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EADMS: A systemic approach to map emotions with Bloom's Affective Domain

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Abstract

The quality of education depreciates as in-person classes were quickly replaced with virtual classes amidst the global pandemic. With the rise of the virtual classroom environment, educators lose the opportunity to interact with students and tailor the teaching style that best suits them. Educators use students' facial expressions and emotional responses to the content to predict the understanding levels subjectively. This paper proposes the Emotion-Affective Domain Mapping System (EADMS) as an alternative tool. The EADMS captures students' facial data during online classes in the form of a video and uses AI to determine emotions like contempt, anger, fear, happiness, disgust, surprise, and neutral state of emotion. The system breaks the video recording into three parts: the start of the class, between class, and the end of class to retrieve facial data and translate it to emotional data. The emotional data is mapped with the 'Affective Domain' of Bloom's Taxonomy to generate a graphical chart that plots the understanding level over the three periods. The EADMS successfully extracted information from videos on the internet and was reasonably reliable when tested with one of the authors.

1 Introduction

Education is crucial to the role of human development. It has a profound implication at a personal, professional, and aspirational level. This essential human need is facing complications as a result of the rapid growth in technology. Most education systems have tried to incorporate technology to improve learning but often struggled to adopt it in a way that fits the traditional education systems [1]-[3]. Despite leveraging new technology, content apprehension has not improved significantly. This state can be credited to the education system's barriers that focus on standardizing content rather than promoting pedagogical experimentations [1]-[3]. It appears that there is a lack of attention towards pedagogical experimentation in cohesion with technology, which seems to have largely gone unnoticed. However, with classes moving to an online, virtual setting, educators are provided with an interface-to-face environment instead of a face-to-face environment that allows educators to iterate and adapt teaching methods on a trial-and-error basis from students' facial expressions [4]. The new education dynamic negatively affects students since an essential pedagogizing agency does not have the same ability to adapt to a virtual environment [5].The education system's flaws have been showing up recently as a direct result of the COVID-19 pandemic. The virtual setting makes it a challenging task for educators to analyze facial expressions and experiment with alternative teaching styles regardless of how advanced our communication technology is. Educational institutes and government bodies have increased expenditure on technology that can elevate the learning experience. However, the spending lacks justification due to the focus on standardized content over pedagogical flexibility. This phenomenon is showcased by a study conducted in Germany that shows that educators proved to be exceptional at communicating with students but have not had similar success when integrating technology into standardized teaching patterns [6]. The problem of poor integration of technology and our education system's inflexibility is set to cost us roughly 0.3 to 0.9 years' worth of education when adjusted for education quality due to the new learning environment [7]. The lack of face-to-face interaction between educators and students makes it significantly harder for educators to assess student comprehension levels subjectively. Leveraging more technology to aid an outdated system could potentially be counterproductive to the intended purpose. Given the situation, there is a need for an iterative framework that unites pedagogical principles and technology to improve the learning experience. For any iterative framework to be successful, there needs to be a testing methodology to validate hypotheses as conclusive proof. This paper proposes the Emotion-Affective Domain Mapping System (EADMS) as a novel solution to improve comprehension assessment that educators used to conduct subjectively. Also, propose the EADMS as a verification tool for any iterative framework developed in the future. EADMS is a prediction tool that leverages the current learning ecosystem. EADMS uses facial data collected from students' webcams during online classes, extracts emotion attributes to map it with the Affective Domain proposed in Bloom's Taxonomy.

2 Literature Review

Education is an area where image recognition is being utilized and implemented at a scale [8]. It is used for attendance, monitoring visitors, and even security in the case of school shootings. In one example, an image recognition system can detect gun-shaped objects from the video footage to protect students against school shootings [8]. Further-more, these systems can determine who is permitted onto the school campus [9]. The system helps teachers tasked with conducting roll calls of large student groups and overcoming fraudulent attendance problems such as fake attendance and proxies [9]. In a virtual environment context, facial recognition technologies are used to ensure the integrity of various aspects of online courses such as authenticating online learners engaging in online courses [10]. Additionally, facial recognition is used to verify the students taking online tests or examinations and confirming their presence during the entire examination period [10]. However, facial recognition systems are used beyond physical security, attendance, or preventing fraudulent attendance in a classroom. In a virtual environment, facial recognition can be used to detect students' engagement by utilizing the learner's facial expression.

Facial expressions provide rich information about an individual's thoughts, mood, and mental state. Therefore, lecturers use the student's facial expression as a basis to modify the presentation according to the student's needs [11]. Facial recognition systems are used to detect the learner's engagement through facial micro-expressions states (FMES) [11]. An experiment conducted on ten undergraduate students in India, indicates a significant correlation between facial expression and student engagement [12]. Eyebrow raising, eyelid tightening, and mouth dimpling are facial expressions that indicate the highest level of engagement [12]. Facial movements can be visually distinguishable from video recordings using the Facial Action Coding System (FACS) [13]. There are two methods to analyse facial expression geometric-based and appearance-based. The geometric based method focuses on extracting facial appearance, such as the shape of the mouth, the position of eyebrows, nose, etc. [13]. The appearance-based method focuses on the sensitive change in illumination such as brightness and shadows, changes in the faces and head motions [14]. The combination of geometric based and appearance-based approach has proven accurate results for detecting the learner's engagement [14]. Additionally, there is significant potential to use facial expressions as an indicator to identify the understanding of a student.

Facial recognition systems determine emotions through facial expression, which involves categorizing active and spontaneous facial expressions to underlying the emotional states [15]. Experiments conducted have indicated a significant correlation between facial expressions and emotion [16]. A study conducted on 80 under-graduate students between the ages of 18 and 22 reveals that eyes opening wide, raising eyebrows, and mouth dimpling are facial expressions that indicate positive emotions [16]. Curling lips, wrinkles on the forehead, and lowering eyebrows are facial expressions that express negative emotions [4]. A study conducted on 67 students revealed a connection between emotions and understanding [17]. Studies have suggested that facial emotions significantly impact the learner's ability to under-stand a concept [18]. Intelligent tutoring systems such as MetaTutor and metacognitive monitoring have defined that emotions are dynamic and fluctuate depending upon the learner's understanding [18]. These systems seem to be limited to measuring the level of human understanding as it is a complex concept which is categorized into three domains: Cognitive, Affective, and Psychomotor, according to Bloom's taxonomy [19]. The cognitive domain, known as the knowledge-based domain, provides the educator with a hierarchical structure to deliver their learning objectives [19]. The psychomotor, also known as the action-based domain, is concerned with physical movements used to interpret information or a concept [20]. The affective domain, as known as emotion-based, the affective domain involves the learners' feelings, emotions, and attitudes towards the information or concept [20]. The entire educational sector has not focused on the affective domain because it is harder to assess students' progress based on their emotions as traditionally, l knowledge is perceived as more important than emotions and values [21]. The affective domain is sub-categorized into five levels that are listed below:

Table 1. Bloom's Affective Domain.

Level	Description
Receiving	The lowest level where the student passively pays attention without no learning.
Responding	The students actively participate in the learning process.
Valuing	The student associates a value to the piece of information they acquired.
Organizing	The student can compare and relate different values and can build their own opinion.
Characterizing	The student can form abstract knowledge.

Some of the mentioned systems use cloud-based emotion recognition services such as Microsoft Azure to analyse the emotions to detect the student's understanding [22]. The system performs three main processes: facial acquisition, feature extraction, and emotion classification. The facial acquisition and feature extraction focus on the location of the facial image and the extraction of facial expressions. The emotions classification process classifies emotions based on facial expressions and detects the learner's understanding.

This research proposes a novel system that uses an existing AI facial recognition tool to determine student understanding using video captured during a class. The AI facial recognition service provides emotional data by analysing the captured video for facial features. The emotional data is then related to Bloom's affective domain to predict the students' comprehension level during the class.

3 Methodology

This study uses the Peffers' Design Science Research Methodology (DSRM) [23] for designing, building, and testing the EADMS. Following the DSRM, first the problem was identified, and the objectives defined, the artifact was developed, demonstrated, and evaluated and the results are presented in this work [23]. The purpose of Design Science Research is to create artifacts to solve real world problems [24]. The problems arising from the trend of online teaching and the issues of technology and its effect on pedagogy are real and relevant to real world problems that need solutions. The solution proposed to address the problem is an artifact that is a system for operationalizing Bloom's Affective Domain through the mapping of emotional data de-rived from AI facial recognition. The aim is to improve the estimation of students' understanding without seeing or administering assessments. In accordance with Peffers [25], the system design draws on current enabling technology and builds on well-established Bloom's Affective Domain theory.

Furthermore, the paper will present the design of the EADMS using a Data Flow Diagram (DFD), which was used to construct the system. The functional components are demonstrated and evaluated through standard system testing and are presented in the testing section.

The EADMS uses Microsoft Azure Face API to analyse the image and provide the system with emotions categorized into contempt, anger, fear, neutral, surprise, sad-ness, disgust, and happiness. The emotions data provided by the Face API are assigned numbers between 0 to 5 that will be used to map with the affective domain of Bloom's Taxonomy to predict the level of understanding. The average accuracy rate of the emotions recognition services for Microsoft Azure is 97% due to the confidence rates and provides a broader range of emotions than other services provided by Google and Amazon [26]. Additionally, preliminary tests were conducted to ensure the Face API's accuracy rate with different sets of expected emotions listed below.

Table 2. Verification of Azure Face API.

Image	Expected Emotion	Result	Description
	Anger	anger: 0.316 contempt: 0.056 disgust: 0.098 fear: 0.002 happiness: 0.008 neutral: 0.501 sadness: 0.003 surprise: 0.016	The image depicts an angry face to test how well Azure Face API detects anger. Face API is only 31.6% confident that the face depicts anger.
	Anger	anger: 0.681 contempt: 0.008 disgust: 0.302 fear: 0.0 happiness: 0.006 neutral: 0.003 sadness: 0.0 surprise: 0.0	The image depicts an angry face to test how well Azure Face API detects anger without spectacles. Face API is 68.1% confident that the face depicts anger. This shows that the Face API's accuracy significantly improves if the subject does not wear spectacles.
	Fear	anger: 0.0 contempt: 0.0 disgust: 0.0 fear: 0.147 happiness: 0.0 neutral: 0.0 sadness: 0.0 surprise: 0.853	The image depicts a fearful face to test how well Azure Face API detects fear. Face API is only 14.7% confident that the face depicts fear.
	Happiness	anger: 0.0 contempt: 0.0 disgust: 0.0 fear: 0.0 happiness: 1.0 neutral: 0.0 sadness: 0.0 surprise: 0.0	The image depicts a happy face to test how well Azure Face API detects happiness. Face API shows a 100% confidence score that the image provided depicts happiness.

The mapping between the emotional data and the affective domain

Table 3. Mapping emotions to Bloom's Affective Domain.

Emotions	Relation to Bloom's Affective Domain	Relation to Bloom's Affective Domain in weights	Predictions
Contempt	No level of understanding	0.0	The student lacks subject knowledge and is unable to understand anything, causing an emotional state of contempt. No understanding has taken place in this emotional state.
Anger	Receiving	1.0	The student fails to find the cohesive nature of the content being thought in the class, causing an emotional state of anger. At this emotional state, the student does not understand but may be able to memorize content.
Fear	Responding	2.0	The student experiences panic due to self-doubt over one's understanding, causing an emotional state of fear. At this emotional state, the student attends to stimuli and responds in return.
Neutral	In between responding and valuing	2.5	The student experiences a mixture of multiple emotions during the transition between validating one's understanding and attaching value to understanding, causing a neutral emotional state.
Surprise	Valuing	3.0	The student experiences an emotional state of surprise as they make connections to their previous knowledge. At this emotional state, the student can cohesively piece together information and attach value to content.
Sad/Disgust	Organizing	4.0	The process of organizing content in a meaningful manner creates sadness and disgust in a student. At this level, the student processes large chunks of information to build abstract concepts.

Happiness	Characterizing	5.0	The student experiences satisfaction from being able to construct abstract ideologies through deep understanding, causing an emotional state of overwhelming happiness. At this level, the maximum level of understanding has taken place.

It is vital to note that a student need not fall precisely at a level of understanding and can instead be in a state of transition between two levels. To ensure that the change in levels is measured, the emotional scale hypothesized is multiplied with the corresponding data from Azure Face API and summed together to derive the projected (or predicted) understanding score.

$$Understanding\ score = \sum \left\{ \begin{array}{c} Contempt\ score * 0 \\ Anger\ score * 1 \\ Fear\ score * 2 \\ Neutral\ score * 2.5 \\ Surprise\ score * 3 \\ [Sad\ score + Disgust\ score] * 4 \\ Happiness\ score * 5 \end{array} \right\}$$

The formula mentioned above ensures that the understanding score derived is a number between zero and five. The model also ensures a complete understanding (understanding score of five) is only derived when the student shows complete happiness. The model allows for this since Azure's data is the normalized confidence score of emotions and adds up to one [27].

The proposed system will capture a single student's raw video and process the video through the proposed mapping approach to produce the understanding score at three different points: start, middle, and at the end of the class. The understanding score is then graphically represented to the educator for further use.

Working of the EADMS

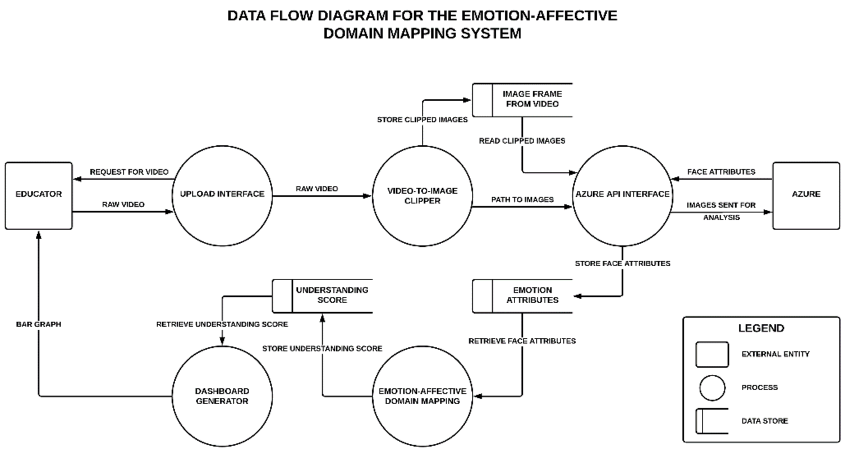


Figure 1. Data flow diagram for the EADMS.

The data flow diagram (DFD) represented above shows the processes that take place within the Emotion-Affective Domain Mapping System. The educator initiates the system and provides the raw video upon request by the upload interface. The raw video passes on to the clipping module, which clips the provided video into three images: start, middle, and the end of class. The images are stored in the local drive, and the path of each image is passed on to the Azure interface. The Azure interface retrieves the stored images and sends it to Azure Face API for analysis and gets the face at-tributes in return. The Azure interface gets rid of unnecessary data and stores the emotion data in a text file. The Emotion-Affective Domain Mapping module retrieves the emotion attributes and maps the emotion data to the Affective Domain as per the theorized mapping system. The mapping process results in the production of an Understanding Score that is stored in the local drive. The Dashboard Generator module retrieves the Understanding Score and plots the data points in a bar graph.

4 Testing

The EADMS was put under a series of tests that verified the functional requirements of the system. The testing process focused on ascertaining whether the system can request a video, clip the videos into images, retrieve the analysed emotional data from Azure and use the proposed mapping model to predict the understanding levels. The first three tests made use of videos readily available online. The final test uses a video of a subject recorded during an online class.

The fourth test was recorded with a series of predicted understanding levels. The prediction involved is that the subject started the class with a very high level of understanding. However, over the course, understanding drops to an average level of roughly around valuing and responding.

Table 4. Results obtained from test case #1.

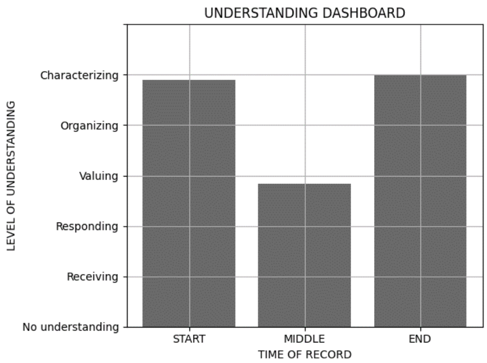
Test Case	Images	Dashboard
1 - Image sourced from YouTube video for facial recognition training [28].	 Start  Middle  End	

Table 5. The understanding score is derived through the multiplication of confidence score provided by azure and the weights assigned to each emotion.

Understanding score at the beginning of the class = {(0.001*0.0) + (0.042*2.5) + (0.957*5.0)}
Understanding score at the middle of the class = {(0.002*0.0) + (0.86*2.5) + (0.138*5.0)}
Understanding score at the end of the class = {1.0*5.0}

Emotion	Relation to Bloom's Affective Domain	Relation to Bloom's Affective Domain in weights	Emotions at the beginning of the class	Emotions at the middle of the class	Emotions at the end of the class
Contempt	No level of understanding	0.0	0.001	0.002	0.0
Anger	Receiving	1.0	0.0	0.0	0.0
Fear	Responding	2.0	0.0	0.0	0.0
Neutral	In between responding and valuing	2.5	0.042	0.86	0.0
Surprise	Valuing	3.0	0.0	0.0	0.0
Sad/disgust	Organizing	4.0	0.0	0.0	0.0
Happiness	Characterizing	5.0	0.957	0.138	1.0
Understanding Score			**4.89**	**2.48**	**5.0**

Table 6. Results obtained from test case #2.

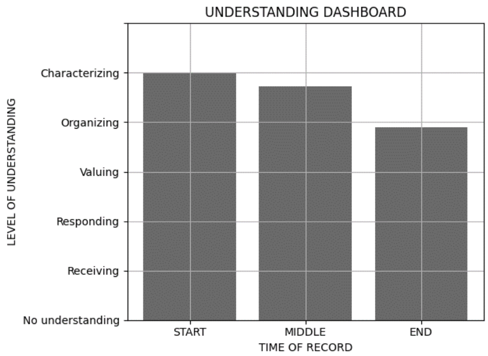
Test Case	Images	Dashboard
2 - Image sourced from YouTube video for facial recognition training [29].	 Start  Middle  End	

Table 7. The understanding score is derived through the multiplication of confidence score provided by azure and the weights assigned to each emotion.

Understanding score at the beginning of the class = {1.0*5.0}
Understanding score at the middle of the class = {(0.106*2.5) + (0.894*5.0)}
Understanding score at the end of the class = {(0.44*2.5) + (0.56*5.0)}

Emotion	Relation to Bloom's Affective Domain	Relation to Bloom's Affective Domain in weights	Emotions at the beginning of the class	Emotions at the middle of the class	Emotions at the end of the class
Contempt	No level of understanding	0.0	0.0	0.0	0.0
Anger	Receiving	1.0	0.0	0.0	0.0
Fear	Responding	2.0	0.0	0.0	0.0
Neutral	In between responding and valuing	2.5	0.0	0.106	0.44
Surprise	Valuing	3.0	0.0	0.0	0.0
Sad/disgust	Organizing	4.0	0.0	0.0	0.0
Happiness	Characterizing	5.0	1.0	0.894	0.56
Understanding Score			**5.0**	**4.735**	**3.9**

Table 8. Results obtained from test case #3.

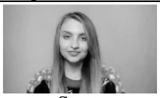
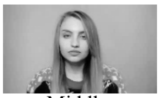
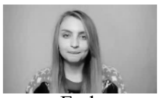
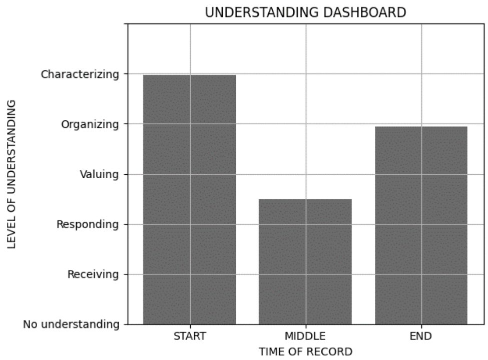
Test Case	Images	Dashboard
3 - Image sourced from YouTube video for facial recognition training [30].	 Start  Middle  End	

Table 9. The understanding score is derived through the multiplication of confidence score provided by azure and the weights assigned to each emotion.

Understanding score at the beginning of the class = {(0.001*0.0) + (0.005*2.5) + (0.994*5.0)}
Understanding score at the middle of the class = {(0.999*2.5) + (0.001*4.0)}
Understanding score at the end of the class = {(0.123*0.0) + (0.177*2.5) + (0.699*5.0)}

Emotion	Relation to Bloom's Affective Domain	Relation to Bloom's Affective Domain in weights	Emotions at the beginning of the class	Emotions at the middle of the class	Emotions at the end of the class
Contempt	No level of understanding	0.0	0.001	0	0.123
Anger	Receiving	1.0	0.0	0.0	0.0
Fear	Responding	2.0	0.0	0.0	0.0
Neutral	In between responding and valuing	2.5	0.005	0.999	0.177
Surprise	Valuing	3.0	0.0	0.0	0.0
Sad/disgust	Organizing	4.0	0.0	0.001	0.0
Happiness	Characterizing	5.0	0.994	0.0	0.699
Understanding Score			**4.9825**	**2.5015**	**3.9375**

Table 10. Results obtained from test case #4.

<table>
<tr><th>Test Case</th><th>Images</th><th>Dashboard</th></tr>
<tr><td>4 - Image captured during an online class.</td><td>
Start

Middle

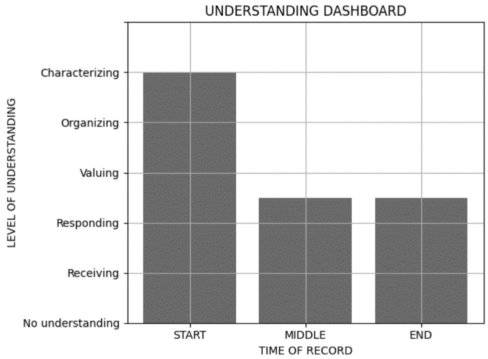
End</td><td>
</td></tr>
</table>

Table 11. The understanding score is derived through the multiplication of confidence score provided by azure and the weights assigned to each emotion.

Understanding score at the beginning of the class = {(0.002*2.5) + (0.998*5.0)}
Understanding score at the middle of the class = {(0.998*2.5) + (0.002*4.0)}
Understanding score at the end of the class = {(0.995*2.5) + (0.005*4.0)}

Emotion	Relation to Bloom's Affective Domain	Relation to Bloom's Affective Domain in weights	Emotions at the beginning of the class	Emotions at the middle of the class	Emotions at the end of the class
Contempt	No level of understanding	0.0	0.0	0.0	0.0
Anger	Receiving	1.0	0.0	0.0	0.0
Fear	Responding	2.0	0.0	0.0	0.0
Neutral	In between responding and valuing	2.5	0.002	0.998	0.995
Surprise	Valuing	3.0	0.0	0.0	0.0
Sad/disgust	Organizing	4.0	0.0	0.002	0.005
Happiness	Characterizing	5.0	0.998	0.0	0.0
Understanding Score			**4.995**	**2.503**	**2.5075**

Additionally, the EADMS was tested with an existing dataset available online [31] to validate the framework using one sample t-test. From the dataset of eight hundred and eighty videos, thirty videos were randomly selected for the test. The dataset contains videos of test subjects watching an entertainment music video. It is reasonable to assume that the test subjects have crossed the state of receiving and responding as per Bloom's Affective Domain, but are yet to reach a state of valuing, in which the subjects associate value to the music video played for them. This would imply that the test subjects are at an understanding level between responding and valuing, which is a score of 2.5 as per the mapping proposed in this paper. Therefore, the test will compare the expected value of 2.5 with the mean of the understanding score provided by the system.

Table 12. One-Sample Statistics.

	N	Mean	Std. Deviation	Std. Error Mean
Average Score	30	2.5297	0.06915	0.01262

Table 13. One-Sample Test.

	Test Value = 2.5						
			Significance			95% Confidence	
	t	df	One-sided p	Two-sided p	Mean Difference	Lower	Upper
Average Score	2.350	29	0.013	0.026	0.02967	0.0038	0.0555

From table 13, the p-value observed is less than 0.05 indicating that the mean value obtained from the system is significant to the expected value. Hence, validating the EADMS against an existing dataset. The one-sample t-test confirms that the EADMS as a system performs the expected tasks and produces results that align with the mapping proposed in this paper. However, to validate the usability of the EADMS in a live classroom environment requires testing the EADMS in an experimental setup that involves subjects attending lectures.

5 Discussions

The EADMS can map the learner's understanding using the emotional data provided by the Face API. The functional requirements of the EADMS were tested using three videos available online. Additionally, a final system test was conducted using a video of the author attending an online class. The final test indicates that the EADMS performs as expected and has the potential to serve as a communication bridge between the students and the educator and aid Active Learning in the classroom that is student-centred and technology-rich [32]. Active Learning plays a major role in involving students in the learning process [32]. Therefore, the EADMS could improve the quality of online learning by inducing active learning that enables students to engage in the learning process.

Additionally, the EADMS can allow a different approach to the learning process that is centred on Agile Frameworks. The Agile Teaching/Learning Methodology (ATLM) is a proposed pedagogical methodology that was derived from the Agile software development framework [33]. The methodology can be applied to the education field as agility in the learning and teaching process improves the learning experience [33]. The EADMS provides the educator information on student's understanding and opens the door of immediate feedback, and opportunities to iterate the lectures to achieve the highest level of understanding. The EADMS upholds the agility aspect in the teaching process that is a fundamental element of ATLM.

The EADMS maps the emotions to one of the categories of the bloom taxonomy. The framework for EADMS can be adapted to employ various models of the bloom taxonomy to measure the complexity and specificity for a student in the learning process. For example, using the cognitive domain (as known as knowledge-based bloom taxonomy) or a psychomotor domain (as known as action-based bloom taxonomy) could be mapped to measure the analytical or behavioural part of a student respectively. The EADMS system is an upgrade to the existing intelligent tutoring system as it tracks the level of understanding and identifies where the student struggles to fully comprehend the subject.

The prototype system has several limitations for future development. First, it cannot examine multiple students' understanding at the same time. Additionally, the system cannot analyse videos that are vertically recorded as the python package called moviepy stretches the images making it unclear for the Face API to analyse the image. The system is limited to using recorded video clips, introducing a lag in the EADMS scores and the students' emotions. The real-time analysis could unlock the potential for an educator to modify the lecture in real-time. The next EADMS version addresses these limitations and adds the following features, analysing multiple students, accepting vertically recorded videos, and real-time analysis. Furthermore, the proposed system could analyse the recording continuously to keep track of the students' understanding to provide a more granular view of the data for educators.

The EADMS uses Azure Face API which limits the mapping of the understanding to the eight emotions. Additionally, more research needs to be conducted on the accuracy of the emotional data provided by the Azure Face API, as different results are obtained for the same facial expression such as when the users wear spectacles. This could potentially lead to inconsistencies. Additionally, age was not considered as a variable when mapping the emotional data to the bloom taxonomy. Future studies need to explore the effects of age on the results of the EADMS system.

Another challenge to Implementing EADMS in a classroom setting would be the growing concerns around facial recognition technologies in democratic society due to ethical and privacy concerns. The ethical concerns about misidentification since the algorithm was not trained to handle people from different skin colour or ethnic background [34]. A study by Crawford and Paglen revealed that in the past five years African American and identical twins faced misrecognition or glitches from facial identification systems [4]. The privacy concerns about facial recognition technologies are the storage of detailed databases about human's actions that control personal information [35]. Personal information can be used against them for commercial or government interests. For example, in local Chinese cities, facial recognition technologies are used to identify jaywalkers and publicly shame them by displaying their name on electronic billboards [35]. Nevertheless, facial recognition technologies are implemented in the educational sector at scale. These facial recognition technologies have aided in student-centric learning approaches such as the agile learning/teaching approach and active learning [36]. Additionally, provided the necessary information to the lecturer about student engagement and understanding that significantly improves the learning process. The EADMS is a prototype developed to validate and verify the proposed mapping of emotional data and Bloom's Affective Domain in the future. The results of future tests and the consequent iterations have the potential to revolutionize the education sector.

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