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# OPTIMIZING CLASS TIMING: AI DRIVEN GROUP ENGAGEMENT'S ROLE IN ACADEMIC SUCCESS

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## ABSTRACT

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| Aim/Purpose | This study investigates the relationship between time of class and the academic performance of Master of Business Administration (MBA) students with 'group engagement' serving as the moderator. Notably, 'group engagement' is measured using a novel computer vision-based deep learning approach. |
| Background | Generally, the first year of MBA programs is a critical phase for students, marked by academic and personal growth challenges. The timing of MBA classes, particularly morning sessions, can disrupt students' circadian rhythms, leading to decreased engagement and academic performance. Existing literature highlights the potential benefits of active learning methods, such as blended learning and collaborative learning, in improving individual student engagement. |

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However, there is a gap in understanding the impact of these methods on group engagement and how this, in turn, influences academic performance.

Methodology
We collated video-recorded data from 54 first-semester MBA students when they were attending their morning and afternoon classes. Notably, we adopted blended and collaborative learning methods in the morning classes to check their impact. The study variables included time of class, group engagement, and academic performance. While we measured academic performance through proctored exams, group engagement was estimated using a vision-based system, whereby we analyzed facial expressions from the recorded videos, employing a Convolutional Neural Network (CNN) model. We trained the CNN model to measure group engagement by categorizing specific emotions (sleepy, bored, yawning, frustrated, confused, and focused). We used these emotions to assess group engagement levels (i.e., low, medium, and high).

Contribution
This study establishes a definite link between morning classes with blended and collaborative learning methods, resulting in improved academic performance. Besides, through group engagement moderation, we get crucial insights into how high group engagement effectively enhances academic performance. Based on the findings, we propose strategies for educators to optimize their teaching methods and foster a conducive learning environment by leveraging insights from students' affective states.

Findings
Broadly, the results indicate that students performed better in morning classes in which both blended and collaborative learning methods were used. The average marks in morning classes increased to 18.74 compared to 15.39 in afternoon classes. There was a high level of group engagement in the mornings, significantly impacting the relationship between class time and academic performance. However, switching from morning to afternoon classes decreased the effect (academic performance) from 0.03 to -5.42. This shows that the use of blended and collaborative learning methods and the presence of high group engagement in morning classes are essential for better educational outcomes.

Recommendations for Practitioners
We recommend integrating active learning methods, such as blended and collaborative learning, into morning MBA classes to optimize academic performance. Our results show that implementing technology-driven group engagement measurement tools enhances real-time insight into emotional states. Educators can use this information to tailor teaching approaches and foster a positive learning environment.

Recommendations for Researchers
Additional research should explore the longitudinal impact of AI-based engagement measurement. Studies could also investigate the scalability and applicability of group-focused strategies across diverse educational settings.

Impact on Society
This study highlights the need to improve teaching methods and group engagement in MBA education. It offers tools for active learning and AI-based engagement tracking. The findings would help both educators and policymakers create better learning experiences.

Future Research
Future research should include more diverse samples to enhance external validity. Studies can explore various learning methods across different cultural contexts. Researchers can develop hybrid systems integrating physiological sensors with computer vision to provide more comprehensive results.

Keywords
class timing, group engagement, academic performance, blended learning, collaborative learning, SOR Model, computer vision, artificial intelligence

## INTRODUCTION

The first year of higher education programs marks a crucial juncture for students; it signifies a transformative period that extends beyond academic pursuits (Murthy et al., 2023; Zighan & EL-Qasem, 2021). At this stage, students from diverse backgrounds face academic and personal challenges, including stress from classroom competition and, at times, they even lack appropriate family support (Ramachandiran & Dhanapal, 2018; Vinson et al., 2010). Stress hinders sleep patterns and contributes to disengagement in morning classes, which in turn impacts test scores and classroom participation (Luo & Wang, 2023; Marbouti et al., 2014).

The time a class is scheduled affects students' receptiveness to information, overall engagement, and academic performance (Muyskens & Ysseldyke, 1998). Interestingly, in high school education and undergraduate university settings, early classes are associated with reduced sleep and diminished engagement, which leads to impaired academic performance (Diette & Raghav, 2017; Yeo et al., 2023). Similarly, STEM classes early in the morning are associated with lower academic achievement due to circadian misalignment and fatigue (Alfonsi et al., 2020; Shapiro & Williams, 2015). Early class timing in dental education, too, seems to contribute to increased absenteeism and lower academic performance (Alamoudi et al., 2021). Although prior studies have highlighted the relationship between the time of class and academic performance across various disciplines, there is a notable lack of research focused on business management programs in higher education.

Existing studies suggest that when used in morning classes, active learning methods (i.e., blended and collaborative learning) enhance academic performance (Marbouti et al., 2018). However, understanding how these methods work does require examining student engagement, as it plays a vital role in understanding the impact of teaching methods on academic outcomes (León & García-Martínez, 2021). While past research has explored the moderating role of student engagement in the relationship between blended and collaborative learning and academic performance (Okolie et al., 2022; Tomas & Poroto, 2023; Yu, 2023), there has been limited focus on group engagement. Group engagement effectively refers to the collective participation of students during lectures. We believe this is a significant gap in the literature because understanding group engagement could provide unique insights. Group engagement could help in knowing how collective participation affects learning outcomes (Conduit et al., 2017).

Further, it may be noted that student engagement measurements have primarily been dominated by self-report surveys (X. Gao et al., 2020). Self-report surveys carry a social desirability response bias (Fei et al., 2018), while observational methods are time-consuming and cumbersome (Harari et al., 2017). In this study, unlike these traditional approaches, we adopted an innovative computer vision-based method to measure group engagement. Our rationale for adopting this method was that it provides a non-intrusive and objective way of measuring engagement. Specifically, we realized similar measurements by considering students' facial emotions, such as focused, sleep, boredom, yawning, frustration, and confusion.

With this as the contextual backdrop, we investigated the impact of blended and collaborative learning in the morning and traditional learning in the afternoon class on academic performance. We particularly focused on higher education programs in business management. Further, we explored whether group engagement moderates the relationship between class time and academic performance. For the theoretical grounding of this study, we applied the stimulus-organism-response (SOR) framework. According to the SOR model, external stimuli (time of class using blended and collaborative learning) interact with internal processes (group engagement) to produce behavioral outcomes (academic performance). This theoretical approach provides a comprehensive basis for addressing the following research questions:

1. Does blended and collaborative learning used in morning classes improve academic performance?

2. How do varying levels of group engagement measured through students' emotional states moderate the relationship between time of class and academic performance?

This study addressed first-year MBA students' unique challenges within a specific cultural and educational setting. The findings provide a more effective teaching approach for first-year MBA students. The use of blended and collaborative learning in the morning class had a significant positive effect on academic performance. However, the moderation of group engagement in this relationship explains an interesting story. We employed an innovative computer vision-based deep-learning approach to measure group engagement. We build on existing methodologies and provide a robust and novel alternative to traditional engagement measures. Notably, this method contributes to current research and opens opportunities for integrating Artificial Intelligence in educational research and practice.

The remainder of this paper is organized as follows. The second section describes the research gaps by reviewing literature related to time of class, group engagement, and academic performance. The third section explains the theoretical framework and hypotheses. This is followed by the fourth section, which details the methodology, including experimental design and group engagement measurement. The fifth section summarizes the results and analysis. Finally, we conclude by discussing the findings and contributions to extant literature and propose practical implications and future research directions while highlighting the limitations.

## LITERATURE REVIEW

### *TIME OF THE CLASS AND ACADEMIC PERFORMANCE.*

Colleges and universities have various goals when determining their class schedules. For instance, they aim to optimize classroom and faculty usage, minimize student scheduling conflicts, and effectively spread classes throughout the day. From the students' perspective, the timing of classes is not just a matter of logistics but is deeply intertwined with their daily routines. It encapsulates the temporal rhythms of their daily lives and the cognitive fluctuations that accompany different times of day (Dikker et al., 2020). Circadian rhythm, an internal body clock that regulates physiological and behavioral processes over a 24-hour cycle, plays a pivotal role in influencing cognitive functions and alertness (Rodríguez Ferrante et al., 2023). Chronotypes that reflect individual differences in circadian rhythms are often classified as morning or evening types. They affect students' alertness and internal motivation for knowledge acquisition and accomplishments. Evening chronotypes that naturally function better later in the day often struggle with early class schedules, which may negatively affect academic outcomes (Önder et al., 2014). This highlights the need for higher education institutions to consider the alignment between class timing and students' biological predispositions to optimize learning outcomes.

Cultural variations further complicate sleep patterns among students. Herein, it may be noted that there is a significant contrast in sleep duration and habits between Asian and Western cultures (Estevan et al., 2021). In the Asian context, societal norms prioritize academic achievement and competition, leading to reduced sleep duration (Schmidt & Van der Linden, 2015). In contrast, Western students often enjoy longer sleep durations because of less academic pressure and better work-life balance (Cheung et al., 2021). These differences underscore how cultural expectations influence students' sleep patterns, along with their cognitive readiness for learning. Additionally, adolescents and young adults undergo various biological, psychological, and social transitions, all of which contribute to sleep difficulties in high school and college students (Rhie & Chae, 2018). A meta-analysis conducted by Biller et al. (2022) highlighted how social and biological factors collectively result in insufficient sleep, further impairing students' focus and learning capacity during morning hours.

Research on class start time and academic performance spans various educational contexts. Early class start times (e.g., 8:00 a.m.) negatively impact university students' performance, confidence, and engagement, but pedagogies, such as flipped classrooms and metacognitive learning, can help mitigate these effects (Luo & Wang, 2023). Yeo et al. (2023) linked early classes to shorter sleep, reduced attendance, and lower GPAs in university students. This is consistent with Alfonsi et al. (2020) and Shapiro and Williams (2015) studies, which found that early morning STEM classes were particularly detrimental to student achievement, primarily due to circadian misalignment and fatigue. Alamoudi et al. (2021) identified early morning classes, weak presentations, and exam preparations as key factors for absenteeism among dental students, impacting overall academic performance.

Furthermore, extant research suggests that class time must be shifted later in the day. For instance, Edwards (2012) showed that class time has a positive impact on attendance and academic performance. T. Kim (2022) showed that delaying school start times to 9:00 a.m. increases sleep duration and academic performance. Wahlstrom et al. (2014) and Watson et al. (2017) found that later school start times lead to better sleep duration and academic performance in adolescents, highlighting the potential of schedule adjustments to improve learning outcomes. However, Desai et al. (2024) noted that there are practical constraints on infrastructure availability, number of students per class, and teacher-student ratios, which effectively make it difficult to implement. Marbouti et al. (2018) and Luo and Wang (2023) highlighted the potential of using active learning methods to mitigate the challenges of early class timings. Our study explores whether such learning approaches in morning classes can enhance academic performance. By focusing on the specific demographic of higher management education, we aim to contribute to the limited literature on enhancing the efficacy of the morning class to improve academic performance.

## *Active Learning Methods, Student Engagement, and Academic Performance*

Active learning represents a pedagogical shift from traditional lecture-based to student-centered approaches. In active learning, students actively consume knowledge in a collaborative and experiential learning environment (Barr & Tagg, 1995). In management education, blended and collaborative learning is increasingly being used as an active learning method (Herrera-Pavo, 2021; Kumar, 2021).

Blended learning combines or integrates two or more distinct teaching methods that can be effectively merged (Hrastinski, 2019); collaborative learning, on the other hand, entails students working together to achieve shared learning goals (Dass et al., 2021). Both blended and collaborative learning have been linked to improved academic performance (Marbouti et al., 2018; Wiggins et al., 2017). Student engagement is a key factor in effective learning and academic performance (Appleton et al., 2008; Krause & Coates, 2008; Tsay et al., 2020). According to León and García-Martínez (2021), in-class contextual factors, such as student engagement, play an important role in the link between instruction methods and academic outcomes.

Furthermore, studies have highlighted the role of student engagement in moderating the relationship between blended learning, collaborative learning, and academic performance (Karuppan & Bararib, 2010; Tomas & Poroto, 2023; Yu, 2023). However, most of these studies focused on individual student engagement. This underscores the need to explore engagement at the group level, whereby collective interactions play a critical role in shaping learning outcomes (Wang & Eccles, 2013).

Learners require an appropriate environment that supports effective learning, an environment in which the learners' engagement can be fostered through collaborative and interactive activities (Gupta et al., 2023). Interactions among class students are often influenced by the extent of their engagement during group activities within the classroom (Fakhar et al., 2022). Assessing how students engage as a group can provide valuable insights into the efficacy of instructional methods in group dynamics and overall learning outcomes (Prameela et al., 2024). To fully understand the extent of learning in a group, it is essential to gather and analyze data related to students' affective states (affective states refer to the emotional or mood-related conditions that a person experiences at a given time) (Kavitha et al., 2023).

Chávez Herting et al. (2020) posited that exploring the relationship between instructional methods and academic performance lacks methodological rigor. It includes limitations, such as a lack of randomization and focus on short-term academic performance. Short-term improvements in grades and test scores, on the other hand, provide limited insight into how teaching methods affect long-term learning outcomes, motivation, and retention (Moulton et al., 2017). Therefore, future studies should focus on longitudinal data to study the impact of instructional methods on academic performance.

In light of previous research, we explore whether active learning methods of blended and collaborative learning in morning classes can enhance academic performance. Our study possibly stands out because we examine group engagement, which refers to the collective engagement of students during lectures. Besides, we also ensure methodological rigor by considering a time frame spanning one semester. It may be noted herein that extant research on group engagement is limited; however, peer interactions have significantly improved academic outcomes (Sinha et al., 2015). Thus, understanding students' behaviors and emotional states within groups would enable us to better assess the impact of instruction methods and refine them to enhance group learning efficiency.

## *EVOLUTION OF ENGAGEMENT MEASUREMENT*

Over the last decade, researchers and policymakers have focused on the concept and assessment of student engagement (Bond et al., 2020). Karimah and Hasegawa (2022) categorized the evolution of student engagement detection into manual methods (self-reporting and observational checklists), semiautomatic methods (engagement tracking), and automatic methods (log file analysis, sensor-based, and computer vision-based). Notably, computer vision-based deep learning approaches have garnered attention because of their unobtrusive nature and cost-effectiveness, which mimics traditional classroom observations (Desai et al., 2024). These methods can analyze nonverbal cues, such as head motion, eye gaze, and body pose, and provide various indicators for determining engagement levels (Ben-Youssef et al., 2019). Their advantage lies in offering insights into learners' behavior without disrupting their ongoing activities, making them a favorable choice for engagement assessment (D'Mello et al., 2017).

A key component of computer vision is its integration with affective computing, which primarily focuses on developing devices and systems capable of recognizing and processing human affect (Ashwin et al., 2020). Human effects, in turn, involve emotions and behaviors; they provide insights into inner feelings and environmental responses. Emotions interwoven with behavioral cues, such as facial expressions and body language, convey valuable information. Within a classroom setting, student behavior is an indicative measure of psychological well-being, reflecting emotional states and mental conditions (Wei et al., 2017). Consequently, the measure of human affect becomes particularly relevant when assessing student engagement, as it supplements the necessity of visible facial expressions (Amin et al., 2023).

Numerous vision-based approaches have recently been introduced in the field of educational technology, primarily intended for online learning environments characterized by a single student within a single video frame (Bosch et al., 2016; Sharma et al., 2022; Whitehill et al., 2014; Zhang et al., 2023). However, these methods must be improved in scalability when applied to physical classrooms with multiple students. Zaletelj and Košir (2017), for instance, have proposed some methodologies for physical classroom settings that aim to automatically estimate students' attention in an offline classroom using non-verbal cues (messages conveyed through body language and expressions). They have used a motion-sensing Kinect One camera and machine learning algorithms of decision trees and k-nearest neighbors (decision trees split data to classify it, whereas k-nearest neighbors predict outcomes based on the closest data points) to assess the non-verbal cues. However, owing to the technological limitations of Kinect cameras, the analysis was restricted to only six students instead of the entire class.

Klein and Celik (2017) developed the Wits Intelligent Teaching System (WITS), which uses a Convolutional Neural Network (CNN) (a deep learning model that processes data using layers for feature detection) approach to give teachers real-time feedback on student engagement by monitoring positive and negative behavioral cues across large offline classrooms. However, their study did not use emotional cues to estimate students' engagement and involved a computational overhead. Zheng et al. (2020) designed a framework to detect students' behaviors such as hand-raising, standing, and sleeping in a classroom setting. They trained their model with an improved Faster R-CNN (an advanced algorithm for quickly and accurately detecting objects in images) object detection algorithm. However, this model only detects specific behaviors and cannot predict overall student engagement using effective academic cues.

Vanneste et al. (2021) proposed a technique for assessing student engagement by recognizing behaviors such as hand-raising and note-taking. Mou et al. (2023) employed deep learning and affective computing to analyze spontaneous learner emotions in offline classrooms, linking emotions like joy and anxiety to engagement and performance through an explanatory model. Pereira et al. (2024) utilized datasets like AffectNet; they focused on facial emotion detection using CNNs for precise individual affect analysis. Y. Gao et al. (2025) proposed a multi-attention network (MAF-ER) to classify classroom emotions, such as resistance, fatigue, and understanding. However, these studies did not test real-time engagement estimation in large classroom settings. In addition, these studies primarily estimated individual engagement and did not address group-level engagement, which is critical for understanding collective classroom behavior.

The current study's methodology overcomes some of these limitations noted thus far by employing a methodology specifically designed for offline, real-world classroom settings. We capitalized on the advantages of a CNN-based deep-learning approach to gauge student group engagement, which we discuss in detail in the Methodology section.

# Research Framework and Hypothesis Development

## *SOR Theory*

The Stimulus-Organism-Response (SOR) model, introduced by Russell and Mehrabian (1974), provides a framework for understanding how external stimuli influence internal cognitive and emotional states, which in turn shape behaviors. Unlike earlier stimulus-response models, it incorporates the 'organism' as a mediator, reflecting the complexities of human behavior beyond simple cause-and-effect relationships. Notably, the stimulus and an organism's internal properties can sometimes act together to produce a response (Young, 2016). Scholars have established SOR models based on situational conditions, enhancing the model's effectiveness in educational settings (Yang et al., 2021). Previous studies using the SOR model have investigated a wide range of stimuli that include flow in the field of consumer behavior (L. Gao & Bai, 2014), interaction as a stimulus for purchase intention (Animesh et al., 2017), and emotions as stimuli for brand engagement (A. J. Kim & Johnson, 2016). In terms of educational settings, several studies have measured academic performance as a response to stimuli, such as boredom and overload (Tafesse et al., 2024; Y. Xu et al., 2022). As shown in Figure 1, we used blended and collaborative learning methods during the morning class, which served as the external trigger (Stimulus), and group engagement was the internal state (Organism), while academic performance was the outcome (Response). It is like a chain reaction, where each part influences the next, painting a bigger picture of how students learn and succeed (Illeris, 2003).

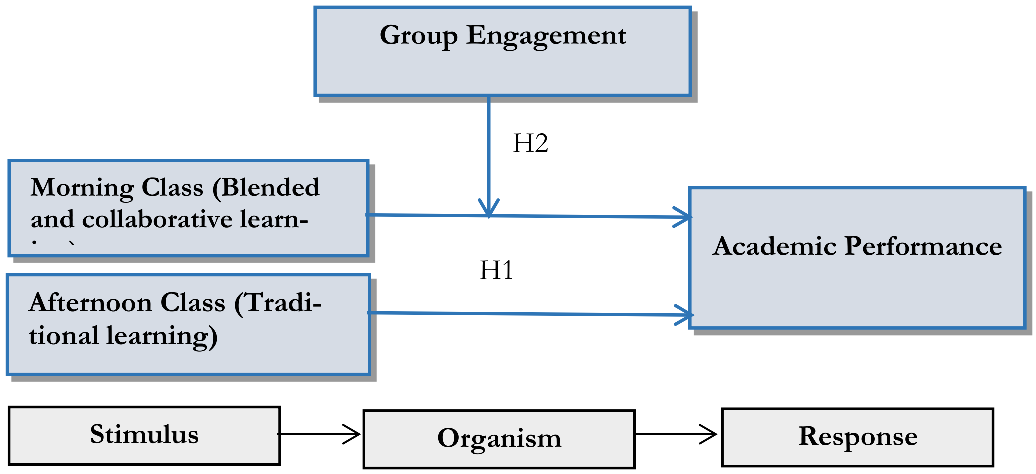


**Figure 1. The proposed research model of the study**

### *Time of Class and Academic Performance*

Previous studies have demonstrated that blended learning, which combines traditional teaching with other interactive learning approaches, and collaborative learning, which fosters peer interaction and shared goals, significantly enhance academic performance (Marbouti et al., 2018; Wiggins et al., 2017). Recent research grounded in the SOR model also validates the positive relationship between instructional methods of blended and collaborative learning and academic outcomes (Lau et al., 2024; Wut et al., 2024). Creating an interactive and stimulating learning environment mitigates the cognitive challenges of morning classes and leads to better academic performance. Based on this understanding gained thus far, we posit:

**H1:** Academic performance is significantly better with the use of blended and collaborative learning in the morning class.

### *Group Engagement*

Student engagement has been shown to moderate the relationship between instructional methods and academic performance (Karuppan & Bararib, 2010; Tomas & Poroto, 2023; Yu, 2023). We examined the moderating effect of group engagement, as peer interactions and collaboration are crucial for improving academic outcomes (Wang & Eccles, 2013). Manresa et al. (2024) validated the SOR model in the workplace context, emphasizing engagement as a mediator between GenAI adoption and performance. F. Z. Xu and Wang (2020) used the SOR model in the hospitality context; they emphasized the moderating role of engagement in bridging customer interactivity and employee innovation. We also used the SOR model to create a framework for examining how group engagement moderates the relationship between time of class and academic performance. We posit:

**H2:** Group engagement moderates the relationship between class time and academic performance, particularly when blended and collaborative learning methods are employed.

## Methodology

### *Sample Size and Demographic Details*

We estimated the sample size using the G*Power 3.1.9.4 software (UCLA Statistical Methods and Data Analysis, n.d.). Hayes (2013) process Macro Model 1 (the method used for statistical analysis) uses a linear multiple regression with a fixed model and a deviation from zero. We calculated the sample size for linear multiple regression using power analysis with input parameters of effect size of 0.35, alpha ($\alpha$) error probability of 0.05, and power ($1-\beta$) of 0.95, along with three predictor variables.

The reason for taking a higher effect size was the strong relationship between variables observed in earlier studies and the results of a pilot study conducted before the experiment. Based on these parameters, the required total sample size was 54, of which 31 males and 23 females were selected for the study. The participants' demographic data highlighted that 43% were female; the majority held bachelor's degrees in commerce (50%), and the average age of the participants was 21.5 years.

## *Experiment*

### Student selection and set up

We contacted students in a business school affiliated with a state university in Southern India for data collection. The respondents were first-semester Master in Business Administration (MBA) students from two divisions (A and B) who voluntarily agreed to participate. The students provided written informed consent. In division 'A,' we collected data in the course Marketing Management (MM), and in division 'B,' data were collected from the Management Accounting (MA) and Marketing Management (MM) courses. At the beginning of the course, the faculty informed the students about the study. Before initiating the data collection process, trial runs were conducted to ensure that all participants adhered to the ethical standards and the integrity of the experiment. We also familiarized the students with the recording process by integrating them into their routine classes, helping them acclimate to the procedure.

### Data collection and proctored exam

During the study, we recorded 36 class sessions comprising three lecture sets, which were the basis for measuring group engagement. The aim was to gain deeper insight into group engagement and academic performance. Therefore, at least 12 sessions were recorded for each subject; of the 36 sessions, 18 were scheduled in the morning (9:00 a.m. to 11:30 a.m. IST), and 18 were scheduled later (12:30 p.m. to 3:30 p.m. IST). The morning and afternoon class times were chosen based on studies that examined the first two morning classes to study the impact of class time on academic performance (T. Kim, 2022; Luo & Wang, 2023). Luo and Wang (2023) in their study stated that morning classes began at 8:00 a.m. and continued until 1:30 p.m. Moreover, as the institute where this study was conducted started at 9:00 a.m., we considered the first two classes starting from 9:00 a.m. for the morning sessions and the next two for the afternoon session. The faculty taking morning classes used blended and collaborative learning methods to align with the study objectives. In the case of blended learning, the teacher used a combination of pedagogies, including interactive discussions, PowerPoint slides, and informative videos. In collaborative learning, students presented topics in the classroom during lectures. The afternoon period was taught using traditional learning methods (PowerPoint presentations and chalk and board). Each division was comprised of two groups of nine students. Across both divisions and three subjects, six groups were used to record videos. Finally, 72 videos were analyzed for group engagement calculations across the 36 classes recorded. Table 1 shows the details of data collection from both divisions subject-wise.

**Table 1. The details of data collection from both the divisions subject-wise**

| SN | Division | Subject | Time of class | Instruction method | Number of lectures | Number of videos |
|---|---|---|---|---|---|---|
| 1 | A | Marketing Management | Morning | Blended and collaborative | 6 | 12 |
| | | | Afternoon | Traditional learning | 6 | 12 |
| 2 | B | Marketing Management | Morning | Blended and collaborative | 12 | 24 |
| 3 | B | Management Accounting | Afternoon | Traditional learning | 12 | 24 |
| Total | | | | | 36 | 72 |

We conducted exams after the data collection period to evaluate students' academic performance. These examinations comprised 24 multiple-choice questions (MCQ). The questions were framed based on the course content covered in the lectures that were recorded. The three groups of students took division-wise exams for marketing management and management accounting. The exam was conducted to prevent potential biases from students becoming overly thoughtful of engagement measurements during lectures, thus ensuring a genuine and fair evaluation of their academic performance. We considered group academic performance in the analysis by taking the average of the group of students in the recorded video. Figure 2 shows a flowchart of the steps in experimenting with the study.

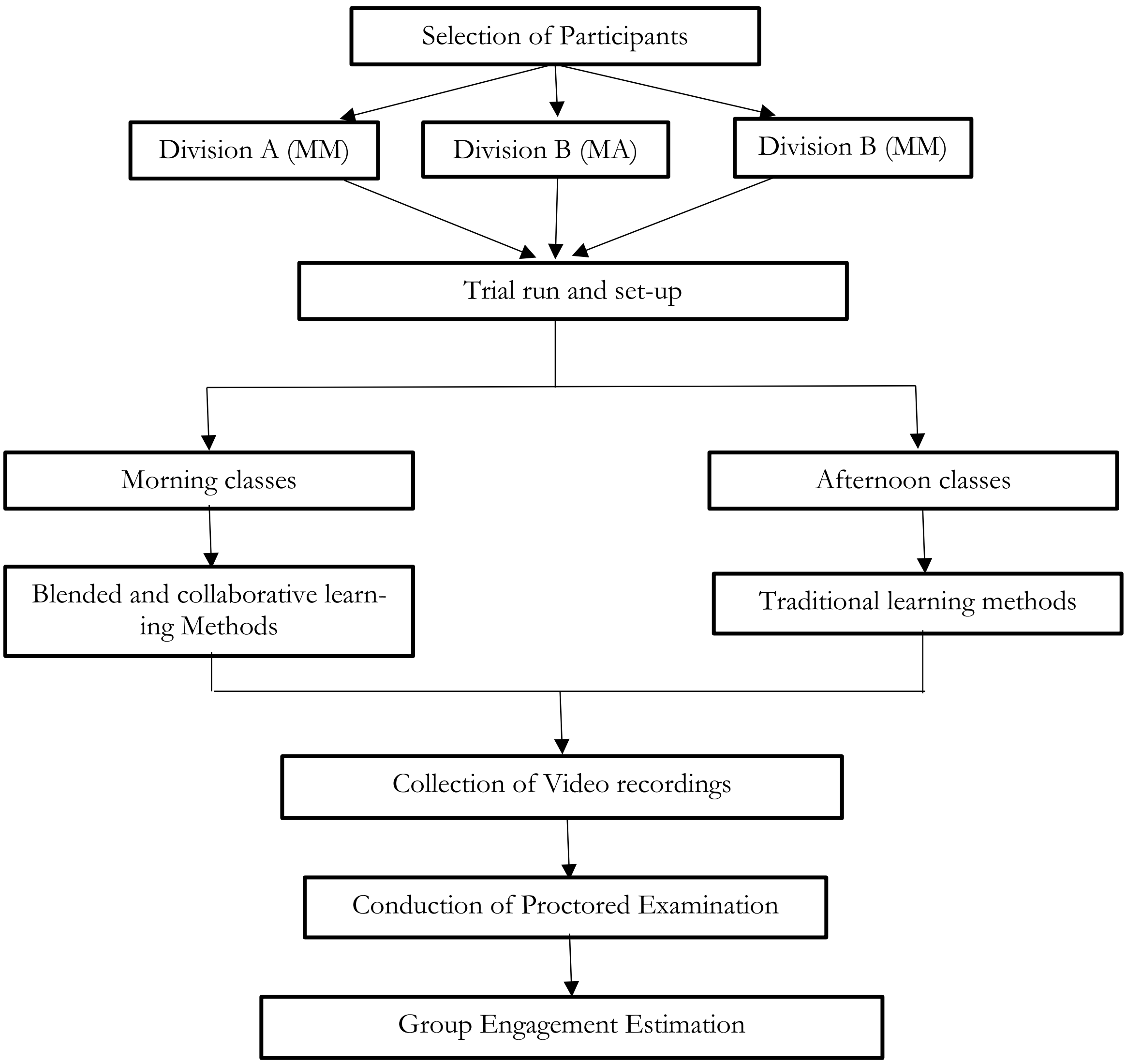


**Figure 2. Flow chart of the steps in the conduct of the experiment**

## Group engagement

We employed a vision-based automated system based on the seminal work of Pabba and Kumar (2022) in order to assess student engagement. This system monitored group engagement in offline classrooms by analyzing students' academic affective states through facial expressions and categorizing them into low, medium, and high engagement levels. The model developed a classroom spontaneous facial expression dataset (CSFED). The dataset comprised 4262 color students' facial images with six facial emotions that reflect student academic and emotional engagement: 'Focused,' 'Confusion,' 'Frustrated,' 'Boredom,' 'Yawning,' and 'Sleepy.' The CSFED dataset was used to train the customized CNN architecture to develop a facial emotion recognition (FER) model. The trained CNN model classifies the faces into six emotions for computing engagement.

## Convolutional neural network (CNN)

A CNN is a specialized deep learning model designed to analyze visual data by mimicking how the human brain processes visual information (Krizhevsky et al., 2012). CNNs operate by passing images through multiple layers that extract and learn hierarchical features. The core building block is the convolutional layer, where filters (kernels) slide over the input to compute feature maps by capturing spatial patterns, such as edges and textures. Rectified Linear Unit (ReLU) activation introduces non-linearity, enabling the model to learn complex patterns. Pooling layers (e.g., max pooling) follow to reduce the spatial dimensions, making the computations more efficient and invariant to small transformations in the input. Finally, the fully connected layers integrate the features learned by the convolutional layers and provide the final output, such as the classification probabilities. CNNs are used in various tasks, including image classification, object detection, semantic segmentation, medical imaging, and facial emotion recognition. For facial emotion recognition, CNNs work by analyzing facial images, learning key features, and classifying emotional expressions. This has practical uses in areas such as human-computer interaction, mental health care, and behavior analysis.

The specificities of the CNN model, along with the engagement level determination employed in the current study, were taken from Pabba and Kumar (2022). Figure 3 depicts the architecture of the CNN model. The CNN architecture illustrated in Figure 3 includes convolutional and max-pooling layers for feature extraction, followed by fully connected layers for classification. It begins with three feature extraction blocks, each comprising two convolutional layers with ReLU activation and one max-pooling layer for down sampling. The first block processed an input image of size 48×48×3, generating 32 feature maps using 3×3 kernels with L2 regularization. Subsequent blocks doubled the number of feature maps to 64 and 128, reducing their spatial dimensions through max-pooling. After feature extraction, the flattening layer converted the 128 feature maps into a 4608×1 vector, which served as the input to the classification block. This block consists of two hidden layers with 1024 neurons each and a softmax output layer with six neurons for emotion classification. The architecture effectively extracts robust features and assigns probability scores to the six emotion classes.

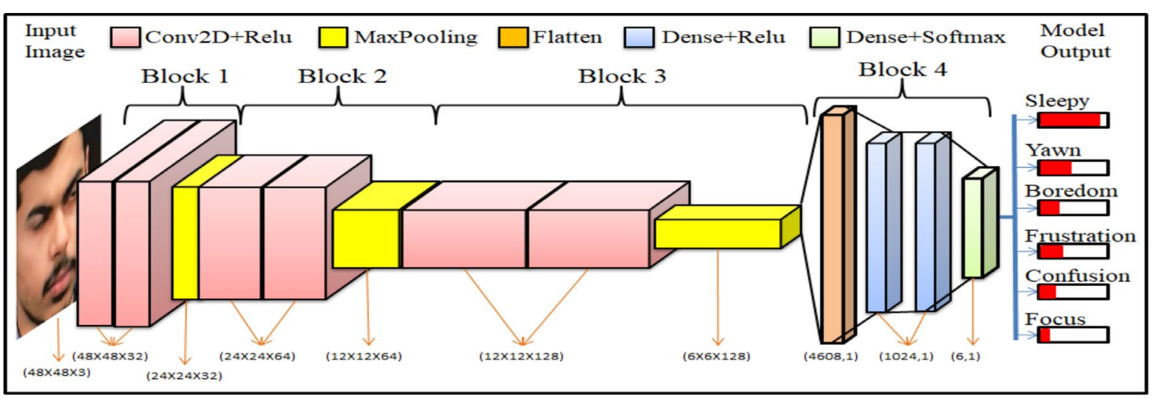


**Figure 3. The CNN model architecture for the facial expression recognition model (Pabba & Kumar, 2022) (reprinted with permission)**

Furthermore, the optimal hyper parameter values that were used in the FER model training are summarized in Table 2.

**Table 2. The CNN model's hyper-parameter values (Pabba & Kumar, 2022) (reprinted with permission)**

| Hyper-Parameter | Value |
|---|---|
| Batch size | 32 |
| Activation function | Rectified Linear Unit (ReLU) |
| Optimizer | Adam with a learning rate of 0.001 |
| Loss function | categorical_crossentropy |
| Range of kernels | 32 – 64 – 128 |
| kernel size | 3X3 |
| Kernel weight initializer | he_normal |
| Kernel_regularizer | L2 with a logarithm scale of 0.01 |
| Padding | Zero padding |
| Stride | Default |
| Pool size | (2,2) |
| Normalization | Batch Normalization |
| Probability of dropout | 0.2 |
| Maximum epochs | 500 |
| Early stopping | 185 |

The trained FER model recognizes students' facial expressions, which indicate their emotional states during a lecture. These expressions are further analyzed to determine the overall engagement level of the group, acknowledging that engagement naturally varies throughout a session. Inspired by prior research (Ashwin & Guddeti, 2019; Zaletelj & Košir, 2017), this work adopts an engagement-level taxonomy to classify students' academic affective states based on their facial expressions.

## Process of estimating group engagement

The video recordings obtained from the classes underwent a step-by-step process, commencing with pre-processing and post-processing, followed by a display of the real-time graph (Figure 4). This pre-processing phase comprises three steps: video frame sampling, face detection, and face alignment. In video frame sampling, the frames are meticulously sampled at consistent one-second intervals, and faces undergo detection, cropping, and resizing to dimensions of 48 × 48 pixels. Further, the faces are detected and aligned.

The post-processing step involved four stages; first, the predicted emotion labels for students were counted frame by frame. Next, these counts were grouped into three engagement levels (EL): Engagement Level 1 (EL1) for 'sleepy' and 'boredom' (low engagement), Engagement Level 2 (EL2) for 'confused,' 'frustrated,' and 'yawning' (medium engagement), and Engagement Level 3 (EL3) for 'focused' (high engagement). This process was repeated for each set of video frames. In the third stage, the counts for each engagement level within a video segment were combined with their corresponding EL labels. Finally, the engagement label with the highest count in the EL accumulators was assigned as the segment's estimated group engagement level (GEL). The estimated engagement level of each segment was then plotted on a real-time student engagement graph. This process was repeated for every video segment to estimate the overall group engagement for the lecture based on the label with the highest accumulated GEL counts. Figure 4 shows the vision-based group engagement monitoring methodology.

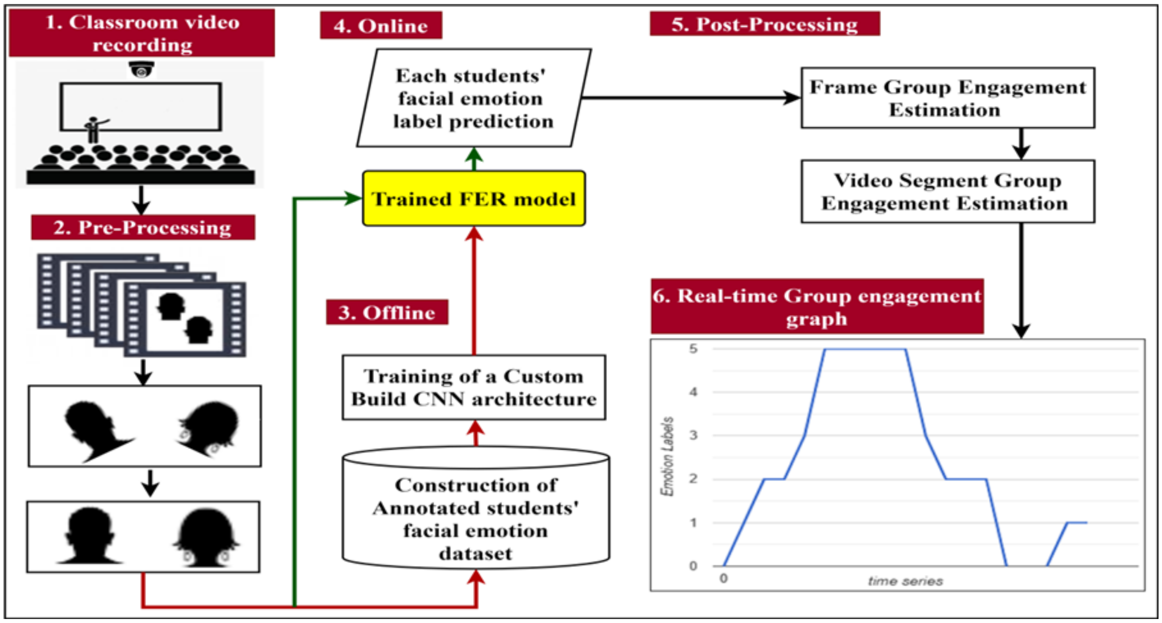


**Figure 4. Vision-based group engagement monitoring methodology (Pabba & Kumar, 2022) (reprinted with permission)**

Figure 4 depicts a methodology for real-time group engagement estimation within a classroom setting. The process begins with classroom video recordings, followed by pre-processing that includes video frame sampling, extracting individual student faces, and face alignment. A custom CNN architecture is trained offline on an annotated dataset of students' facial emotions. Then, this trained model was used to predict the emotional state of each student in real-time, enabling the estimation of engagement levels for each frame. Subsequently, these frame-level estimates are aggregated across video segments to provide a more stable measure of engagement. Finally, the system generates a real-time graph visualizing the estimated group engagement levels over time, offering valuable insights into the classroom's dynamic engagement patterns.

The analyzed video shows each face read and analyzed by the model for each frame, as shown in Figure 5. The values were reflected in post-analysis Excel sheets. The Excel sheet comprised the affect state data for every frame, as shown in Appendices A and B.


**Figure 5. The input video frame and analyzed video frame**

The model's process of arriving at the group engagement can be explained as follows. Column A lists the number of frames. Notably, the recorded video consists of 30 frames per second (fps) every 15th frame and is analyzed by the software; two frames would be analyzed per second to avoid redundancy in analysis. Further, the frames of multiple of fifteen are analyzed. Column B shows the detected faces. Column C shows the predicted faces for the affective states, while Column D shows the number of sleepy faces, and Column E shows the number of faces that were experiencing boredom. Column F shows the number of faces yawning, and Column G shows the number of faces that were frustrated. Column H shows the number of faces that were confused, and Column I shows the number of faces that were engaged. Column J shows the cumulative number of faces that were sleepy and bored; the same was the measure of the low engagement state. Column K shows the cumulative number of faces that were yawning, frustrated, and confused; the same is the measure of the medium engagement state. Column L shows the cumulative number of focus/engaged faces; the same is the measure of the high-engagement state.

The analysis continued until the frame number reached the 300th frame (i.e., 10s and further each second with 30 frames). The maximum number of low, medium, and high states (0, 1, 2) is taken as the level of engagement for the 10-second band, as shown in the second output Excel sheet as shown in Appendix B. For example, in the 10-second band, there are more faces in the engaged/focused state (Column L) compared to the other two states; therefore, for the first 300 frames, the group engagement was noted to be high (Level 2). The same process is repeated for the entire video; the engagement level was decided based on the maximum of low, medium, and high for the series of 10-second bands.

The robustness of the model was evaluated with other metrics, such as the confusion matrix (tabular summary of prediction accuracy, showing true and false positives and negatives), precision (proportion of true positive predictions in all positive predictions), recall (proportion of true positive predictions in all actual positives), and F1-score (balanced metric combining precision and recall, especially useful for uneven class distributions), as depicted in Figure 6 and Table 3 respectively. The CNN model also exhibited robust performance, with a training accuracy of 78.70% and a testing accuracy of 76.90%, indicating its effectiveness in accurately assessing student engagement in traditional classroom settings, as shown in Figure 7.

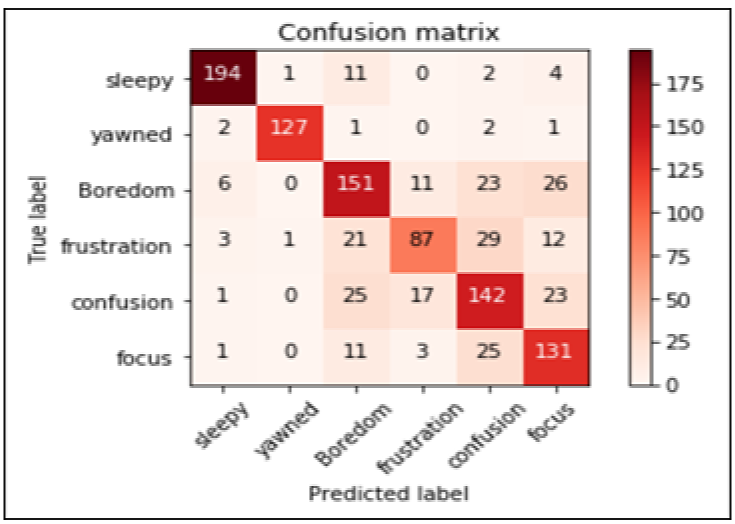


**Figure 6. The trained FER model's confusion matrix (Pabba & Kumar, 2022) (reprinted with permission)**

**Table 3. The FER model's evaluation report (reprinted with permission)**

| | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| Sleepy | 0.94 | 0.92 | 0.93 | 212 |
| Yawning | 0.98 | 0.85 | 0.97 | 133 |
| Boredom | 0.69 | 0.70 | 0.69 | 217 |

| | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| Frustrated | 0.74 | 0.57 | 0.64 | 153 |
| Confused | 0.64 | 0.68 | 0.66 | 208 |
| Focused | 0.66 | 0.77 | 0.71 | 171 |
| Accuracy | - | - | 0.76 | 1094 |
| macro avg. | 0.77 | 0.76 | 0.77 | 1094 |
| weighted avg. | 0.77 | 0.76 | 0.76 | 1094 |

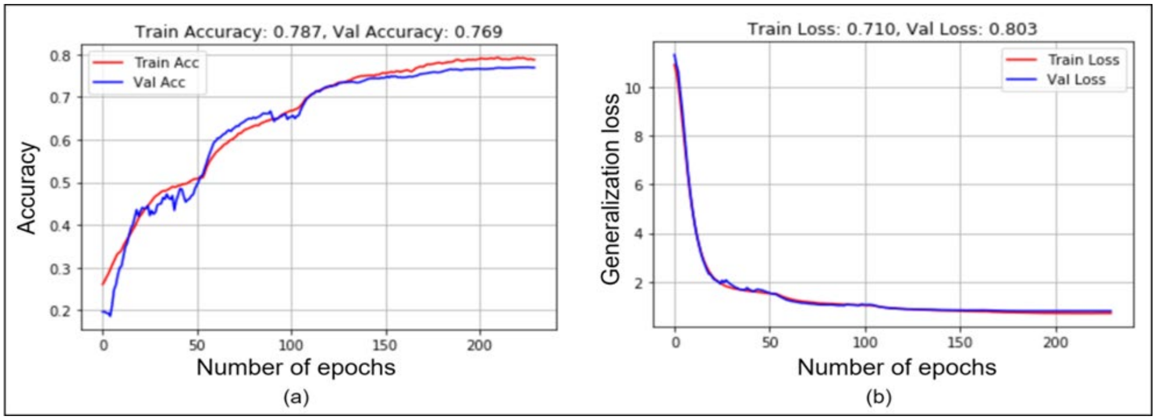


**Figure 7. The FER model training curves (a) Train accuracy, (b) Train loss (Pabba & Kumar, 2022) (reprinted with permission)**

### Validation of CNN based engagement assessment

The methodology was validated by Pabba and Kumar (2022) using 19 classroom video samples, each 15 minutes in duration. During the recordings, students were instructed to self-report their engagement levels every five minutes, using a standardized form based on established methods, such as NSSE and SEI (Appleton et al., 2008; Kuh, 2003). Of the 19 videos, six were labeled with low engagement levels (EL), seven with medium EL, and six with high EL as ground-truth results. These videos were then analyzed, using the proposed methodology, which predicted three videos with low EL, 11 with medium EL, and five with high EL. A confusion matrix (Table 4) revealed that the system predictions matched the ground truth for 14 out of 19 videos, achieving an accuracy of 73.68% in the process.

**Table 4. Confusion matrix of predicted and actual engagement results (Pabba & Kumar, 2022) (reprinted with permission)**

| | | Predicted results | | |
|---|---|---|---|---|
| | | Low | Medium | High |
| Ground truth | Low | **3** | 2 | 1 |
| | Medium | 0 | **7** | 0 |
| | High | 0 | 2 | **4** |

### Enhancements to vision-based engagement measurement

We extended the study conducted by Pabba and Kumar (2022). We used a common mobile camera as the recording instrument instead of fixed cameras. Mobile cameras offer enhanced accessibility and ease, enabling the dynamic and efficient capture of classroom changes. To maintain uniformity in data collection, the position, place, and type of mobile camera used were the same throughout the study. We strategically positioned the mobile camera so that the students' faces could be correctly and completely captured. Ample and congruent lighting was also provided because the deep learning algorithm was sensitive to variations in light. The seating arrangement in the classroom was carefully planned to ensure that students were seated based on their height; taller students were placed at the back, while the shorter students were seated in the front. This arrangement was designed to prevent any issues of occlusion (referring to the phenomenon in which another object wholly or partially obscures an object in an image or scene) during lessons. The positions and locations of the students were kept the same throughout the study. These steps effectively capture students' facial expressions and affective states. This approach enhanced the reliability and comprehensiveness of the engagement measurement process and overall experiment. To accommodate the mobile camera input, the program was re-coded at 30 fps to align with the recording speed of the mobile camera. This adjustment ensured an optimal analysis by synchronizing the video input with the processing capabilities of the system, allowing for an accurate estimation of group engagement.

### Statistical test selection

The variables we used had distinct characteristics. Time of class served as a nominal variable representing morning and afternoon classes, while group engagement was ordinal in nature, representing three levels of low, medium, and high. Academic performance was a continuous variable, measured on a scale based on students' scores. Given the ordinal nature of the moderator, we identified ordinal regression as the most appropriate statistical method (Aydin, 2020). In ordinal regression, one category of the independent variable is used as the base case, and the effects of the other categories are measured against this base case.

We used Hayes' (2013) Process Macro Model 1 to test the hypotheses and moderation effect. Notably, this model is particularly well suited for this study, as it accommodates ordinal moderators and examines both the main and interaction effects. The main effect was tested to examine the impact of class time on academic performance. Furthermore, interaction effects were tested to observe how the strength of the relationship between time of class and academic performance varies at different levels of group engagement. Hayes process macro employs a bootstrapping procedure that does not rely on normality assumptions and is less influenced by small sample sizes (Preacher & Hayes, 2008). Accordingly, a bootstrapping procedure with 5,000 samples was applied to generate bias-corrected 95% confidence intervals (CI).

## RESULTS AND ANALYSIS

The Hayes process macro model 1 tested how morning classes, using blended and collaborative learning, affect academic performance with the afternoon class as the reference or base case. It also examined how group engagement moderated the relationship between time of class and academic performance.

Table 5 presents descriptive statistics for students' academic performance in the morning and evening classes. The average score for the morning class was 18.74, with a standard deviation of 3.23, indicating slightly higher scores and more variability than the evening class. Conversely, the evening class had a lower mean score of 15.39 with a standard deviation of 2.06.

Interaction effects 1 and 2 represent the moderating effects of medium and high group engagement compared with the base case of low group engagement. Table 6 shows the results of the hypotheses testing. The analysis revealed that the constant term (representing academic performance in the morning class) was significant (β = 14.67, SE = 0.71, t = 20.79, $p < 0.001$), with a confidence interval ranging from 13.26 to 16.08. The results indicated that the baseline academic performance scores of students in the morning class were significantly higher. The afternoon class variable, used as a comparison group, did not significantly affect academic performance (β = 0.03, SE = 0.80, t = 0.04, p = 0.97), with a confidence interval of -1.57 to 1.64.

**Table 5. Descriptive statistics of time of class and academic performance**

| Time of class | Number of classes | Mean (Marks) | Standard Deviation |
|---|---|---|---|
| Morning Class | 24 | 18.74 | 3.25 |
| Evening Class | 12 | 15.39 | 2.06 |

**Table 6. Hypothesis testing and moderating effect of the group engagement**

<table>
<tr><th>Particulars</th><th>β</th><th>SE</th><th>T</th><th>P</th><th>LLCI</th><th>ULCI</th></tr>
<tr><td colspan="7">Morning class and academic performance</td></tr>
<tr><td>Constant</td><td>14.67</td><td>0.71</td><td>20.79</td><td>0.00</td><td>13.26</td><td>16.08</td></tr>
<tr><td>Afternoon class</td><td>0.03</td><td>0.80</td><td>0.04</td><td>0.97</td><td>-1.57</td><td>1.64</td></tr>
<tr><td>Interaction effect 1</td><td>-1.95</td><td>1.18</td><td>-1.65</td><td>0.1</td><td>-4.31</td><td>0.41</td></tr>
<tr><td>Interaction effect 2</td><td>-5.45</td><td>1.23</td><td>-4.42</td><td>0.00</td><td>-7.91</td><td>-2.99</td></tr>
<tr><td>R-Sq</td><td>0.71</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td colspan="7">Conditional effects of the focal predictor at the values of the moderator</td></tr>
<tr><td></td><td></td><td>Effect</td><td>SE</td><td>t-value</td><td>LLCI</td><td>ULCI</td></tr>
<tr><td rowspan="3">Effect of time of class and academic performance moderated by group engagement</td><td>Low level</td><td>0.03</td><td>0.8</td><td>0.04</td><td>-1.57</td><td>1.64</td></tr>
<tr><td>Medium level</td><td>-1.92</td><td>0.86</td><td>-2.22</td><td>-3.64</td><td>-0.19</td></tr>
<tr><td>High Level</td><td>-5.42</td><td>0.93</td><td>-5.80</td><td>-7.28</td><td>-3.55</td></tr>
</table>

The interaction terms represent the moderating effect of group engagement on the relationship between time of class and academic performance. Interaction effect 1, which measures the moderation effect of medium group engagement, was not statistically significant (β = -1.95, SE = 1.18, t = -1.65, p = 0.10), with a confidence interval of -4.31 to 0.41. However, interaction effect 2, which measures the moderation effect of high group engagement, was significant (β = -5.45, SE = 1.23, t = -4.42, $p < 0.001$), with a confidence interval of -7.91 to -2.99. This finding suggests that high group engagement significantly moderates the relationship between time of class and academic performance. There was a substantial decrease in performance from morning to afternoon classes (Figure 8).

It is evident that group engagement positively affected academic performance in the morning class. When the group engagement transited from low to medium to high levels, the effect throughout the day decreased from 0.03 to -1.95 and further to -5.45 (Figure 8). The model explained a substantial portion of the variance in academic performance with an R-squared value of 0.71.

Therefore, both H1 and H2 are supported.

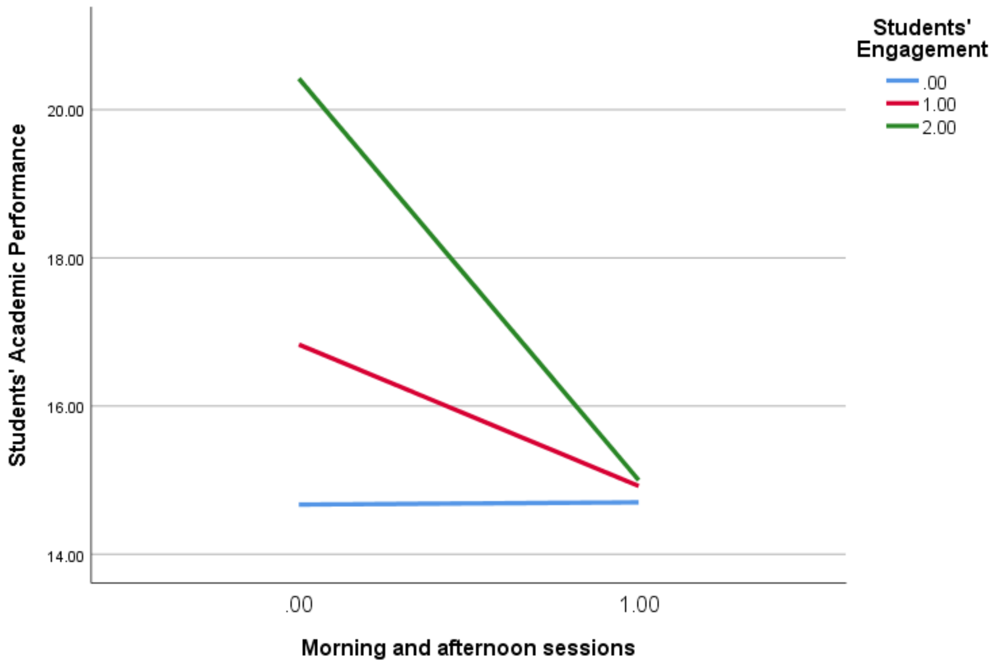


**Figure 8. Moderating effect of the group engagement on time of class and academic performance**

## DISCUSSION

The results indicated a significant positive relationship between the morning classes with the use of blended and collaborative strategies and academic performance. Furthermore, high levels of group engagement significantly moderated this relationship, suggesting that highly engaged students demonstrate heightened responsiveness and achieve better learning outcomes. Broadly, these results concur with the study of Marbouti et al. (2018), who found that student engagement has a positive influence on the relationship between active learning methods and academic performance. We extended this finding of Marbouti et al. (2018) by focusing on group engagement and providing deeper insights into its nuances in the process. In fact, the blended and collaborative methods shift the focus from passive reception of information to active participation. Active participation effectively encourages critical thinking, collaboration, and experiential learning. Consequently, students are more likely to retain information and demonstrate a more profound understanding. Notably, prior research also supports the positive impact of blended and collaborative learning on learners' emotions and attitudes. The use of such learning strategies nurtures a proactive learning position, reducing frustration and cultivating a positive learning environment (Amin et al., 2023).

The moderating effect of group engagement on the time of class and academic performance offers valuable insight. High group engagement significantly moderates the relationship between blended learning and academic performance. This indicates that highly focused students are better able to comprehend class discussions in morning classes, where a blended learning environment and collaborative learning were used. These findings align with those of a previous study that used another active learning method of flipped classrooms in morning classes (Luo & Wang, 2023). In the context of afternoon classes, group engagement did not significantly influence academic performance.

The methodology section identifies the specific affective states associated with high, medium, and low group engagement. The states of sleepy and boredom were associated with low group engagement. Confusion, frustration, and yawning were associated with medium group engagement, whereas high engagement was characterized by the state of focus. A closer look at these affective states provides key insights; for instance, the state of sleepy, boredom, confusion, frustration, and yawning among students did not significantly impact academic performance, regardless of whether blended or collaborative learning methods were used in the morning class. In fact, these states often occur when students struggle to understand the material, try to catch up, or feel bored during a session. The descriptive results for academic performance offer an additional context; while the average grades of students in the morning class increased, the standard deviation also increased. This suggests that not all students were able to effectively adapt to this mode of learning. Moreover, this variation highlights the complexity of the relationship between time of class, group engagement, and academic performance; it emphasizes the need for further research to better understand these dynamics and develop more generalizable conclusions across different educational contexts.

We validated the SOR framework and examined the role of group engagement as the 'organism' within the theory. This validation highlights the framework's flexibility in adapting to situational conditions; it offers valuable insights into the relationship between time of class, group engagement, and academic performance. Additionally, this study paves the way for theoretical models to incorporate both individual and group engagement, and this expanded perspective enhances the applicability of the SOR framework to educational settings. Additionally, the interaction between the time of class and group engagement not only aligns with the principles of SOR but also provides empirical evidence of its relevance in shaping behaviors and learning outcomes in group contexts.

Using an artificial intelligence-based deep learning module to measure group engagement provided a standardized and effective method compared to traditional approaches. While existing computer vision research is dominant and focuses on e-learning and individual student engagement, we measure group performance in an offline classroom setting. Moreover, it may be noted that while we primarily focused on first-year MBA students, its implications extend beyond this specific demographic. The insights gathered from our study may be applied to other educational settings, such as undergraduate programs, STEM education, and high school education. In fact, within this context, the interplay between class timing, instructional methods, and engagement remains a critical determinant of academic success. Furthermore, this detailed approach offers valuable insights for educators to optimize teaching methods and enhance learning outcomes by identifying prevalent affective states and applying appropriate teaching methods. Educators could use these insights to develop more effective teaching strategies that prioritize group engagement, leading to improved academic outcomes.

Administrators and policymakers can benefit from this research by leveraging insights into optimizing educational strategies, scheduling classes at optimal times, using active learning methods, and investing in technology-driven engagement measurement methods to enhance overall educational effectiveness. Theoretical insights from the SOR framework can guide policy development and administrative decisions for scheduling classes that support optimal learning environments. Furthermore, leveraging insights from students' affective states can enhance teaching methods, mentoring systems, instructional methodologies, and curriculum designs. This holistic approach ensures that educational practices are continuously refined to better support student learning, foster deeper engagement, and optimize educational outcomes for all learners.

## CONCLUSION

This study sheds light on the critical interplay between time of class and group engagement in shaping the academic performance of first-year MBA students. By introducing a computer vision-based deep-learning model, we present a novel approach for measuring group engagement. Students with high group engagement exhibited superior academic outcomes, particularly during morning classes that employed blended and collaborative learning methods. We extend extant literature by shifting the focus from individual to group engagement, offering nuanced insights into collective learning behaviors. Additionally, we validate the SOR framework by demonstrating how external stimuli (class timing) and internal processes (group engagement) drive academic success, thus contributing to both theory and practice. Importantly, our findings have significant implications for both policy and pedagogical frameworks. Educators are encouraged to adopt active learning strategies during morning classes and utilize technology-driven methods to effectively assess engagement. Policymakers could incorporate these insights into scheduling and resource allocation guidelines while ensuring that educational institutions support optimal learning conditions. Holistically, these measures can collectively enhance teaching efficacy, improve student outcomes, and create a dynamic learning environment.

## LIMITATIONS

The limitations of this study must be acknowledged; for instance, the relatively small sample size and demographic characteristics limit the generalizability of the findings across all higher education streams. A larger and more diverse sample could validate these findings across various educational contexts, thereby providing more generalizable results. The study design involved morning classes with Marketing Management and afternoon sessions with additional Management Accounting. While this may introduce some variation, it should be considered when interpreting the findings. While AI-based engagement tools are innovative, they do depend on visual indicators, limiting their effectiveness for students who engage in other ways. However, although comprehensive, this computer vision method can fail to measure engagement if a student does not face the camera and keenly listens to the lecture. Moreover, the system is sensitive to light; therefore, occlusion instances must be handled carefully during data collection. Additionally, the use of different learning methods in the morning and afternoon classes adds context to the findings; however, future research could examine their individual effects more distinctly.

## FUTURE RESEARCH DIRECTIONS

Future research could include more extensive and diverse samples to enhance the external validity of the results. Expanding the study to other educational settings, including STEM education and undergraduate programs, could test the robustness of the findings. Additionally, future studies could incorporate hybrid systems that merge computer vision with physiological sensors; this would address the current limitations and create a more comprehensive engagement measurement framework. Besides, this approach could also explore diverse cultural contexts, whereby it could look to address how various demographic factors effectively influence engagement and academic outcomes. Such an expansion would provide deeper insights into the complex dynamics of group engagement and academic performance. Finally, while this study focused on blended and collaborative learning methods, future studies could explore a broader range of active learning approaches and thereby investigate their effects across different cultural contexts.

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# APPENDICES

## APPENDIX A: OUTPUT EXCEL SHEET SHOWING AFFECTIVE STATES OF THE RESPONDENTS

| A | B | C | D | E | F | G | H | I | J | K | L |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Frame number** | **Detected faces** | **Predicted faces** | **Sleepy _E0** | **Bore-dom _E1** | **Yawned _E2** | **Frustrate _E3** | **Confuse _E4** | **Engage _E5** | **EL1 (E0+E1)** | **EL2 (E2+E3 +E4)** | **EL3 (E5)** |
| 0 | 10 | 10 | 3 | 1 | 0 | 0 | 0 | 6 | 4 | 0 | 6 |
| 15 | 10 | 10 | 1 | 2 | 0 | 0 | 0 | 7 | 7 | 0 | 13 |
| 30 | 9 | 9 | 1 | 2 | 0 | 0 | 0 | 6 | 10 | 0 | 19 |
| 45 | 9 | 9 | 1 | 0 | 0 | 0 | 0 | 8 | 11 | 0 | 27 |
| 60 | 9 | 9 | 0 | 1 | 0 | 0 | 0 | 8 | 12 | 0 | 35 |
| 75 | 9 | 9 | 1 | 1 | 0 | 0 | 0 | 7 | 14 | 0 | 42 |
| 90 | 10 | 10 | 2 | 1 | 0 | 0 | 0 | 7 | 17 | 0 | 49 |
| 105 | 10 | 10 | 2 | 0 | 0 | 0 | 0 | 8 | 19 | 0 | 57 |
| 120 | 10 | 10 | 2 | 0 | 0 | 0 | 0 | 8 | 21 | 0 | 65 |
| 135 | 10 | 10 | 2 | 1 | 0 | 0 | 0 | 7 | 24 | 0 | 72 |
| 150 | 10 | 10 | 1 | 1 | 0 | 0 | 0 | 8 | 26 | 0 | 80 |
| 165 | 10 | 10 | 1 | 1 | 0 | 0 | 0 | 8 | 28 | 0 | 88 |
| 180 | 10 | 10 | 2 | 0 | 0 | 0 | 0 | 8 | 30 | 0 | 96 |
| 195 | 10 | 10 | 2 | 0 | 0 | 0 | 0 | 8 | 32 | 0 | 104 |
| 210 | 10 | 10 | 3 | 0 | 0 | 0 | 0 | 7 | 35 | 0 | 111 |
| 225 | 10 | 10 | 3 | 1 | 0 | 0 | 0 | 6 | 39 | 0 | 117 |
| 240 | 10 | 10 | 2 | 2 | 0 | 0 | 0 | 6 | 43 | 0 | 123 |
| 255 | 10 | 10 | 1 | 2 | 0 | 0 | 0 | 7 | 46 | 0 | 130 |
| 270 | 10 | 10 | 2 | 0 | 0 | 0 | 0 | 8 | 48 | 0 | 138 |
| 285 | 10 | 10 | 3 | 0 | 0 | 0 | 0 | 7 | 51 | 0 | 145 |
| 300 | 10 | 10 | 2 | 1 | 0 | 0 | 0 | 7 | 3 | 0 | 7 |

# Appendix B: Output Excel Sheet Showing the Engagement Level for Every 10 Seconds Band

| Frame | Engagement level |
|---|---|
| 285 | 2 |
| 585 | 2 |
| 885 | 2 |
| 1185 | 2 |
| 1485 | 2 |
| 1785 | 2 |
| 2085 | 2 |
| 2385 | 2 |
| 2685 | 2 |
| 2985 | 2 |
| 3285 | 2 |

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