This is a comprehensive perspective of your data throughout the student lifecycle, which will not only improve the entire student experience but will also assist you in meeting your institutional goals.

In Figure 2, the Harvard - course content viewed and Total contents in the Harvard was explained The yellow legend explains the contents viewed by the user and the red represents the total content.

3. Methods To Measure Learning Outcomes

Close and consistent monitoring of user activity is crucial to provide adaptive critique to both learners and practitioners of education. It includes observing the attitude and subconscious behaviour of the learner towards the concept. This refers to the activities that the user is unaware of yet influences their behaviour and prospective learning decisions.

A. Sensing Systems

The definition of a sensor being used in this review is: “a physical or virtual object used for tracking, recording or measuring.” overview of the identified sensor s together with their measured properties and identified usages is shown in Appendix A. Sensing technology or sensors, in general, are used to obtain information by detecting the physical, chemical, or biological properties. Multi-sensory systems detect the feature quantity of a measuring item and transform it into a readable form, which is then shown on an instrument. Real-time monitoring and gathering of data is performed by these systems for control, analysis and reporting of anomaly. These systems are the most accurate resources for measuring delicate user interactions and beyond. For instance, [1] suggested the use of sensor eyewear to detect whether the learner looked at the keyboard and analyze the relationship between a learner’s eye gaze and touch-typing skills. This can be used in online examinations to prevent malpractice.

[2], [3]presented an interesting a pilot study conducted on a group of Devanagari script learners. The authors connected few sensors to an application that evaluated the mental efforts of the learners and correlated it with feedback from the trainers to measure it’s insightfulness. Similarly, [4],[5]extensively discussed about the introduction of affordable sensors in classroom environments as a way of improving the assessment in agile practices, while [6] developed a multimodal sensor-based application, Presentation Trainer (PT), in order to support the development of public speaking skills and incorporated a Virtual Reality real-time feedback module (VR module) that yielded positive results.

[16] Discussed ’i-Campus’ as the future of education that incorporated the use of Internet-of-Things (IoT) enabled e-learning environments. In a later study, [17], [18]proposed a framework to enhance decision-making process in smart education that introduced an IoT-enhanced Learning Management System.

In this manner, sensors improve teaching efficiency and quality while assuring compliance with best practices. In recent years, there is an increasing trend in research works dedicated to incorporating sensors in education [7]- [9], [12] and more recent works revolve around the idea of using sensor components in distant learning or e-learning environments.

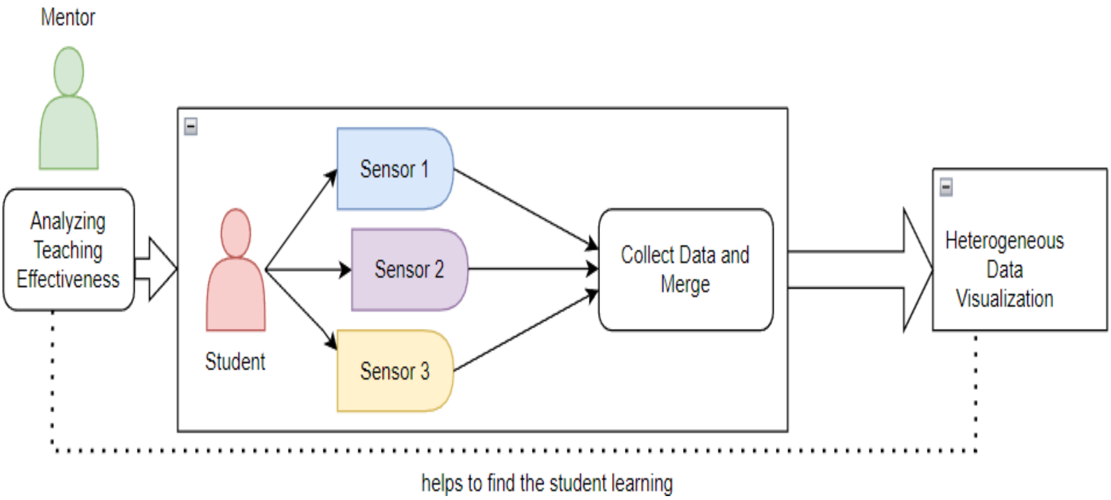

Fig.3.Learner-MonitoringHeterogeneousdataCapturedDuringOnlineExam.

Converting heterogeneous data into a homogeneous format for input into a Business Intelligence (BI) tool is a common challenge in data analysis and reporting. Heterogeneous data refers to data that comes from various sources, with different formats, structures, and data types. Homogeneous data, on the other hand, is data that has been standardized into a consistent format for easy analysis and reporting. Here are several methods to convert heterogeneous data into homogeneous data for BI tool input:

1) BI Tool Data Preparation:

Some BI tools, such as Tableau and Power BI, offer built-in data preparation features that allow you to clean, transform, and reshape data within the tool itself, reducing the need for extensive preprocessing.

2) Data Virtualization:

Consider data virtualization platforms that allow you to access and query heterogeneous data sources as if they were a single, homogeneous source without the need for extensive physical data transformation.

Ultimately, the choice of method will depend on the specific data sources, the BI tool in use, and the organization's data integration and transformation capabilities. A combination of these methods may also be necessary to achieve the desired level of data homogeneity for effective BI analysis and reporting.

Sensors are transforming the field of education by providing valuable data and insights into various aspects of the teaching and learning process. They are used to monitor learner behavior, evaluate cognitive load, enhance assessment, and create interactive, data-driven educational environments. The application of sensor technology in education is diverse and continually evolving, offering new possibilities for improving teaching efficiency, personalizing instruction, and ensuring compliance with best practices. As technology advances, we can expect more innovative uses of sensors to further enhance the educational experience.

B. Management Systems (MS)

MS software automates the learning process by registering users, keeping track of courses, recording learner data, and managing reports. MS consists of a server component that develops, administers, and delivers courses, authenticates users, and serves data and notifications, and a client-side user interface. [13]-[15]briefly discusses the advantages of implementing and utilizing a LMS such as Google Classroom and a Content MS (CMS) like Moodle, within an education system.

[10],[11] studied the relationship be-tween the type of computing device from which students accessed the LMS and how it affected their performance. Various computing devices serving as data-collecting sensors were used to monitor students from elementary school until bachelor's degree level. The authors concluded that students who accessed LMS showed a significant improvement in performance.

[21] Pioneered the concept of Attention Awareness Systems (AAS) that maintained student performance in learning environments by capturing their attention states. The authors noted that AAS must be capable of responding to and supporting human attentional processes, particularly in multitasking, frequent contacts with other users, and surroundings with a high degree of dynamicity. [22], AAS must consider and monitor the different attention states for effective learning. The objective was to merely capture the user's attentional focus, which can then be utilized to provide individualized education and dynamically promote learning. In addition, they suggested that AAS in e-learning offers the benefit of estimating and responding in real-time without interrupting the student.

4. Analyzing Teaching Effectiveness

Educational Intelligence (EI) analyzes students' topic interests and performance trends to reshape the teaching and learning activities accordingly, to enhance student results, retention, and satisfaction.

[19] Stated that the data captured by MS platforms, the material or content can be adapted and customized to the learner's needs. The authors further emphasized that MS-didactic teaching enhanced learner interest, comprehension, and elevated success in learning outcomes. In 2017, [20] showed that by incorporating an analytics tool, students' performance can be evaluated automatically in a LMS by means of effectively capturing using interactions and taking in account several input factors, including the overall login frequency to the LMS, the time spent in the system, the number of downloads, interactions with peers, the number of completed exercises and so on.

5. The Integration of Multiple Sources In Real-Time Data

Many sensors - heart rate, temperature, sound, motion, camera, brightness, humidity (and so on) - can be deployed in a smart education environment. Based on the literature [23], we present a 3-step framework for analyzing learning outcomes as EI.

Data Collection: Data captured by sensors and MS can be fed into a BI tool for analysis and gaining insights for futuristic decisions. Here, the input data is a combination of implicit and explicit learning factors according to the iceberg model [24].

Union Operation: The union operation is performed over the collected heterogeneous data that is present as a table. Primarily, it is utilized to bring together the contents of two or more tables.

Merge Operation: When there exists a mismatch in the Features of the tables on which the Union operation is performed, NULL values are added to the resultant table. The merge operation is an ideal step to eliminate NULL values, provided that the Features are closely related.

The above paragraph highlights the importance of integrating data from multiple sensors and systems in the context of smart education. By combining data from various sources, educators and administrators can gain a holistic view of the learning process and make data-driven decisions to enhance educational outcomes. The 3-step framework presented ensures that data is collected, unified, and merged effectively for analysis, making it possible to leverage the diverse set of data generated in modern educational environments.

The approach emphasizes the potential of Educational Intelligence (EI) as a means to harness real-time data for improving the quality of education. It's indicative of a growing trend in using technology and data analytics to inform educational practices and adapt teaching methods to the individual needs and behaviors of learners. In conclusion, the integration of sensors and data analysis techniques holds great promise for enhancing the educational experience and driving continuous improvement in the field of smart education. For instance, consider a set D that denotes the heterogeneous collectioninput data, that is D = {Si, MSj | 1 $\leqslant$ i $\leqslant$ m, 1 $\leqslant$ j $\leqslant$ n}, where Si and MSj denote the set of features collected by the ithofm sensors and j^{th} of n MS that are typically used in a smart education environment. Each S_i (or MS_j) is a time-series data that contains a list of features denoted by $f_{i,k}$ (or $f_{j,k}$), where k is the total number of features captured by the sensor (or MS). That is, $S_i = \{f_{i,1}, f_{i,2} \cdots f_{i,k-1}, f_{i,k}\}$ (or$MS_j = \{f_{j,1}, f_{j,2} \cdots f_{j,k-1}, f_{j,k}\}$)
m sensors and jth of n MS that are typically used in a smart education environment. Each Si (or MSj) is a time-series data that contains a list of features denoted by fi,k (or fj,k), where k is the total number of features captured by the sensor (or MS). That is, Si = {fi,1, fi,2 · · · fi,k−1, fi,k} (orMSj = {fj,1, fj,2 · · · fj,k−1, fj,k}).
Then the resultant database obtained by performing union of datasets can be expressed as:
D′ = mi=1 Si. If ∀p, q ∈ m, Sp
Sq = ∅, then the number of features in D′ is $|Sp| + |S_q|$.
If$\forall p, q \in m$, $S_p\ S_q \neq \emptyset$, then $|D'| = |S_p| + |S_q| - |S_p \cap S_q|$.
Additionally,$\forall f \in (S_p \cap S_q)$ the total number of records is $|f_{Sp}| + |f_{Sq}|$.

This union operation introduces NULL values and if a case persists where some records within are duplicate or any subset of features present closely relevant records, then they shall be merged for insightful analysis.

The explanation provided for the above mathematical representation of a data structure used in the context of a smart education environment. Let's break it down step by step:

1. Definition of D: D is a set that represents a collection of input data. It is a heterogeneous collection of data, which means it includes various types of data from different sources.

2. Components of D: D is composed of elements Si and M Sj, where i and j are indices representing different sensors and MS (presumably, data sources in a smart education environment). These sensors and MS collect features over time.

- Si represents the set of features collected by the ith sensor.
- MSj represents the set of features collected by the jth MS. Each Si and MSj contain time-series data,

Meaning they record data points over time. These data points are represented as fi, k for Si and fj,k for M Sj, where k is the total number of features captured by the sensor or MS.

$S_i = \{f_{i,1}, f_{i,2} \cdot \cdot \cdot f_{i,k-1}, f_{i,k}\}$ (or $MS_j = \{{}^{f}j,1 {}^{,f}j,2 \cdot \cdot \cdot {}^{f}j,k-1 {}^{,f}j,k\}^{).}$

3. Resultant Database D': D' represents the result of performing the union of all these datasets (Si and M Sj) into a single database. This operation combines data from all sensors and MS into one comprehensive dataset.

D' = (union) Si (for all i from 1 to m)

4. Handling Overlapping Data: The explanation discusses two cases based on whether there is overlap between the features collected by different sensors or MS.

- If for all pairs of sensors Si and Sj (for i, j in m), their intersection (Si Sj) is empty, meaning they have no common features, then the number of features in D' is the sum of the features in Si and Sj, i.e., $|S_i| + |S_j|$.

- If there is an intersection between features from different sensors or MS (Si Sj is not empty), then the number of features in D' is the sum of the features in Si and Sj minus the number of features they have in common.

5. Handling Records with Overlapping Features:

Additionally, for features that are common between Si and Sj (belonging to the intersection Si Sj), the total number of records is calculated as $|fS_i + fS_j|$. This implies that when there is feature overlap, the data for those features is combined from the different sources.

6. Handling Duplicate Records: The explanation mentions that the union operation introduces NULL values and that if there are cases where some records are duplicate or closely related, they should be merged for insightful analysis. This suggests that data cleaning and integration steps may be required to ensure the quality and accuracy of the data in the combined dataset.

In summary, the provided explanation outlines the mathematical representation and operations for combining data from multiple sensors and data sources in a smart education environment, considering cases where data may overlap, and emphasizing the need for data cleaning and merging when necessary.

A. Teaching outcomes

Why are learning outcomes important for students? Explicitly stated learning goals give students a way to think and talk about what they have learned. They make it easier for students to "know what they know" and give students a language to communicate what they know to others.

- Transmission: effective delivery of content (an objectivist approach)
- Apprenticeship: modelling ways of being (learning by doing under supervision)
- Developmental: cultivating ways of thinking (constructivist /cognitivist) nurturing:

facilitating self-efficacy (a fundamental tenet of connectivism MOOCs) social reform: seeking a better society.

1) Improving Teaching outcomes:

- Use ICT tools and digital game-based learning.
- Differentiate between students.
- Use the flipped classroom model.
- Encourage cooperative learning.
- Create a welcoming environment. B. Learning outcomes

Learning Outcomes is a description of what students will be able to demonstrate after going through the course. Therefore, online course development, activities and assessments must be aligned with the learning outcomes.

Through this research, we aim to provide a data-driven approach to improving learning outcomes, shedding light on how these diverse sources of information can be harnessed to enhance the educational experience and, subsequently, student achievement.

This paper explains the methods used to measure student learning outcomes. First, start with the sensing systems and management systems. Analyzing teaching effectiveness using EI. The Integration of multiple sources in real-time data also be measured.

6. Working Model

This section demonstrates the workings of our 3-step framework by integrating data from multiple sources such as feed-back questionnaires, sensors, and LMS (refer Table I). The study was performed on 58 students pursuing the third year of their undergraduate degree in computer science at the SRM Institute of Science and Technology, Kattankulathur, India.

Source - 1: Mid-course feedback consisting of 25 questions was circulated to understand the learners' attitude towards the course, instructor, assignments, and other learning components.

Description: A mid-course feedback process was implemented, consisting of 25 questions designed to assess the learners' perceptions of various aspects of the educational, experience, including the course, instructor, assignments, and other key components.

Access: The feedback questionnaire can be found online at the following URL:The source GitHub link for the project: https://github.com/MuneeswariS1991/Sensor-Based-Learning-Approach.git

Source - 2: Online Sensor-Based Assessment The same batch of students were subjected to an online assessment with a system of sensors (comprising of microphone, oximeter and camera) to capture the implicit learning factors. The obtained time-series data was saved for further analysis.

Description: Students from the same group were engaged in an online assessment, employing a set of sensors that included a microphone, oximeter, and camera. These sensors were utilized to capture implicit factors related to the learning process.

Data Collection: The data collected by these sensors was in the form of time-series data and was stored for subsequent analysis.

Source - 3: Learning Management System (LMS)

Assessment The said online assessment was conducted on an LMS. The analysis report generated at the end of the assessment captured the amount of time spent by individuals on each question.

Description: The online assessment was conducted through a Learning Management System (LMS), a commonly used platform in educational settings. This assessment provided valuable insights into the time spent by individual students on each question, contributing to our understanding of the learning process.

Research Question

The research questions are solved using statistical methods:

RQ1: Are there any notable academic performance variations between online and face-to-face students taking an online course.

This question seeks to determine whether there are significant differences in academic performance between students who take an online course and those who take the same course in a face-to-face setting. The analysis will involve comparing the academic achievements of these two groups of students, focusing on any noteworthy variations. It aims to uncover if the mode of instruction (online or face-to-face) has an impact on student performance.

RQ2: Are there any gender variations in an mathematics course between online and face-to-face students'   performance? RQ2 delves into the realm of gender differences in the context of a mathematics course. Specifically, it aims to understand if there are variations in the performance of male and female students when taking the same course, both in online and face-to-face formats. The analysis will explore potential disparities in academic, achievements based on gender, shedding light on whether males and females exhibit different levels of success in mathematics in these instructional modes.

https://github.com/MuneeswariS1991/Sensor-Based-Learning-Approach.git

RQ3: In terms of class rank, are there appreciable variations between online and face-to-face students' performances in a Mathematical course? This research question focuses on the students' class rank and its potential effect on their performance in a mathematical course, comparing online and face-to-face settings. By assessing appreciable variations, it seeks to understand whether students who hold high class ranks (e.g., top students) perform differently from those with lower class ranks when undertaking a mathematical course. This analysis offers insights into how class rank might relate to academic success in the context of different instructional modes.

These research questions guide the investigation into various facets of academic performance, including instructional mode, gender differences, and class rank, providing a comprehensive view of factors that may influence student outcomes in a mathematical course. https://www.frontiersin.org/articles/10.3389/fcomp.2019.00007/full

Table 1. Sensors and its Description

Feature	Sensor	Description		Down-scaled range

Sound	Microphone	To capture the noise level	1	- Very noisy
			5	- Silent
Pulse	Oximeter	To capture the pulse of learner	3	- Normal (Calm)
			5	- High (Very Nervous)
Face Visibility	Camera	To capture the face visibility of learner	1	- Poorly Visible
			3	- Partially Visible
			5	- Completely Visible

In this table can describe the performance of each sensor (Camera, Microphone, and Pulse Oximeter) with respect to different performance metrics (e.g., accuracy, data capture rate, etc.) in the” Performance Metric” columns. Make sure to replace” Describe the performance” with specific details about how each sensor performed in your prototype.

B. Performance Metrics by Sensor:

The table provides a comprehensive breakdown of the performance metrics for the sensors.

Camera: Image Quality: Evaluates the clarity and sharpness of the images produced by the camera.

Focus Speed: Assesses how quickly the camera can adjust its focus.

Frame Rate: Measures the number of frames captured per second.

Field of View: Describes the extent of the area that the camera can capture.

Low-Light Performance: Evaluates how well the camera performs in low-light conditions.

Noise Level: Measures the amount of background noise or interference picked up by the microphone.

Frequency Response: Evaluates the microphone’s ability to capture various frequencies of sound accurately.

Sensitivity: Measures how well the microphone detects and records quiet sounds.

Latency: Indicates any delay between sound input and output.

User-Friendliness and Accuracy: Evaluates how easy it is for users to operate the Pulse Oximeter and the accuracy of its readings. Data Capture Rate: Assesses the speed at which the Pulse Oximeter records and updates data.

Durability: Measures the device’s ability to withstand wear and tear over time.

Battery Life: Indicates the duration for which the Pulse Oximeter can operate on a single battery charge.

Portability: Describes the convenience of carrying the Pulse Oximeter from one place to another.

This table offers a structured way to evaluate and compare the performance of different sensors in the prototype across various critical aspects. It provides a valuable reference for assessing the capabilities of each sensor in the context of the project or research.

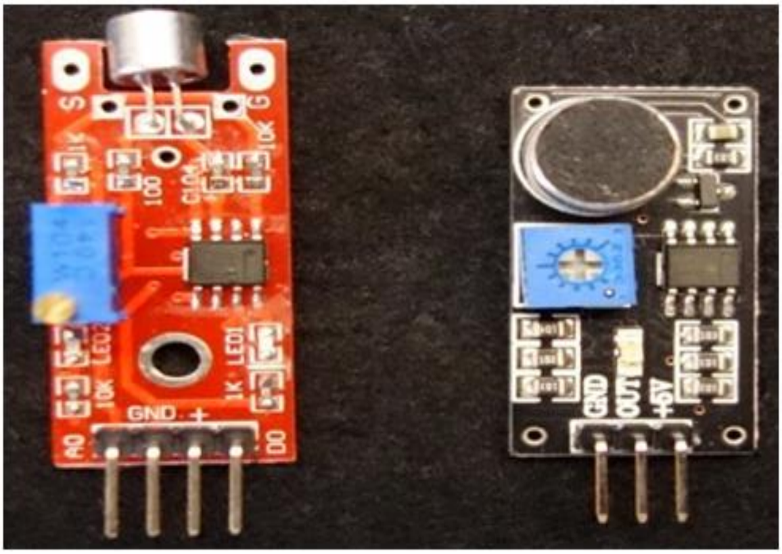

Fig.4.Learner-soundmonitoring-Microphone

Fig. 5.Monitoring Camera

2) Microphone: Accuracy: Assesses the microphone’s ability to accurately capture and reproduce sound.

The Table III row explains to represent an observation associated with an event related to sensors 1, 2 and 3. Here’s

Table2. Performance of Sensors with Prototype

Sensor	**Metric1**	**Metric2**	**Metric3**	**Metric4**	**Metric5**

Camera	ImageQuality	FocusSpeed	FrameRate	FieldofView	Low-LightPerformance
Microphone	Accuracy	NoiseLevel	FrequencyResponse	Sensitivity	Latency
PulseOximeter	User-FriendlinessandAccuracy	DataCaptureRate	Durability	BatteryLife	Portability

Table 3. Sensors and Its Possibilities

Heartrate	**Time**	**Camera**	**Sound**	**TimeSpentonQA**
S_1	S_1	Null	Null	Null
Null	S_2	S_2	Null	Null
Null	S_3	Null	S_3	Null
Null	S_4	Null	Null	S_4

Each cell in the table row means:

Heart rate: No specific heart rate data is available.

Time: The time of this event corresponds to Sensors.

Camera: No specific camera data is available.

Sound: No specific sound data is available.

Time Spent on QA: No specific time spent on questions and answers is available.

C.Explanation

1) Microphone: The microphone sound sensor, as the name says, detects sound. It gives a measurement of how loud a sound is. The most common is with the Arduino. At the leftmost side, you can see the KY-038 and at the right the LM393 microphone sound sensor. Both sensor modules have a built-in potentiometer to adjust the sensitivity of the digital output pin. The source Image link: https://randomnerdtutorials.com/guide-for-microphone-sound-sensor-with-arduino/

2) Oximeter: What is Pulse Oximeter? Pulse Oximeters are low-cost non-Invasive medical sensors used to continuously measure the Oxygen saturation (SPO2) of hemoglobin in blood. It displays the percentage of blood that is loaded with oxygen.

Principle of Pulse oximeter: The principle of pulse oximetry is based on the differential absorption characteristics of oxygenated and deoxygenated hemoglobin. Oxygenated hemoglobin absorbs more infrared light and allows more red light to pass through. Whereas deoxygenated hemoglobin absorbs more red light, allowing more infrared light to pass through.

Each pulse oximeter sensor probe contains two light emit-ting diodes, one emitting red light and the other emitting near infrared light, it also has a photodetector. The photodetector measures the intensity of transmitted light at each wavelength. And using the differences in the reading, the blood oxygen content is calculated. The probe is placed on a suitable part of the body, usually a fingertip or ear lobe. Methods for Monitoring Oxygen Saturation in Blood Two different methods are used for transmitting light through the transmitting medium.

1. Transmission Method: Transmission methods refer to the techniques and technologies used to convey data or information from one point to another, often within a communication or networking context. These methods are essential for sending data over various types of networks, such as wired, wireless, or optical networks.

2. Reflectance Method: Reflectance methods are analytical techniques used to determine the properties of substances by measuring the amount of light or electro-magnetic radiation they reflect. These methods are commonly employed in various fields, including chemistry, materials science, remote sensing, and spectroscopy, to obtain information about the composition, structure, and optical properties of objects or materials. The source Image link: https://www.dnatechindia.com/basic-working-pulse-oximeter-sensor.html

3.Camera:The source Camera Image link: https://www.forbes.com/sites/forbesdigitalcovers/2018/07/19/the-inside-story-of-papa-johns-toxic-culture/?sh=43ff3e773019

Advanced AI Capabilities that can smartly detect notify whenever a person is detected 24x7 Continuous Recording just enable it in the app settings and always be in the know Advanced Low Light Technology allows you to see colours even in low light conditions. Work with Alexa and Google Assistant with the convenience of a voice command.

If you are looking for the perfect smart camera for your home, office, and shops, then, buy the Qubo 360 Smart CCTV Security Camera. The multi-directional turn of the focal point guarantees that there are no vulnerable sides. Qubo Smart Cam 360 is intended to be utilized inside, as it were. Secure every one of your accounts on distributed storage situated in India. Your private home minutes stay with you regardless of whether the gadget is taken. There are a wide variety of these sensors.

7. Result and Discussion

The paper presented a 3-step framework to perform operations on heterogeneous data to obtain an inferential analysis. Additionally, it discussed the various methods to measure learning outcomes and discussed few use cases. The work is concluded by analyzing real-time data 4 captured from sensors, MS, and feedback questionnaire to monitor a learner during an online examination. A line chart (Figure 7) is drawn as per the presented framework, and an inference is made that the student has spent the most time on the 25th question. During this time, data captured by sensors indicates a high noise level in the learners' surroundings, nervousness, and poor face visibility. This suggests that the learner might have indulged in malpractice during this time. Sensor data shows a high noise level, a raised pulse rate, and poor face visibility. Likewise, the use of EI tools can lead to effective analysis of heterogeneous data in education.

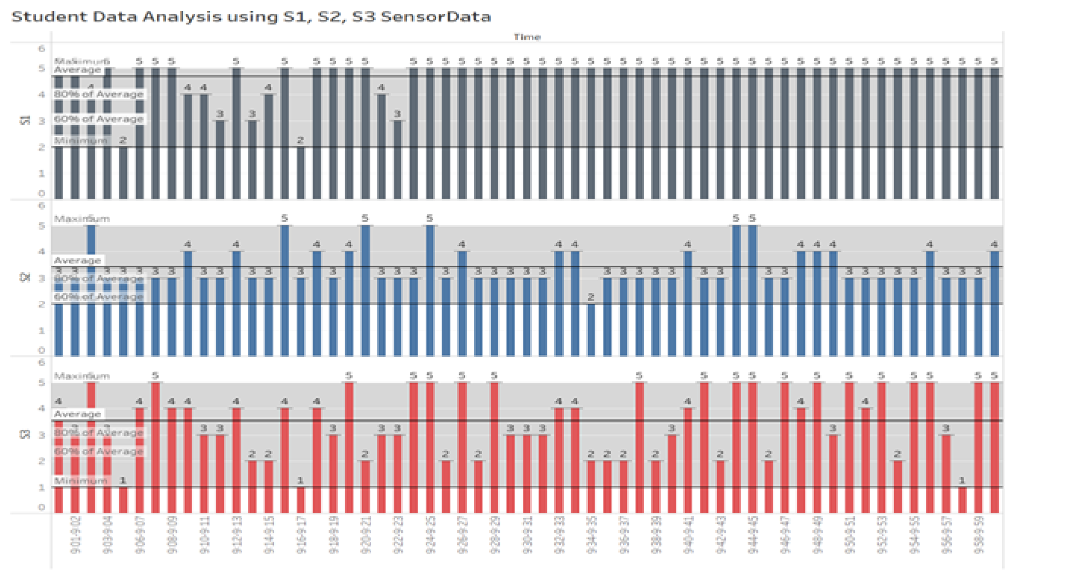

Fig.6.Learner-monitoringheterogeneousdatacapturedduringonlineexams

Table 4. Sensors and its Possibilities

Heartrate	Time	Camera	Sound	TimeSpentonQA
S_1	S_1	Null	Null	Null
Null	S_2	S_2	Null	Null
Null	S_3	Null	S_3	Null
Null	S_4	Null	Null	S_4

Table5. Learning Monitoring

Heartrate	Time	Camera	Sound	TimeSpentonQA
S_1	$S_1/S_2/S_3/S_4$	S_2	S_3	S_4

The Table IV Sensors and its Possibilities and Table V Learning Monitoring - Conclusion.

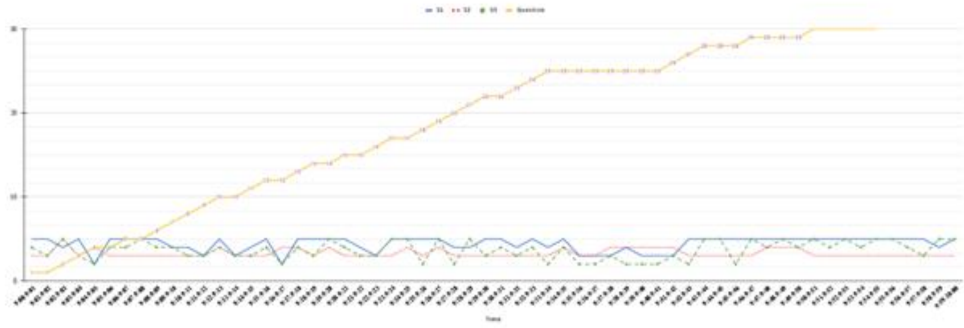

Fig. 7. Learner-Monitoring Heterogeneous Data Captured During Online Exam

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