



University of  
**Southern**  
**Queensland**

**CREATING AN ARTIFICIAL INTELLIGENCE MODEL  
TO IMPROVE STUDENT ENGAGEMENT BASED ON  
TEACHER'S BEHAVIOURS AND MOVEMENTS IN  
VIDEO CONFERENCING**

A Thesis submitted by

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## ABSTRACT

The prevalence of online learning in higher education is driven by its numerous benefits, such as accessibility, flexibility, cost efficiency, and the global impact of COVID-19. Despite these advantages, lack of student engagement arises as a significant challenge. This study aims to address this issue by providing an Artificial Intelligence (AI) model designed to improve online student engagement based on teachers' behaviours and movements in video conferencing. A design-based research (DBR) approach was employed to develop an AI model capable of auto-generating reports on engagement-enhancing teachers' behaviours and movements as characteristics and indicators of engaging teaching videos. The study is structured with three phases. In the initial phase, a systematic literature review identified 11 characteristics and 47 indicators of engaging teaching videos. During the second phase, an AI model was developed and trained using the identified characteristics and indicators under the guidance of an AI expert. Prototype 1 (model 1) was trained using manual annotations of 25 Zoom-recorded lectures. Prototype 2 (model 2) was refined using oversampling techniques to address data imbalance and misleading metrics obtained in Prototype 1 (model 1), resulting in improved model performance. In the final phase, the AI model underwent three levels of evaluation, analysing and comparing its reports with those generated by human experts. Comparison results revealed a low similarity rate between the AI model and the expert reports, indicating the need for further refinement to align the model's performance more closely with human experts. This research contributes a comprehensive list of characteristics and indicators of engaging teaching videos, aiding in enhancing online student engagement. The provided manual annotation procedure supports similar AI model development in the future. Moreover, collaboration between educators (experts) and AI engineers to develop and evaluate AI models in education is emphasised, thereby breaking the barriers between educators and AI scientists. The reports generated by the model will also support educational institutions in promoting continuous enhancements in teaching methods and practices.

## CERTIFICATION OF THESIS

I, Navdeep Verma, declare that the PhD Thesis entitled *Creating an Artificial Intelligence tool to improve student engagement based on teacher's behaviours and movements in video conferencing*, is not more than 100,000 words in length, including quotes and exclusive of tables, figures, appendices, bibliography, references, and footnotes.

This thesis is the work of Navdeep Verma where otherwise acknowledged, with the majority of the contribution to the papers presented as a Thesis by Publication undertaken by the student. The work is original and has not previously been submitted for any other award, except where acknowledged.

Date: 14 March 2024

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## STATEMENT OF CONTRIBUTION

**Paper 1:** Verma, N., Getenet, S., Dann, C., & Shaik, T. (2023). Characteristics of engaging teaching videos in higher education: a systematic literature review of teachers' behaviours and movements in video conferencing. *Research and Practice in Technology Enhanced Learning*, 18, 040.

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I (Navdeep Verma) have contributed 60% to this paper. Collectively [Seyum Getenet, Christopher Dann and Thanveer Shaik] contributed the remainder.

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I (Navdeep Verma) have contributed 60% to this paper. Collectively [Seyum Getenet, Christopher Dann and Thanveer Shaik] contributed the remainder.

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I (Navdeep Verma) have contributed 70% to this paper. Collectively [Seyum Getenet, Christopher Dann and Thanveer Shaik] contributed the remainder.

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## ABBREVIATIONS

Abbreviation	Definition
<b>3D Data</b>	Three-dimensional Data
<b>AI</b>	Artificial Intelligence
<b>AUC</b>	Area Under the Curve
<b>CNN</b>	Convolutional Neural Network
<b>COVID-19</b>	Coronavirus Disease 2019
<b>DBR</b>	Design-based Research
<b>DSR</b>	Design Science Research
<b>DSS</b>	Decision Support System
<b>GPT</b>	Generative Pre-trained Transformer
<b>HDR</b>	Higher Degree Research
<b>LLM</b>	Large Language Model
<b>MLFAF</b>	Mobile Learning Framework for Assessment Feedback
<b>PRISMA</b>	Preferred Reporting Items for Systematic Reviews and Meta-analyses
<b>PST</b>	Preservice Teacher
<b>RNN</b>	Recurrent Neural Network
<b>RPTEL</b>	Research and Practice in Technology Enhanced Learning
<b>VIA</b>	VGG Image Annotator

# CHAPTER 1: INTRODUCTION

This chapter introduces the study focused on creating an AI model aimed at enhancing online student engagement by processing recorded lecture videos and identifying engagement-enhancing teachers' behaviours and movements. Section 1.1 highlights the research problem and outlines the research questions guiding this study. Section 1.2 gives a summary of the study's background. The goals and objectives of the study are discussed in section 1.3, while section 1.4 highlights the significance of the study. Lastly, an overview of the succeeding chapters is provided in section 1.5.

Due to the significant growth of online learning in higher education, ensuring an effective online learning environment is crucial, which can be achieved by addressing the most critical challenges of students, such as engagement. The research indicates that engaging students in online learning is more complex than traditional face-to-face learning (Olsen et al., 2020; Salta et al., 2021; Serhan, 2020). According to Azkiya and Syarif (2021), online learning entails utilising technology for educational purposes. Within this framework, video conferencing emerges as the primary technology for facilitating communication and collaboration, consequently enhancing student engagement (Al-Samarraie, 2019; Correia et al., 2020; Kumar et al., 2015). Teachers are the ones who facilitate video conferencing; therefore, they must have the required knowledge, skills and attitudes to teach effectively in a videoconferencing environment (Grammens et al., 2022). Teachers' engagement-enhancing behaviours and movements in videos could establish and enhance their presence, increasing student engagement (Cents-Boonstra et al., 2021; Dewan et al., 2019).

This study centred around creating an AI model to improve online student engagement based on the insights derived from teachers' behaviours and movements during video conferencing, which unfolded across three distinct phases. The initial phase involved a systematic literature review to gather the characteristics and indicators of engaging teaching videos. In the second phase, Zoom-recorded lecture videos were annotated manually to identify the characteristics and indicators gathered in the initial phase. The reports exported from this manual annotation process assisted the AI engineer in training and refining the AI model. The model aims to provide valuable insights and feedback to higher education teachers through

the reports it generates, enabling them to enhance their teaching practices and create engaging online learning experiences. The final phase focused on evaluating the AI model created in the previous phase. This phase also provides an evaluation procedure suitable for evaluating similar tools for enhancing online student engagement.

The model developed and evaluated in this study currently requires an AI expert for operation due to its complexity and various system requirements. Consequently, in the recommendations for future research section, a proposed plan is outlined to develop a software around the AI model. This software development initiative aims to enhance the user-friendliness and accessibility of the AI model, transforming it into an accessible software to teachers and educational institutions worldwide. The software will enable them to easily generate reports based on their behaviours and movements during video conferencing and identify areas for improvement, thereby enhancing their teaching methodologies and fostering more effective and engaging learning experiences.

### **1.1 Research Problem/Questions**

Studies have highlighted the importance of online student engagement for students' positive learning experience, course completion, course satisfaction, attention, skill development, academic achievement, deep-level learning, and emotional connectivity for improved success (Byrd, 2016; Cents-Boonstra et al., 2021; Kahu et al., 2019). Correspondingly, a notable concern in online learning is the lack of student engagement (Astani et al., 2010). Student engagement can be enhanced with a combination of effective utilisation of technology such as video conferencing and the presence of engagement-enhancing teachers' behaviours and movements. However, no studies provide the characteristics and indicators of engaging teaching videos based on these teachers' behaviours and movements. To identify these behaviours and movements from the videos automatically, a designed based research (DBR) approach was employed to create an AI model, and the focused question was:

*“To what extent can an AI model be designed to generate a report for characteristics and indicators of engaging teaching videos based on teachers' behaviours and movements?”*

To answer this broader research question, this study was conducted in three phases, and each phase focused on sub-questions that assisted in creating an AI model. The supportive questions, their focus, and the phase in which they have been addressed are mentioned below:

1. What are the characteristics and indicators of engaging teaching videos?

This question focused on identifying the characteristics and indicators of engaging teaching videos and was addressed in Phase 1.

2. How will the AI model improve teaching and learning practices in higher education?

This question was addressed in Phase 2, along with the process of creating an AI model identifying the characteristics and indicators of engaging teaching videos.

3. How accurately can an AI model generate a report for indicators and characteristics of engaging teaching videos based on teachers' behaviours and movements?

This question focused on evaluating the AI model and was addressed in Phase 3.

## **1.2 Background**

This research project began with a problem that I experienced both at a personal and professional level. When the global issue of COVID-19 impacted Australia, educational institutions were forced to adopt an online mode of delivery. During that time, I was a full-time student enrolled in a higher education program and worked part-time in college, providing education to international and domestic students. When both my university and workplace changed their mode of delivery, I noticed that teachers were finding it very hard to engage their students during videoconferencing. Teachers lacked online teaching experiences and were not trained for this sudden transition. They had no clear guidelines on what actions they should perform to engage their students. Therefore, I decided to do research in this area and aim to identify what teachers can do to improve their teaching by enhancing online student engagement.

## **1.3 Research Aims**

The research aims to address the most significant challenge of online learning: the lack of student engagement. To overcome this challenge, an AI model was

designed to enhance student engagement in video conferencing, with a particular focus on engagement-enhancing teachers' behaviours and movements. This model aims to improve teaching and learning practices in higher education.

The objectives of the research are:

- Identify the characteristics and indicators of engaging teaching videos from literature to assist in establishing a benchmark for teachers to enhance online student engagement.
- Create a manual video annotation procedure that assists in developing AI models to improve teaching and learning practices in online learning.
- Develop an AI model to identify the characteristics and indicators of engaging teaching videos and generate a report every time a video is processed.
- Create an evaluation procedure to test the AI model's accuracy to ensure they provide supportive information to enhance online student engagement.

The main aim of this study was to enhance online student engagement particularly in higher education. To achieve this, the study sought to identify the engagement-enhancing teachers' behaviours and movements in the form of characteristics and indicators of engaging teaching videos. Since manually identifying these characteristics and indicators can be time-consuming and prone to bias, the study also aimed to develop an AI model that can automatically generate reports for each processed video. To develop and train the AI model, manual annotation of data indicating these characteristics and indicators was necessary. Thus, this research aimed to provide a manual annotation procedure (refer to Appendix B) that is suitable for developing AI models to enhance online student engagement. Lastly, the study aimed to ensure the reliability and accuracy of the model by evaluating it with the use various metrics.

#### **1.4 Significance**

The significance of this research lies in identifying the characteristics and indicators of engaging teaching videos to enhance online student engagement. Incorporating AI provides an innovative method to identify and analyse engagement-enhancing teachers' behaviours and movements. The characteristics and indicators identified can enhance students' learning experience by fostering an interactive

atmosphere during video conferencing sessions. Teachers and educational institutions can derive benefits from these characteristics and indicators to enhance their teaching and learning practices. Further, this research provides a manual video annotation procedure (refer to Appendix B) that can assist future researchers in developing similar AI models to enhance online student engagement. Through collaboration with an AI expert, an AI model was successfully developed. The model is capable of automatically identifying engagement-enhancing teachers' behaviours and movements in recorded lecture videos. This AI-based identification significantly increases the scalability as the model can process videos faster and auto-generate a report every time a video is processed through it. This research also highlights the significant importance of educators' roles in developing and evaluating AI models in education. Further, an evaluation method that can be used to evaluate AI models used to enhance online student engagement is provided in this study. Finally, this research provides a roadmap for developing software around the evaluated model, which will be made publicly available to educators worldwide. This software will enable them to generate reports on engaging teaching videos based on their behaviours and movements during video conferencing sessions.

## **1.5 Overview**

The thesis is composed of seven chapters. This chapter introduces the research study, providing an overview of the key research questions. The background section explains why the focus is on using AI to identify engaging teaching videos based on teachers' behaviours and movements in higher education. The research aims are also described and centred around improving teaching and learning practices in higher education. The chapter also discusses the significance of the study, highlighting its importance and contribution to the existing knowledge about effectively integrating AI in education. Its primary purpose is to set the stage for the following sections. Following this introductory chapter is Chapter 2, which outlines a literature review. Chapter 3 details the study's methodology, outlining the data collection and analysis procedures across its three phases. Chapter 4 provides a comprehensive overview of the outcomes from phase 1, which involved a systematic literature review to compile a list of key characteristics and indicators of engaging teaching videos. The chapter also explores the implications of these findings for enhancing online learning in higher education. In Chapter 5, the focus shifts to the

results of Phase 2, where an AI model was developed to identify the characteristics and indicators of engaging teaching videos within recorded lecture videos. This chapter delves into the implications of this tool and sets the stage for the next phase of the research. Chapter 6 encapsulates the insights gained from Phase 3, which involved evaluating the performance of the developed model. The chapter discusses the broader implications of this evaluation in the field of education, particularly within the context of online learning, and emphasises the significance of utilising AI models in online educational settings. Chapter 7 synthesises key insights from the overall study by discussing its pedagogical and research implications, acknowledging limitations, and providing recommendations for teachers and educational institutes as well as future research. A summary of the general findings wraps up the chapter.

The next chapter, Chapter 2, will give an overview of related literature involving topics such as online learning in higher education, student engagement in online learning, the use of technology and its impact on student engagement, teachers' behaviours and movements in video conferencing, and the role of AI in education.

## **CHAPTER 2: LITERATURE REVIEW**

The preceding chapter introduced the DBR study by detailing its research questions, primary objectives, background, research aims, and significance. This chapter presents a literature review with the goal of offering a comprehensive overview of the existing knowledge and research related to engaging teaching videos in online learning in higher education.

### **2.1 Online learning in higher education**

Online learning involves the use of digital and commonly internet-based technology in the learning process (Greenhow et al., 2022). Further, it has become an integral part of the growing global trend, transforming the educational landscape with the emergence of online learning environments (Ferrer et al., 2020). Hence, there has been a consistent rise in the adoption of online learning strategies in higher education over recent decades (Salas-Pilco et al., 2022).

Online learning is not solely attributed to the rapid globalisation trend. The widespread transmission of COVID-19 globally compelled both learners and educators in higher education institutions to undergo a compulsory shift from traditional face-to-face classes to online classes (Abou-Khalil et al., 2021). This sudden shift to online learning presented challenges for teachers and students who were not fully prepared for this new educational setting (Salas-Pilco et al., 2022). One major challenge in adopting online learning is fostering student engagement. Studies show that student engagement is low among students who participate in online learning (Hollister et al., 2022).

### **2.2 Student engagement in Online learning**

Student engagement is generally defined as investing time and effort in learning activities (Karasavvidis, 2021). Pedler et al. (2020) described student engagement as a flexible and multi-faceted concept encompassing three key aspects: behavioural, emotional, and cognitive engagement. As more and more students opt for online learning instead of traditional on-campus classes, it becomes vital to understand the significance of motivation and engagement in this particular setting (Ferrer et al., 2020). Regardless of the varying learning contexts, numerous

studies have focused on student engagement due to its association with academic success.

Keeping students engaged is crucial in fostering their connection with the course and overall learning progress (Li et al., 2023). Engaged students tend to take an active role in their education, participate actively in discussions and are more likely to ask questions (Pandita and Kiran, 2023). Similarly, student engagement plays a pivotal role in attaining learning objectives and enhancing students' motivation, participation, and attitudes toward learning (Elshami et al., 2022). Studies suggest that highly engaged students tend to have better chances of succeeding academically (Salas-Pilco et al., 2022). Elshami et al. (2022) underscored the significance of employing technology proficiently in communication as a crucial strategy to actively engage students in online learning.

### **2.3 Use of technology and student engagement**

Educational technology has become an essential part of higher education, playing a vital role in influencing student engagement (Teng & Wang, 2021). Ku (2021) highlighted that incorporating technology into the teaching and learning process enhances classroom engagement. Similarly, to engage students in student-content interactions during online learning, students must be able to utilise various technologies (Hollister et al., 2022).

The emergence of online learning technology has resulted in the widespread adoption of video conferencing as one of the most widely used tools in teaching (Roth et al., 2020). Correspondingly, video-based instruction has demonstrated a positive influence on the teaching and learning process (Leung et al., 2021). Video conferencing can facilitate online teaching and learning by supporting, watching, and interacting with teachers and learners from anywhere (Themelis & Sime, 2020). Various video conferencing tools are accessible to teachers, enabling them to digitise and modernise their teaching and learning methods (Mishra et al., 2020). These video conferencing tools include Zoom, Microsoft Teams, Moodle, and Google Classroom for teaching and learning purposes (Bailey et al., 2022). Although these video conferencing tools provide various functions such as wireless screen sharing, collaborative whiteboard tools, interactive chat functionalities, polling options for gathering opinions, and discussion platforms to enhance online teaching and learning, student engagement significantly enhances teaching quality and video

conferencing. Thus, it is necessary to determine how teachers can promote and encourage student engagement during lessons.

## **2.4 Teachers' behaviour and movements in video conferencing**

Multiple studies have indicated that motivating teaching behaviour positively impacts student engagement. Aelterman et al. (2019) emphasised that when teachers exhibit motivating behaviours, it increases student engagement, boosts their feelings of competence, and fosters a sense of connection with others. According to Gillies (2022), these motivating behaviours include engaging students in group and pair activities, giving them praise and encouragement, offering positive feedback, sharing stories of successful learners, using various teaching materials, rewarding them symbolically, and ensuring equal opportunities for participation in class activities. Furthermore, prior research indicated that specific body movements and non-verbal cues can enhance student engagement in video conferencing sessions. To increase the effectiveness of video conferencing, teachers employ non-verbal cues such as eye contact, silence, suitable facial expressions, and acceptable body language (Jia et al., 2021; Trenholm et al., 2019).

Identifying the engagement-enhancing teachers' behaviours and movements is important to make video conferencing more effective and engaging for students. Therefore, a method is needed to measure and evaluate teaching videos based on these engaging behaviours and movements. According to Halverson and Graham (2019), measuring student engagement becomes possible with the use of clear indicators. Thus, they recommended a framework that includes cognitive and emotional engagement indicators. In their study, Lee et al. (2019) also emphasised the significance of indicators that positively influence learning and engagement and stressed the need for an appropriate measurement tool to ensure the quality of education and student engagement. However, manually identifying these indicators from recorded lecture videos is a time-consuming process and can also result in human bias. In this regard, AI models can be employed to identify the characteristics of student engagement in online learning and improve the quality of teaching videos later by incorporating elements that promote engagement.

## 2.5 AI and Education

The rise of new technologies has been revolutionising the methods of teaching and learning (Zhang & Aslan, 2021). AI is spreading rapidly, and its utilisation is expanding at a fast pace. It has become integrated into everyday routines, including how people acquire knowledge and learn (Tahiru 2021). Holmes and Tuomi (2022) defined AI as a distinct area of study and advancement rather than merely an artificial form of intelligence, highlighting that useful and usable AI definitions rely on their specific applications and purposes.

The influence of AI on higher education is already evident, although there is a wide range of perspectives among teachers and students regarding their use and implications (Rodway & Schepman, 2023). AI-driven education holds significant benefits, considering the current economic landscape heavily relies on higher education (Nguyen et al., 2022). According to Davies et al. (2020), AI is currently being acknowledged as a potential remedy for perceived challenges in the field of education. Edwards and Cheek (2018) have proposed substituting certain roles traditionally held by teachers with robots through AI, making teaching and learning personalised, engaging, and efficient. When it comes to enhancing education, AI programs can be loosely classified into three main categories: Guidance, Learning, and Teaching. Additionally, chatbots, intelligent tutoring systems, and automated grading and assessment are examples of AI applications that can boost efficiency, save teachers' time, and provide precise and consistent feedback (Harry, 2023). These categories encompass a range of AI approaches, such as generating personalised student recommendations, auto-grading essays, and enhancing educational resources (Nguyen, 2023).

The launch of Chat Generative Pre-trained Transformer in the latter part of 2022, commonly known as "ChatGPT", has called global attention in the field of AI (Nah et al., 2023). ChatGPT falls under the umbrella of the Generative Pre-trained Transformer (GPT), a framework that includes Large Language Models (LLMs) employing deep learning techniques and undergoing comprehensive training with extensive datasets (Casella et al., 2023).

Techniques like neural networks are employed to teach computers how to perform tasks without the need for human intervention (Perrotta & Selwyn, 2020). The machine learning algorithms currently making waves in the news, such as 'deep learning' and 'neural networks', have existed for over four decades (Xu et al., 2021).

AI algorithms have undergone significant advancements throughout the years, enabling them to process data in raw and unstructured form. As a result, mining unstructured data, including raw text and images, has become achievable. AI algorithms like deep learning and reinforcement learning have evolved to a point where specific algorithms, including Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), have gained recognition for their ability to process various forms of data, including audio, images, and even video (Dwivedi et al., 2023).

In conclusion, there have been numerous studies emphasising the significant transformation brought about by online learning in higher education, further accelerated due to recent global events such as COVID-19 (Greenhow et al., 2022; Abou-Khalil et al., 2021). Consequently, one key challenge that emerges is the issue of student engagement in online learning, as many learners struggle to maintain active participation, which is vital for their academic success (Hollister et al., 2022; Ferrer et al., 2020). The integration of technology plays an important role in enhancing student engagement, with video conferencing tools (Zoom, Microsoft Teams, Moodle and Google Classroom) facilitating improved interactions between students and educators (Mishra et al., 2020; Bailey et al., 2022). In this context, teachers' behaviours and movements during video conferencing become crucial, as their motivating strategies and effective non-verbal cues can significantly impact student engagement (Aelterman et al., 2019; Jia et al., 2021; Trenholm et al., 2019). Although AI is recognised as a potential solution to the challenges in education with its significant advancements and application in education that could revolutionise teaching and learning practices (Davies et al., 2020; Zhang & Aslan, 2021; Harry, 2023), there is still no existing model capable of automatically identifying the specific characteristics and indicators that define engaging teaching videos.

The next chapter, Chapter 3, focusing on the methodology, unfolds in three phases. It details the data collection and analysis procedures during each phase, highlighting the development of Prototype 2 (model 2) in Phase 2 to address issues encountered in Prototype 1 (model 1). This chapter provides a roadmap for the systematic approach taken to identify characteristics and indicators of engaging teaching videos through integrating technology and AI.

## CHAPTER 3: METHODOLOGY

Chapter 2 presented a review of existing literature pertinent to the subject matter. This chapter, Chapter 3, elaborates on the research methodology and outlines the data collection and analysis procedures conducted across its three distinct phases.

This study seeks to improve online teaching and learning practices in higher education by concentrating on teachers' behaviours and movements that can enhance student engagement during video conferencing sessions. The design-based research (DBR) method was employed to develop an AI model to identify engagement enhancing teachers' behaviours and movements in recorded lecture videos. The DBR approach is relevant in this research as it offers a systematic approach to designing and refining the tool aimed at improving online student engagement.

Unlike traditional experimental research, which prioritises isolating variables to test and refine theories, DBR emphasises understanding contexts, designing effective systems, and making meaningful changes for participants (Barab & Squire, 2004). While traditional research methods generate valuable insights into how the world operates, they often impact practice indirectly. In contrast, DBR purposefully integrates the refinement of both theory and practice, making it a well-suited method for this study (Collins et al., 2004).

In an educational context, DBR is a methodology involving iterative designs to generate knowledge to enhance educational practices (Van Zyl & Karsten, 2022). According to Haagen-Schützenhöfer et al. (2024), DBR has emerged as a unique approach combining knowledge generation through basic research and practical utility in real-world situations. In recent years, the DBR methodology has been increasingly recognised within the realm of educational research. Numerous researchers have emphasised its potential to facilitate the creation of research processes with strong practical applicability (Getenet, 2019; Tinoca et al., 2022).

In their study, Fahd et al. (2021) utilised a combination of Design Science Research (DSR) and DBR in their approach to systematically develop and assess an educational Decision Support System (DSS) tool capable of identifying students in jeopardy and enhancing both student retention and completion rates. Ada (2018) introduced a Mobile Learning Framework for Assessment Feedback (MLFAF), which

was created through a DBR approach. The framework offers design considerations and implementation guidelines for incorporating mobile technology into assessment feedback, aiming to enhance student engagement and promote dialogic communication channels for feedback. Lee and Yeo (2022) employed DBR to craft an AI chatbot aimed at refining preservice teachers' (PSTs) responsive teaching skills, particularly questioning skills, within authentic and open-ended teaching scenarios.

Squires (2023) highlighted that integrating AI with DBR methodologies can transform the educational environment, envisioning a scenario where tools previously considered futuristic become essential components of the teaching and learning process.

This research project used the DBR methodology to develop an AI model, as this approach is better suited for technological interventions. DBR aims to generate quantifiable changes in student learning regarding a specific educational issue (Anderson & Shattuck, 2012; McKenney & Reeves, 2013; Scott et al., 2020). Similarly, this research focuses on a significant problem of student engagement in online learning based on teacher's behaviours and movements. It provides an AI model that can identify characteristics and indicators of engaging teaching videos and generate a report. As no existing tool was available to identify the characteristics and indicators of engaging teaching videos, implementing a DBR approach was deemed essential. This approach provides flexibility and facilitates the necessary modifications to ensure the tool's effectiveness (Barab, 2014).

Further, DBR allows HDR students to assume dual roles as instructors and researchers, allowing them to conduct investigations within an authentic, localised context. This research aligns with the attributes characteristics of theses employing the DBR approach highlighted by Kennedy-Clark (2013). Firstly, the DBR approach adheres to the characteristics presented in the literature. Secondly, it employed phases in research design. Thirdly, the research was conducted within an educational setting.

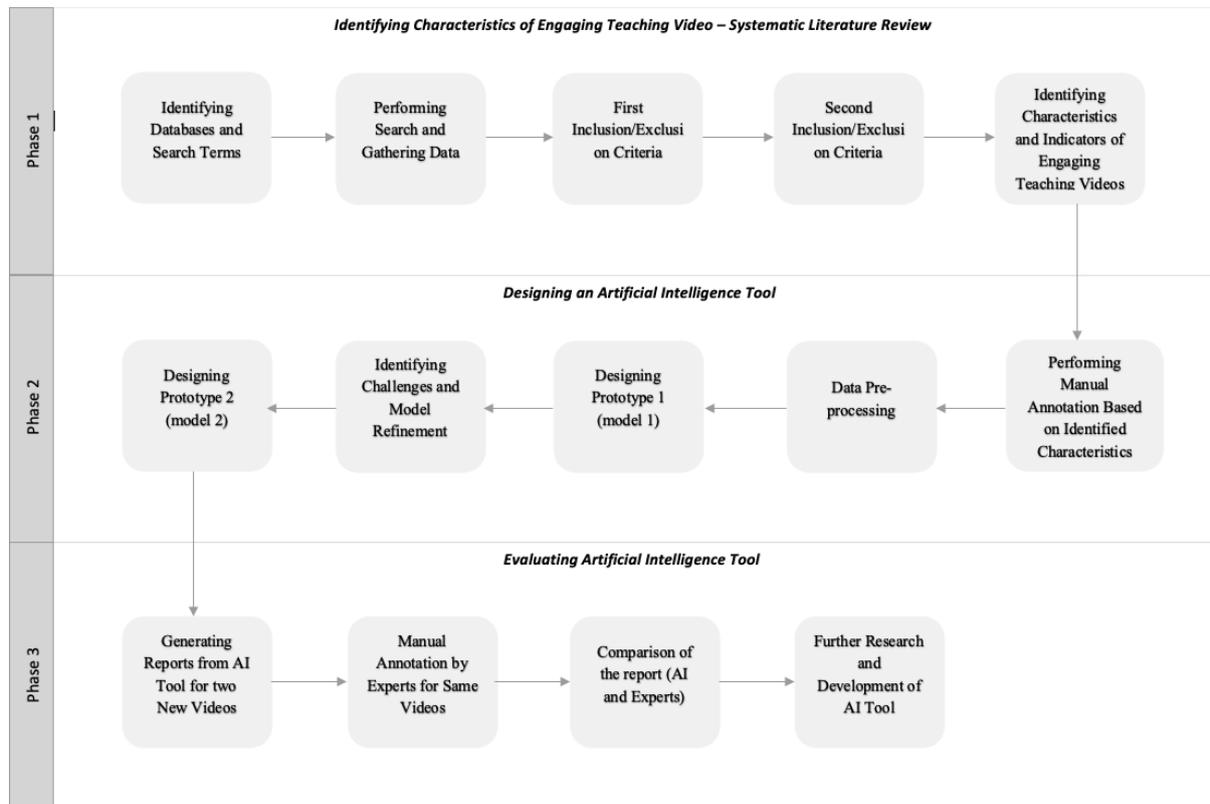
Adhering to the principles of DBR, the model was designed in phases. The subsequent sections describe the study's three phases in the context of DBR.

### 3.1 Phases of the Study

The figure below serves as the comprehensive roadmap delineating the procedural journey of the research study across three distinct phases. Following the DBR guidelines proposed by Plomp (2013), each phase is treated as an individual study due to variations in research questions, data sets, and data analysis procedures. In line with these recommendations, the research comprises three distinct phases: initial research, prototyping (model creation and refinement), and evaluation phase.

Further, the DBR approach focuses on developing tools that address the practical and theoretical concerns of a particular learning problem (Scott et al., 2020). Similarly, in this study, the first phase focused on theoretical and practical considerations of student engagement in video conferencing based on teachers' behaviours and movements. The systematic literature review serves as the foundation for the process of this phase (Verma et al., 2023a). It was initiated by identifying databases and search terms, followed by executing searches and gathering data. Subsequently, the collected data underwent filtering via two sets of inclusion/exclusion criteria, culminating in identifying characteristics and indicators of engaging teaching videos. Based on the recommendations of DBR research, the tools are tested in real-world settings (Hoadley, 2004). Likewise, in the second phase of this research, two prototypes (model 1 and model 2) were created and tested with Zoom-recorded lecture videos delivered by lecturers from a regional university in Australia. Building upon the findings from the initial phase, phase 2 commenced with manual annotation of lecture videos, followed by preprocessing tasks such as segmentation, image conversion, labelling, and dataset partitioning. Prototype 1 (model 1) was then built and tested. A few challenges such as data imbalance and misleading metrics were identified from the testing of Prototype 1 (model 1), and by overcoming those challenges through oversampling, Prototype 2 (model 2) was created. Anderson and Shattuck (2012) highlighted that the third phase of DBR entails evaluating the tool's effectiveness. As such, the AI model underwent evaluation in the Phase 3 of this research. The evaluation process commenced by subjecting a set of two videos to processing by the AI model while simultaneously, two experts manually annotated the same videos. Subsequently, the reports from the AI model and the experts were analysed at three levels to assess the tool's accuracy in identifying indicators and consistently recognising recurring indicators within lecture videos. The

evaluation also aimed to ascertain whether the AI model's performance aligned with the experts' capabilities by comparing the reports.



**Figure 1.** The Research Phases

### **3.1.1 Phase 1: Systematic Literature Review**

During the initial research phase, a needs and context analysis was performed, existing literature was reviewed, and a framework was established for the study. This first phase of a DBR study aligns with common practices in HDR contexts, where research students formulate proposals grounded in a literature review and incorporate a conceptual or theoretical framework (Kennedy-Clark, 2013; Plomp, 2013). Likewise, this preliminary research phase conducted a systematic literature review to identify the characteristics and indicators of engaging teaching videos focused on teachers' behaviours and movements.

#### **3.1.1.1 Data Collection and Analysis**

The study commenced with a systematic literature review to identify characteristics and indicators of engaging teaching videos based on teachers' behaviours and movements. The review complied with Preferred Reporting Items for

Systematic Reviews and Meta-analyses (PRISMA) guidelines and involved four authors to ensure validity. Various databases and specific search terms were employed to obtain relevant studies. The initial search yielded a substantial number of studies, with duplicates removed, resulting in a pool of peer-reviewed articles. The inclusion/exclusion criteria were then applied through a two-step process. The selected articles underwent detailed analysis to identify and categorise characteristics of engaging teaching videos based on teachers' behaviours and movements.

### **3.1.1.2 Procedures**

The review process involved all four authors to ensure validity. The first author identified pertinent characteristics and indicators from existing literature, while the second and third authors validated the interpretation and analysis of findings. The last author devised the AI methodology for future research, examined the project scope, and validated the results.

The systematic literature review was chosen for its suitability in identifying, critically appraising, and summarising existing evidence related to engaging teaching videos. The PRISMA guidelines, specifically the PRISMA 2020 statement, were employed to organise the data and ensure a rigorous review process. The entire process involved the identification of 1,170 articles, removal of duplicates, initial screening, and a subsequent thorough review to determine the eligibility of studies.

Seven selected databases were utilised for the database search. The inclusion and exclusion criteria were applied in two steps. In the first step, criteria based on abstract, topic name, data type (peer-reviewed articles), sample size, and publication period (2010-2021) were employed, resulting in 63 retained articles. In the second step, the remaining 63 articles underwent a thorough review, with the first author assessing and the second and third authors validating the results, which narrowed the selection to 34 articles included in the final review.

### **3.1.2 Phase 2: Designing an Artificial Intelligence Tool**

This section outlines the systematic data collection and analysis procedures involved in the creation of the AI model, highlighting the incorporation of Convolutional Neural Network (CNN) models and the subsequent development of two Prototypes (model 1 and model 2) to address the issues encountered along the

process. In DBR, prototyping (model creation and refinement) is used to enhance the reliability of the design prior to the final fieldwork study (Van Zyl & Karsten, 2022). This phase offers researchers the opportunity to fine-tune the design and acquire a deeper understanding of the factors influencing the success or failure of an innovation within that specific context (Plomp, 2013).

### **3.1.2.1 Data Collection and Analysis**

The AI model was developed in collaboration with an AI expert. Twenty-five Zoom recorded lecture videos covering various disciplines from a regional university in Australia were gathered. The video selection ensured a variety of presenter settings, including placements in the top right corner, middle, and bottom right corner. Poor, average, and good-quality videos were included to train the deep learning model in various settings. Additional variables, such as instances where students had their cameras on and videos where the presenter's camera position changed during the lecture, were also considered. These selected videos were manually annotated using the VGG Image Annotator (VIA) tool (refer to Appendix B). The reports exported from the manual annotation were utilised to develop and train the AI model.

### **3.1.2.2 Participants**

The research involved a set of twenty-five manually annotated recorded lecture videos, showcasing a diverse group of presenters consisting of thirteen females and twelve males. Demographic information such as age, location, and academic background was not collected. These videos were meticulously selected to represent a broad spectrum of disciplines within higher education, spanning law, health, engineering, education, business, sciences, and arts.

In upholding the principles of responsible and ethical research conduct, particularly concerning the involvement of human participants, the study diligently pursued and obtained ethics approval from the University of Southern Queensland. This approval, granted under reference number H20REA185, emphasises the commitment to ensuring the welfare, rights, and dignity of all participants involved in the research process.

### **3.1.2.3 Procedures**

The process of manually annotating twenty-five recorded lecture videos conducted via Zoom utilised VIA software. Each video underwent manual annotation at the indicator level, with all indicators, characteristics, and their primary themes detailed in Appendix A. The deep learning model was trained based on these indicators. The reports generated from the manual annotation process assisted the AI engineer in training the AI model. For a detailed description of the manual annotation procedures, please refer to Appendix B. Two Prototypes (set of models) were developed, with Prototype 2 (model 2) specifically addressing the identified challenges in Prototype 1 (model 1) by incorporating data oversampling technique. The oversampling technique was chosen to address the issue of dataset imbalance, where certain classes had significantly fewer samples than others. This imbalance can cause machine learning models to become biased toward the majority class, leading to poor performance in predicting the minority class.

Oversampling, specifically the use of SMOTE (Synthetic Minority Oversampling Technique), was selected for several reasons:

1. Unlike undersampling, which reduces the number of majority class samples, oversampling does not discard any data. This is particularly important when valuable information may be lost by removing majority class samples, potentially affecting the overall model performance.

2. SMOTE was used to generate new, synthetic samples for the minority class by interpolating between existing samples. This approach not only increases the size of the minority class but also introduces diversity within the minority class, which helps the model learn more generalisable patterns.

3. By balancing the class distribution, oversampling ensures that the model receives a more even exposure to both the majority and minority classes during training. This helps reduce the risk of the model becoming biased toward the majority class and improves its ability to accurately predict minority class instances.

Once the challenges were addressed, the videos were segmented into frames using the extracted temporal coordinates from manual video annotations. These frames were labelled with teaching indicators and split into training and testing sets for model training and evaluation.

A Convolutional Neural Network (CNN) model was employed for deep learning, aiming to classify images with three-dimensional data (3-D), including

dimensions like width, height, and colour channels (e.g., RGB). The CNN model was intentionally chosen for its inherent ability to autonomously learn spatial hierarchies of features from input data. It is well-suited for video classification, particularly in understanding teaching behaviours with crucial spatial features. The adaptable architecture of CNNs allowed for meticulous network design and optimisation to address the specific characteristics and challenges associated with classifying teaching behaviours. Additionally, the scalability of CNNs ensured readiness for future research expansion with larger datasets. The strength of the CNN model lies in its effective management of the high dimensionality present in images by preserving essential information while compacting the overall data structure. The intricate learning workflow involves preprocessing input image frames through a 2D convolution layer, where filters break down the image into smaller sub-images for detailed feature examination. The subsequent pooling layer selects significant values, creating a down-sampled representation that reduces computational complexity and enhances model robustness. The flattened features are then processed in the CNN's output layer, computing probabilities for potential classification labels. A specific threshold is applied to translate these probabilities into definitive class labels, showcasing the CNN model's sophistication in deciphering complex spatial and temporal patterns within teaching videos.

The model's performance was evaluated using various metrics, including accuracy, precision, recall, F1-score, Cohen's Kappa, and Area Under the Curve (AUC). Accuracy measures the model's ability to correctly predict labels in relation to all labels generated. Precision evaluates the model's capacity to generate accurate labels compared to the total labels it produces. Recall assesses the true positive predictions, with a high recall indicating that the model correctly identifies most of the videos that belong to a certain theme. The F1-score, a widely used metric for classification tasks, measures the model's accuracy by considering both precision and recall. Balanced accuracy, on the other hand, calculates the average recall across all classes, evaluating the recall for each class individually and providing an overall accuracy score. Cohen's Kappa is employed to gauge the agreement between two raters while also accounting for the probability of random agreement. On the other hand, the AUC quantifies the area under the curve, offering a threshold-independent assessment of a binary classifier's capacity to differentiate between the classes. Taking into account these metrics, challenges such as data imbalance and

potentially misleading metrics were identified in Prototype 1 (model 1), leading to the development of Prototype 2 (model 2), which addressed these issues and yielded promising results.

#### **3.1.2.4 Development of Prototypes (Model 1 and Model 2)**

The process of refining the AI model for processing teaching videos is summarised in this section. Prototype 1 (model 1) involves video annotation and evaluation using various metrics, revealing challenges like dataset imbalance and misleading metrics. Prototype 2 (model 2) addresses these issues through oversampling and alternative evaluation metrics, resulting in significant performance improvements across teaching themes, characteristics, and indicators.

#### **3.1.2.5 Prototype 1 (Model 1)**

In the development of Prototype 1 (model 1), video annotation was performed at different label levels on preprocessed videos, categorised into themes, characteristics, and indicators. Six evaluation methods were utilised to report results: precision, recall, F1-score, balanced accuracy, Cohen's Kappa, and Area Under the Curve (AUC).

#### **3.1.2.6 Issues Identified in Prototype 1 (model 1)**

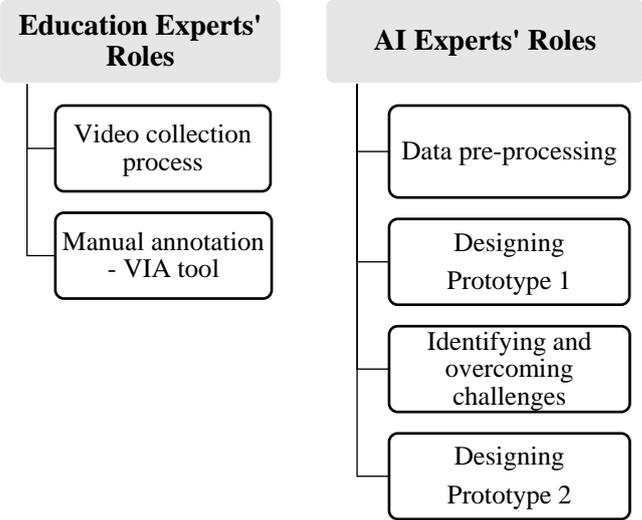
The analysis of Prototype 1 (model 1) revealed two significant issues, an imbalanced dataset and misleading metrics, critical to the development of a reliable tool for classifying teaching videos. Verma et al. (2023b) explicitly discussed these challenges in their paper titled "Designing an artificial intelligence tool to understand student engagement based on teachers' behaviours and movements in video conferencing" on page 8. Thus, Prototype 2 (model 2) was introduced, incorporating oversampling as a key solution. This addresses the class imbalance issue and enhances the model's capacity to accurately classify instances from all classes. In addition to the imbalanced dataset, Prototype 1 (model 1) encountered challenges related to misleading metrics. The process of oversampling, while addressing class imbalance, can introduce complications in evaluating the model's performance. In response to this issue, alternative evaluation metrics such as precision, recall, and F1-score were adopted. These alternative metrics provided a more accurate

assessment of the model’s effectiveness, considering the specific context of oversampled data. By acknowledging and addressing these, significant steps were taken toward refining the model’s classification accuracy and ensuring reliable results in the analysis of teaching videos.

**3.1.2.7 Prototype 2 (Model 2)**

Prototype 2 (model 2), the enhanced iteration, showed significant enhancements in performance across teaching themes, characteristics, and indicators. It demonstrated higher precision, recall, F1-score, balanced accuracy, Cohen’s Kappa, and AUC values, indicating improved accuracy and classification capabilities. The model performed strongly at the theme and characteristic levels, with balanced datasets contributing to reliability. Indicator-level results also improved, addressing challenges observed in Prototype 1 (model 1). Comparative analysis with traditional models highlighted the CNN model’s superiority, making it a promising tool for classifying teacher behaviours in video data and advancing the understanding of teaching practices.

Figure 2 outlines the roles of the education experts and the AI expert in designing the AI model.



**Figure 2.** Roles of Education Experts and AI Expert in AI Model Design

**3.1.3 Phase 3: Evaluating Artificial Intelligence Tool**

This section describes the final phase of the DBR, which is dedicated to the evaluation of the AI model designed in the previous phase. This phase aimed to determine how effectively the investigation’s results align with the predetermined

criteria for resolving the problem (Plomp, 2013). Involving experts in the evaluation process is essential to create moderation and study validity. Hence, experts were involved in evaluating the AI model.

### **3.1.3.1 Data collection and analysis**

The evaluation of the AI model's ability to recognise engagement-enhancing teachers' behaviours and movements during video conferencing involved human experts who manually annotated two videos alongside the AI-generated reports. The results obtained from the AI model and the human experts were analysed at three distinct levels throughout the evaluation process: tallying the total number of indicators identified by both the AI model and two human experts, assessing the consistency of their recognition of the indicators across multiple video segments, and subsequently comparing their findings to establish similarity scores.

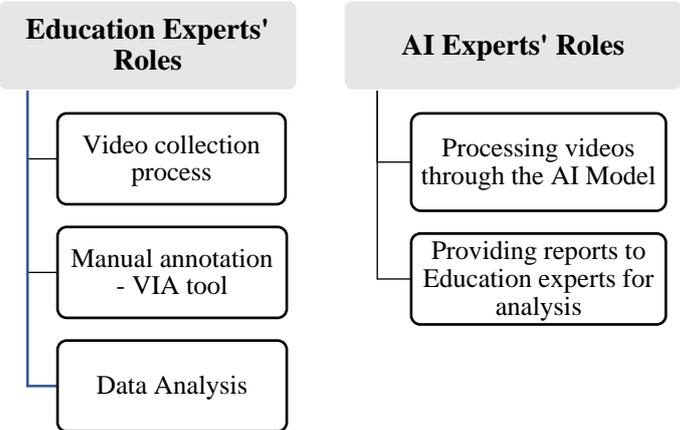
Two videos of varying durations were utilised for this purpose: one lasting 49 minutes and 3 seconds, divided into 11 segments, and the other lasting 58 minutes and 40 seconds, segmented into 23 sections. These videos featured presenters with diverse camera settings. The research was conducted with ethical clearance from the University of Southern Queensland (ethics approval number H20REA185). However, demographic details about the lecturers, such as their age, location, and academic background, were not collected.

### **3.1.3.2 Procedures**

The evaluation was conducted across three levels. The total count of indicators identified independently by the AI model and the two human experts was determined at the initial level. The second level focused on assessing the consistency between the AI model and the experts in identifying the same indicators across multiple segments of the video. In the third level, outcomes for each video were compared in three scenarios: matching AI-generated results with Expert 1's findings, comparing automated outcomes with Expert 2's findings, and comparing Expert 1's findings with those of Expert 2. Statistical analysis was performed using percentage calculation to determine similarity percentage, indicating agreement between the AI model's and human experts' identification of indicators across scenarios. Percentage was computed by dividing the count of identical indicators by the total listed indicators and multiplying by 100 using the formula  $(\text{value}/\text{total value})$

X 100. Timestamps corresponding to the identification of identical indicators were provided, indicating segments in the video where each indicator was recognised. This thorough evaluation aimed to validate the effectiveness of the model by aligning its outcomes with the assessments made by human experts, providing valuable insights into its accuracy and reliability in identifying indicators of engaging teaching videos. The methodology employed in the research study has been introduced, emphasising DBR as a holistic approach to enhance educational practices. The relevance of DBR in educational research is highlighted through examples of its application in developing decision support systems, mobile learning frameworks, and AI chatbots for teaching improvement. The chapter then delves into the three phases of the study. Phase 1 detailed a systematic literature review to identify characteristics and indicators of engaging teaching videos. The development of an AI model capable of identifying characteristics and indicators of engaging teaching videos was highlighted in phase 2. Phase 3 focuses on evaluating the AI model’s performance, employing a comparative analysis with human experts to ensure impartiality and accuracy in generating reports.

Figure 3 presents the roles of the education experts and the AI expert in evaluating the AI model.



**Figure 3.** Roles of Education Experts and AI Expert in AI Model Evaluation

The forthcoming chapter, Chapter 4, explores the preliminary phase of the study, which typically entails a systematic literature review. This process involves carefully examining academic articles to gather comprehensive insights into the subject matter.

# **CHAPTER 4: PAPER 1 – CHARACTERISTICS OF ENGAGING TEACHING VIDEOS IN HIGHER EDUCATION: A SYSTEMATIC LITERATURE REVIEW OF TEACHERS' BEHAVIOURS AND MOVEMENTS IN VIDEO CONFERENCING**

In the preceding chapter, Chapter 3, a thorough overview of the research methodology and its practical application in advancing the study's aims was presented. This chapter, Chapter 4, delves into the initial phase of the DBR study. As introduced in section 4.1, this phase centred on conducting a systematic literature review to gather the characteristics and indicators of engaging teaching videos. In section 4.2, the published paper unveils the systematic literature review process and details the acquisition of the list of characteristics and indicator. Lastly, section 4.3, the concluding section, presents the implications of the paper and establishes a Connection to the subsequent phase of the research.

## **4.1 Introduction**

The contents of this chapter have been published in “Research and Practice in Technology Enhanced Learning” (RPTEL) which holds a Q1 rank in both the Scimago Journal Rank and Media Technology categories. The paper is accessible via the following link: <https://doi.org/10.58459/rptel.2023.18040>.

Marking the initial phase of a comprehensive three-phase DBR study, this paper focused on the identification of the characteristics and indicators that can support teachers in setting benchmarks for online teachers to enhance online student engagement, making learning more effective and enhancing the overall learning experience among students.

In this initial phase, a systematic literature review was performed to analyse and identify the characteristics and indicators of engaging teaching video based on teachers' behaviours and movements while adhering to the PRISMA guidelines. The systematic literature review best suits the project's needs because it aims to identify, critically appraise, and consolidate the current body of evidence regarding the topic (Martin et al., 2017). It has also helped in identifying concepts and understanding the evolution of terminology in a particular field of study (Cook et al., 2008).

The studies that made up this extensive review of related studies were collected from seven different databases and were chosen through the application of inclusion/exclusion criteria in two rounds based on sample size, the type of data (peer-reviewed articles), and period of publication (from 2010 to 2021). The first inclusion/exclusion criteria were applied to the abstract and topic name. After the initial exclusion process, the remaining data underwent the second step, during which each retained peer-reviewed article, book, journal, and conference paper went through further review for categorisation. In the second application of inclusion and exclusion criteria, the remaining 63 articles underwent thorough examination. Subsequently, 34 articles met the criteria and were included in the review. From these chosen studies, the characteristics and indicators of engaging teaching videos were identified, organised, and explained.

Consequently, 11 characteristics and 47 associated indicators of the characteristics critical in enhancing student engagement were identified and classified into three categories: teachers' behaviours, teachers' movements, and use of technology. This methodical identification, categorisation, and explanation of identified characteristics and indicators directly relate to the research question guiding this study: What are the characteristics and indicators of engaging teaching videos? In this systematic literature review, categorisation helped in summarising and synthesising relevant literature, identifying gaps, and positioning the current study within the existing body of knowledge. The characteristics and indicators gathered during this phase were utilised in the succeeding phase to train an AI model capable of generating reports of characteristics and indicators of engaging teaching videos found in recorded lecture videos. These characteristics and indicators also support the establishment of a benchmark for online teachers in assessing the gap in their teaching performance in an online environment and position the higher education institutes in regulating the teachers' online teaching practices.

## 4.2 Published paper

Verma et al. *Research and Practice in Technology Enhanced Learning* (2023) 18:40  
<https://doi.org/10.58459/rptel.2023.18040>

Research and Practice in  
Technology Enhanced Learning

RESEARCH

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# Characteristics of engaging teaching videos in higher education: a systematic literature review of teachers' behaviours and movements in video conferencing

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### Abstract

Online learning is in high demand due to benefits such as convenience, flexibility, cost efficiency, and improved accessibility. In online learning, video conferencing is an effective technology for collaboration and increasing online student engagement. This study is part of a larger study conducted using design-based research (DBR) to develop a video annotation tool using artificial intelligence (AI) methodologies such as machine learning and deep learning. This systematic literature review is the foundation of the process which identifies the characteristics and indicators of engaging teaching videos. The studies included in this systematic literature review have been gathered from seven databases and selected by applying inclusion/exclusion criteria in accordance with the Preferred Reporting Items for Systematic Reviews. From the selected studies, we identified, categorised, and explained the characteristics and indicators of engaging teaching videos based on teachers' behaviours and movements. In this study, we identified 11 characteristics and 47 associated indicators of the characteristics critical in enhancing student engagement. Teachers and higher education institutions can use these characteristics and indicators as a benchmark to improve the quality of engaging teaching videos and later improve teaching and learning. In the final stage of DBR, the identified indicators can be used to train a machine learning tool, a form of AI. This tool can provide a report on engaging teaching videos by highlighting the teachers' behaviours and movements.

**Keywords:** Artificial intelligence, Online learning, Student engagement, Teacher presence, Video conferencing, Teachers' behaviours and movements, Characteristics of engaging teaching videos



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## Introduction

Online learning continues to rise in popularity in higher education across the globe to provide teachers and students with more access to educational opportunities in a flexible manner. Notably, the recent global issue of Covid-19 increased online learning, forcing educational institutes to shift their face-to-face delivery mode to an online delivery method (Nghah et al., 2022). However, besides the benefits of online learning, there are some challenges that students might face, including a lack of engagement (e.g., feelings of isolation and lack of interaction with tutors and other students) (Cesari et al., 2021). With increasing numbers of students choosing online education as an alternative to traditional on-campus classes either because of its various benefits or Covid-19, it becomes more critical to engage students in online learning.

Online learning is technology-based learning, where video conferencing is the most effective web-based technology for teaching and communication, offering more opportunities for collaboration and increasing online student engagement (Al-Samarraie, 2019). Video conferencing allows teachers to provide immediate feedback to students and increase their presence, enhancing student engagement, which is necessary for fostering positive student behaviour and learning in online classrooms (Hew, 2018). However, there are no clear evidence and criteria for measuring for identifying engaging teaching videos.

The research has established that teachers' behaviours and movements in online learning increase their presence, enhancing student engagement (Cents-Boonstra et al., 2021; Dewan et al., 2019; Olitsky, 2007). However, there are no studies or clear consensus which define the characteristics of student engagement based on these human behaviours. Identifying these characteristics and indicators of engaging teaching videos may make learning more effective and enhance students overall learning experience.

This study employed a systematic literature review to identify the characteristics and indicators of engaging teaching videos. It aims to answer the research question: What are the characteristics and indicators of engaging teaching videos? We aim to add new knowledge to the existing literature on engaging teaching videos to improve students' experience in online learning. These identifying characteristics of teachers' behaviours and movements in video conferencing could assist in training deep learning algorithms. Artificial intelligence (AI) is assisting people in transforming education and fundamentally changing teaching, learning, and research. AI has the ability to understand student feedback in text format using natural language processing (NLP) techniques (Shaik et al., 2022) to process and learn temporal and spatial components in a video (Liu et al., 2022). However, no studies have been conducted to identify and categorise these characteristics to create a database of such behaviours, which can further use to develop a video annotation tool.

### **Previous research**

This study aimed to identify the characteristics and indicators of engaging teaching videos. Five areas inform the study, and these areas were identified based on their relevancy to the research and have been described further in the following sections.

### **Online learning in higher education**

Online learning has been defined as using technology and media to deliver, support, and enhance learning and teaching (Howlett et al., 2009; O'Doherty et al., 2018). Similarly, Chen et al. (2018) highlighted that online learning is augmented by adopting advanced digital tools and other technological platforms. Generally, researchers agree that technology is a crucial and effective medium for providing education and enhancing social interaction in online learning (Chen et al., 2018; Howlett et al., 2009; O'Doherty et al., 2018).

In recent decades, online learning has gained increasing attention in higher education. Further, Covid-19 has also forced the higher education sector to undergo a massive digital transformation due to the sudden closure of face-to-face teaching (Carolan et al., 2020). This change required universities to evolve toward online teaching by having the technological resources available and involving teachers who lack technological capacities for online teaching (García-Morales et al., 2021). Unfortunately, many educational institutions were not ready for this new experience. In his research, Stott (2016) highlighted that many online courses in higher education involving “poor levels of student engagement pose challenges to institutions, instructors and learners” (p. 51).

### **Student engagement in online learning**

Student engagement is essential to improving the quality of learning and teaching. Student engagement plays a critical role in student achievement and learning (Kahu et al., 2019), and it is fundamental for students' satisfaction, motivation, and performance (Hu & Li, 2017). Over the years, there have been multiple definitions of the term “student engagement” in research. Student engagement was referred to as student involvement, student experience, academic integration, academic engagement, and student efforts (Krause & Coates, 2008). Kahu et al. (2019) defined student engagement as students' emotional, behavioural, and cognitive connection to their study, directly impacting their success and achievement. When students are engaged in the learning process, they are emotionally connected, which has improved student success.

Fredricks et al. (2004) discussed three types of engagement – behavioural, emotional, and cognitive – described in the literature, along with the approaches researchers used to measure engagement. Adding collaborative and social to the behavioural, emotional, and

cognitive dimensions described by Fredricks et al. (2004), Redmond et al. (2018) proposed an online engagement framework for higher education with five dimensions. Redmond et al. (2018) also identified descriptive indicators for each engagement dimension. For example, students' cognitive engagement can be described as thinking critically, justifying decisions, distributing expertise, integrating ideas, activating metacognition, and developing deep discipline understandings.

Several studies relate students' engagement and learning outcomes to online learning. Muir et al. (2019) suggested that educational outcomes, student retention rates and completion time can be improved in online learning by understanding the factors that influence student engagement. The literature on pedagogic excellence has placed student engagement as central to effective and deep-level learning, student satisfaction and retention (Cents-Boonstra et al., 2021; Kahu et al., 2019; Kuh et al., 2008). The above literature establishes the importance of student engagement in general but needs to be more focused on engaging teaching videos.

Consistent with the literature mentioned above, Zepke and Leach (2010) also provided that, in online learning, teachers' presence is the key to engagement. Abou-Khalil et al. (2021) added that teachers must understand which engagement strategies are the most effective for engaging students in online classes.

These studies on online engagement looked at engagement as a whole, not specifically focusing on engaging teaching videos. There are no studies or clear consensus which define the characteristics of student engagement in video conferencing based on teachers' behaviours and movements.

### **Use of technology in online learning**

Technology such as learning management systems, interactive tools, and video conferencing presents an opportunity for teachers and institutions to engage students innovatively in their learning. Ullah et al. (2019) noted that technology provides support, develops contact between teachers and learners, and causes us to re-evaluate our education methods to fulfil the requirements of students for changing learning. Researchers (Hsu & Hsieh, 2011; Johnson et al., 2008; Revere & Kovach, 2011) agreed that if technology is applied appropriately in online learning, it can foster student engagement and enhance their performance and course satisfaction.

With the advancement in technology in online learning, video conferencing has become one of the most common tools for synchronous and asynchronous teaching (Roth et al., 2020). Video conferencing allows teachers and learners to communicate in real time via live audio and video (Lieux et al., 2021). There are currently several video conferencing platforms, including Zoom, Skype for Business, WebEx, Microsoft Teams and GoTo

Meeting (Döring et al., 2022). In this designed-based project, the researchers will use video recording via Zoom.

Video conferencing allows wireless screen sharing, whiteboard sharing, interactive chat rooms, opinion polls, and discussion platforms. Video conferencing enhances the sense of human connection, permitting educators and students to establish their presence in online learning (Burke et al., 2022). In their research, Wang et al. (2018) stated that students' engagement is highly needed to utilise video conferencing tools and conduct online learning successfully. Video conferencing provides an opportunity for interaction and engagement, enabling the participants to bridge the psychological and communication distance between trainers and participants and among participants (Torrato et al., 2021). The relation between video conferencing and student engagement has been established above; however, there is a lack of literature on the characteristics and indicators of student engagement in video conferencing.

### **Teacher presence and role in enhancing student engagement**

Teachers' presence, expertise, and commitment to online learning significantly ensure quality learning. According to Stone and O'Shea (2019), such presence plays a critical role in online learning by establishing a connection with students and enhancing their engagement. In another study, Ergün and Kurnaz Adıbatmaz (2020) defined effective online teachers as those who discover the needs of their students and provide a safe learning environment in which students believe they can learn. Teachers who support their students through timely, proactive and embedded support can establish their presence and actively engage students through synchronous and asynchronous methods (Stone & O'Shea, 2019). Similarly, various studies have suggested that effective teacher presence and mutual relations between teacher and student can also prevent learner isolation, which might inhibit student engagement (Harbour et al., 2014; Starr-Glass, 2020). In general, the effects of teachers' behaviours and movements on student engagement in online learning have attracted many researchers' attention (Cents-Boonstra et al., 2021; Ma et al., 2015).

### **Engaging teachers' presence and role in enhancing student engagement**

As discussed, teachers' behaviours and movements in online learning significantly impact student engagement. In this regard, Aelterman et al. (2019) further highlighted that teachers' motivating behaviours enhance student engagement, feelings of competence, and relatedness support. These behaviours consist of (a combination of) autonomy support, a structure to enhance students' sense of competence, and relatedness support (Aelterman et al., 2019; De Meester et al., 2020). Teachers' motivating behaviours might be addressing students' interests or opinions by asking questions, offering choices, encouraging independent problem-solving, providing support and constructive feedback, and providing

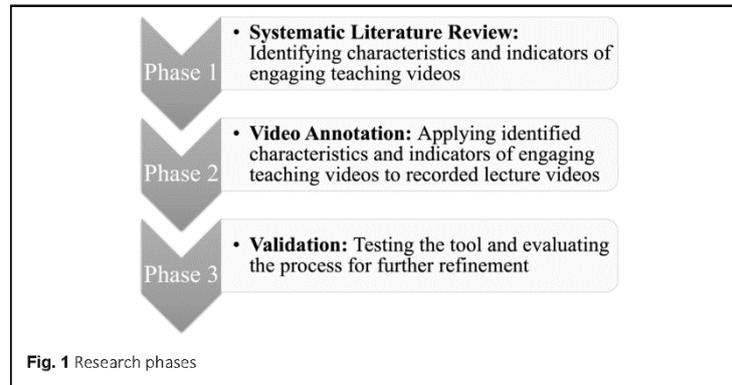
warmth and regard to develop mutually positive relationships with students (Aelterman et al., 2019; Haerens et al., 2013).

In conclusion, numerous investigations have been conducted on the effects of teacher presence in enhancing student engagement in video conferencing. Technology mediates teacher presence, with video conferencing being the most used technology. Teachers' non-verbal cues, such as facial expressions and body language afforded by video conferencing tools, promote high immediacy, social presence, and a sense of connectedness, facilitating learning and increasing learners' engagement. Similarly, their motivating behaviours, such as asking questions, providing feedback, addressing student concerns, and establishing social and cognitive presence, can further enhance student engagement. Through this systematic literature review, we identify characteristics and indicators of engaging teaching videos based on teachers' behaviours and movements. These characteristics and indicators might include measurable teachers' behaviours and body movements that enhance student engagement in video conferencing. Aladsani (2021) described body movements as non-verbal cues, such as facial expressions, gestures, and eye movements. According to Olitsky (2007), these characteristics, including behaviours and movements, help motivate, inspire, and engage students in online classes.

## Method

This study is part of a larger study that employed design-based research (DBR) to design a machine learning instrument that autogenerates a report every time a video (recorded lecture) is processed against formal behaviours and movements. DBR and similar approaches have become familiar and well-regarded strategies for designing interventions and solving classroom problems in various contexts (Getenet, 2019). Although DBR is considered a long-term and concentrated approach to educational inquiry, it can also be an effective methodology for a short-term project (Goff & Getenet, 2017; Pool & Laubscher, 2016). It has also proven especially suitable for technological interventions (Anderson & Shattuck, 2012). Based on the principles of DBR, the larger study was structured in three phases to design a machine learning instrument. These phases are listed in Figure 1.

The first phase comprised contextual analysis, which includes identifying characteristics and indicators of engaging teaching videos through a systematic literature review. The first phase is where the current study focuses, which will provide background information and the basis for designing the video annotation prototype. The second phase involves video annotation, where these identified characteristics and indicators will be applied to recorded lecture videos. In the second phase, the focus will be on explaining how these characteristics of engaging teaching videos will be used to train deep learning algorithms, which act as a classification tool for the video annotation tool. The last phase of the study is testing the tool and evaluating the whole process for further refinement of the deep



learning strategies. This study represents the first phase of a study that focuses on identifying the characteristics and indicators of engaging teaching videos.

We have conducted a systematic literature review to identify and analyse engaging teaching video characteristics and indicators based on teachers' behaviours and movements. Each author contributed to the study at various levels to ensure the validity of the systematic review process. The first author identified the characteristics and indicators of engaging teaching videos from the literature, the second and third authors validated the interpretation and analysis of the findings. The fourth author designed the AI methodology for future research, formally analysed the project scope, and validated the results. This process helped to validate the results.

The systematic literature review best suits the project's needs as it aims to identify, critically appraise, and summarise the existing evidence related to the topic (Martin et al., 2017). It has also assisted us in determining concepts and understanding the evolution of terminology related to a field of inquiry (Cook et al., 2008). The Preferred Reporting Items for Systematic Reviews and Meta-analyses (PRISMA) have been used to organise the data for a systematic literature review. The flow diagram describes the reports' identification, screening, eligibility, and inclusion criteria that fall under the scope of a review (Selcuk, 2019). We have used the PRISMA 2020 statement, the updated version of the PRISMA 2009 statement. This revised statement includes new reporting guidance that reflects advances in methods to identify, select, appraise, and synthesise studies (Page et al., 2021).

#### Database and search terms

The researchers collected all possible studies on a given topic and designed, reviewed, and analysed their results. Based on the selection criteria, the researcher has selected databases for search (please refer to Tables 1 and 2 selection criteria and list of databases). The researcher has applied inclusion and exclusion criteria in the systematic literature review.

**Table 1** Selection criteria for databases

Selection criteria	Description
Availability of relevant topics	The databases contain the data (peer-reviewed) related to education and can be narrowed down to modes of delivery such as online/video/e-learning.
Availability of data in full text	The data should be available in full text, and the selected databases provide most data in full text.
Boolean Operator	The database must support Boolean Operators or any other operators that help combine keywords for search.
Availability of data on all aspects of Educational Technology and E-Learning	Even though the study focuses on video learning, part of e-learning, all aspects of Educational Technology and E-Learning may provide similar engagement characteristics.
Geographical coverage	The research will broadly focus on global student engagement in video learning; hence, international data will play a crucial role.
English Language	The research will include the relevant data available in the English Language.
Consultation with Research Librarian (Expert Opinion)	Research Librarian suggested a group of databases focusing on learning and teaching (related to the topic).

Meline (2006) stated that inclusion and exclusion criteria justify the purpose of a systematic literature review. Inclusion criteria are everything a study must have to be included in the review. In contrast, exclusion criteria are the factors that would make a study ineligible to be included in the review. Table 1 summarises the selection criteria for databases. Seven databases were selected based on the criteria listed and described in Table 1.

The exact search phrase is applied on database A+ Education, Academic search ultimate, EBSCOhost Megafire ultimate, LearnTechLib and ProQuest One Academic, while for Scopus, it is different. The list of the databases and the relevant search phrase used in each database is shown in Table 2.

**Table 2** Selected databases

Database	Search phrase
A+ Education	(Characteristic* OR factor* OR Indicator*) AND
Academic search ultimate	{“video learning” OR “eLearning” OR “e-learning”}
EBSCOhost Megafire ultimate:	AND {“student engagement” OR “student
- eBook Collection (EBSCOhost)	involvement”) AND {“higher education” OR
- Education Research Complete	university OR college}
- E-Journals	
- ERIC	
LearnTechLib	
ProQuest One Academic	
Taylor & Francis Online	
Scopus	(Characteristic* OR factor* OR Indicator*) AND
	{{video learning} OR {eLearning} OR {e-learning}}
	AND {{student engagement} OR {student
	involvement}} AND {{higher education} OR university
	OR college}

The general search terms for all databases included main and unique keywords, and quotation marks and asterisks were applied to the keywords and connected using Boolean Operators.

### Inclusion and exclusion criteria

This search resulted in 1,170 studies. There were 70 duplicates removed, and we were left with 1,100 peer-reviewed articles. However, additional inclusion and exclusion criteria were applied to obtain relevant and consistent data. This process has two steps. First, after gathering the papers from different databases, we removed the duplicates and passed the data through the first exclusion process. The first inclusion/exclusion criteria (please refer to Table 3) were applied to the abstract and topic name.

After applying the first inclusion/exclusion criteria to the abstract and topic name, we were left with 63 articles. These criteria were based on the type of data (peer-reviewed articles), sample size, and period of papers published from 2010 to 2021.

Second, after the first exclusion process, including reading the topic and abstract, the remaining data went through the second step. Each remaining peer-reviewed article, book, journal, and conference was reviewed for further category. The first author reviewed the articles, and the second and third authors validated the results. Table 4 represents the second step of inclusion and exclusion criteria.

**Table 3** Step 1 - Inclusion and exclusion criteria

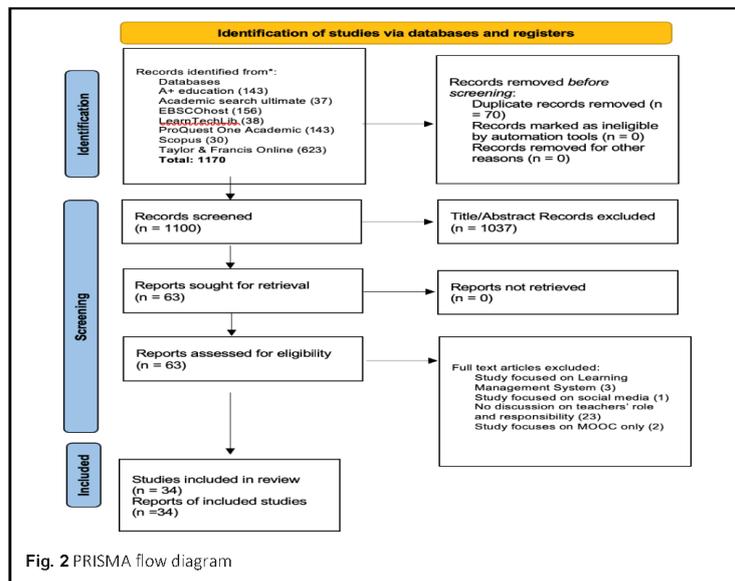
Inclusion criteria	Example/s
Peer-reviewed	Any peer-reviewed articles, books, journals, and conference proceedings
Sample size	Any peer-reviewed study has 50 or more participants
Time period	Any peer-reviewed study published from 2010 to 2021
Linguistic range	Any peer-reviewed study published in languages other than English can be translated into English
Mode of learning	Any peer-reviewed study focused on online, e-learning, video, and blended learning
Level of education	Any peer-reviewed study focused on higher education, university education and college
Geographical location	Any peer-reviewed study conducted in any geographical location
Exclusion criteria	Example/s
Different modes of learning	The study focused on mobile/intelligent phone learning The study focused on learning via video games The study focused on MOOCs (massive open online courses)
Study with a different focus	Any peer-reviewed study does not examine the indicators/factors/characteristics of student engagement in online, e-learning, video, and blended learning
Time period	Any peer-reviewed study published before 2010
Grey literature	Any data which is unpublished or has been published in a non-commercial form

**Table 4** Step 2 - Inclusion and exclusion criteria

Inclusion criteria	Exclusion criteria
The study focused on engagement indicators and characteristics.	The study focused on the learning management system only.
The study focused on teachers' role in student engagement.	The study focused on social media only.
	No discussion on teachers' role and responsibility to enhance engagement.
	The study focused on MOOCs only.

In the second inclusion and exclusion criteria, we reviewed all the remaining 63 articles thoroughly. After the second step, inclusion and exclusion criteria, we were left with 34 articles that were included in the review. From these 34 articles, we identified, analysed, and categorised the characteristics of engaging teaching videos based on teachers' behaviours and movements in the results section.

The summary of the whole process is shown in Figure 2 using a PRISMA flow diagram. As shown in Figure 2, 1,170 peer-reviewed articles were identified from seven databases, and 70 articles were duplicates and removed before the screening. Based on the title and abstract, 1,037 articles were removed in the first screening. In the second screening, the pending 63 articles were assessed for eligibility, and 29 were excluded based on the second step of the exclusion process. In the end, 34 studies were included in the review.



**Fig. 2** PRISMA flow diagram

## Results

This systematic review of literature aimed to identify the characteristics and indicators of engaging teaching videos. The research question guiding this study was: What are the characteristics and indicators of engaging teaching videos? We have reviewed 34 studies showing 11 main characteristics of engaging teaching videos. We further identify the indicators which can describe each characteristic. The identification and categorisation of indicators into the 11 main characteristics are supported by the significant findings in the reviewed study and research concerning teaching video engagement. These characteristics can be grouped into three broad areas: teachers' behaviours, teachers' movements, and use of technology. Table 5 represents the 11 characteristics and three broad areas of an engaging teaching video, followed by a description.

**Encouraging active participation:** The first characteristic that emerged was the presence of teachers encouraging participation in various forms. According to Almutairi and White (2018), one of the five benchmarks when measuring effective educational practice is the active and collaborative learning happening in the classroom. The extent to which students are involved in or invited to interact and work with other students might affect their devotion to the academic experience. The students must be allowed to participate in purposeful classroom activities. This characteristic is described in various studies with multiple indicators for encouraging active participation. The description of each indicator and the relevant studies where these are described are shown in Table 6.

As listed in Table 6, six descriptive indicators of encouraging active participation have been identified. For example, Jia et al. (2021) highlighted two indicators to encourage active participation, creating a safe and open environment to allow students to ask questions and inviting students to turn on their webcams.

**Using technology effectively:** The second characteristic identified from this systematic literature review is using technology effectively. In 2018, Bolliger and Martin pointed out that satisfaction with online teaching experiences is generally related to three components – students, instructors and institution (Walters et al., 2017). Out of the three mentioned

**Table 5** Areas of engaging teaching videos characteristics

Teachers' behaviours	Teachers' movements	Use of technology
Encouraging active participation	Using non-verbal cues	Using technology effectively
Establishing teacher presence		
Establishing social presence		
Establishing cognitive presence		
Questions and feedback		
Displaying enthusiasm		
Establishing clear expectations		
Demonstrating empathy		
Demonstrating professionalism		

**Table 6** List of indicators, descriptions, and relevant studies for “encouraging active participation”

Indicators	Description	Relevant studies
Encouraging students’ participation in discussion	Teachers to engage students in discussions or debates to yield their interest and motivate a deeper understanding.	Farrell and Brunton (2020)
Encouraging students to share their knowledge and ideas	Teachers to ask for students’ participation in active learning methods by sharing their perceptions, knowledge, and ideas.	Almarghani and Mijatovic (2017)
Encouraging students to ask questions	Teachers to create a safe and open environment that allows students to ask their questions to enhance the student interaction experience.	Jia et al. (2021)
Encouraging collaborative learning activities	Teachers to create opportunities for students to interact with each other through group activities or collaborative work.	Carraher Wolverson et al. (2020)
Encouraging meaningful interaction	Teachers to construct a welcoming and efficient online learning environment by fostering regular and meaningful communication with students, and providing meaningful answers to students’ enquiries.	Stone and Springer (2019) Walters et al. (2017)
Encouraging students to turn on their webcams	Teachers to stimulate face-to-face communication by turning on and inviting students to turn on their webcams.	Jia et al. (2021)

areas, the student-related and instructor-related satisfaction levels are said to be from students having accessible online technology and teachers providing reliable and effective technology, respectively (Walters et al., 2017). These indicators, with a brief description and the relevant studies reviewed, are shown in Table 7.

**Table 7** Indicators, relevant descriptions, and relevant studies for “using technology effectively”

Indicators	Description	Relevant studies
Screen sharing & Enabling chat, camera, and microphone	Teachers to assure students of their presence and positively impact student engagement and satisfaction by communicating in real time through chat, camera, microphone and screen-sharing.	Roque-Hernández et al. (2021)
Varying the presentation media	Teachers to vary the presentation media (e.g., videos, slides, note sharing, etc.) to capture student attention and foster engagement.	Jia et al. (2021)
Providing technical support to students	Teachers to provide technical support when needed as a demonstration of teachers’ pedagogical skills in addressing the challenges of delivering effective online learning experiences.	Fatani (2020)
Providing multiple communication channels	Teachers to promote satisfactory and effective learner-instructor interaction by taking the initiative in providing multiple communication channels.	Bolliger and Martin (2018)
Providing interactive software tools	Teachers to increase the value of online lesson by incorporating interactive software tools into the lesson.	Roque-Hernández et al. (2021)
Enabling class recording for later review	Teachers to increase the value of the online learning experience by enabling class recording, which allows students access to classroom sessions from the comfort of their home and if they can want to review afterwards.	Leslie et al. (2015)

As seen in Table 7, we have identified six indicators for the effective use of technology. For example, Roque-Hernández et al. (2021) described the impact of real-time communication on student engagement and interactive software tools.

**Establishing Teacher Presence:** The third characteristic identified was establishing teacher presence. The lack of teacher presence contributes to disengagement in online classrooms due to students' feelings of isolation (McNeill et al., 2019). Therefore, it is critical to create an environment in which the teacher's presence is maintained so that students are more motivated and, thus, performance is positively influenced. The indicators in Table 8 demonstrate how teachers can be present and supportive in an online learning environment as used in the studies reviewed.

**Table 8** Indicators for establishing teacher presence

Indicators	Description	Relevant studies
Clear and concise explanations of information	Teachers to enhance students' comprehension of the knowledge and information by providing clear and concise explanations of information through means such as teachers' discourses, demonstrations, replications, perceptions, or slides.	Ullah et al. (2019)
Recognising and considering learners' differences	Teachers to consider learner differences when choosing the formats for delivering the information. The differences can be in an individual's learning preferences, technical skills, prior knowledge, and learning and technological needs.	Ergün and Kurnaz Adibatmaz (2020)
Using an appropriate style of presentation	Teachers to maximise the efficiency of the classroom in online education by using any appropriate style of presentation that can hold students' interest.	Fatani (2020)
Allowing sufficient time for students' information processing	Teachers to maximise the efficiency of the classroom in online education by demonstrating the capability to understand and provide students with sufficient time to take notes on the lesson while presenting and explaining the information.	Fatani (2020)
Providing learning resources	Teachers to provide students with various learning resources, videos, etc., to increase students' active participation.	Tanis (2020)
Giving clear instructions	Teachers to be clear and detailed in communicating the instructions, expectations, roles and responsibilities to show commitment to meeting the course goals.	Gina (2017)
Using a range of teaching strategies	Teachers vary the perspectives they bring to the lessons and use various teaching strategies. The multiple roles teachers might take during the teaching help increase the effectiveness of learner-instructor interaction.	Gómez-Rey et al. (2016)
Appropriate speed of lecture delivery	Teachers to deliver the lecture at an appropriate speed to meet the students' expectations of instructor engagement in the teaching process (through instructors' way of presenting or teaching the knowledge).	Richards and Velasquez (2014)

Table 8 shows eight indicators of establishing teacher presence, their description, and relevant studies. For example, Fatani (2020) described the use of the appropriate style of presentation and providing sufficient time for students to take notes as indicators to maximise the efficiency of the classroom.

**Establishing Social Presence:** The following characteristic identified from this systematic literature review was establishing a social presence. Lim et al. (2021) adopted the definition of Gunawardena and Zittle (1997), which relates social presence to ‘the degree to which a person perceives their communication partners to be “real” in mediated communication’. With that being established, Lim et al. (2021) would argue that the social presence students might experience in the classroom would be from their engagement in class discussions, team projects or conversations with their instructor. It can be understood that social presence is related to students’ willingness to engage in online learning activities, which may also be related to their online classroom satisfaction level. The indicators in Table 9 reflect how social presence is demonstrated in engaging teaching videos in various studies.

As shown in Table 9, we have identified four indicators for establishing a social presence. For example, according to Muir et al. 2019 social presence can be established by maintaining regular, active, and constructive communication with students.

**Table 9** Indicators for establishing a social presence with their description

Indicators	Description	Relevant studies
Maintaining constant teacher-student interaction	Teachers to maintain their social presence in the online classroom by constantly being involved in students’ learning to avoid creating the isolated and lonely feelings students might have behind the screen.	Gómez-Rey et al. (2016)
Encouraging student-student interaction (Peer collaboration)	Teachers to allow students to take part in student-student interaction through collaborative learning activities to enhance the comfortable and supportive learning environment.	Paulsen and McCormick (2020)
Active and constructive communication	Teachers must establish a robust and consistent presence by maintaining regular, active, and constructive communication. The engagement of lecturers can reflect their impact on students.	Muir et al. (2019)
Taking on multiple roles	Teachers to take on multiple roles of planners, models, coaches, facilitators and communicators in the classroom to demonstrate engaging online communication and active participation. The more involvement from instructors, the more productive the learning environment can be, and students are more prompted to respond to online communication.	Seaton and Schwier (2014)

**Table 10** Indicators for establishing a cognitive presence

Indicators	Relevant studies
Giving students a sense of puzzlement (trigger)	Jia et al. (2021)
Providing opportunities for students to reflect (exploration)	Jia et al. (2021) Purarjomandlangrudi et al. (2016)
Leading students to think and learn through discussion with others (integration)	Jia et al. (2021) Stone and Springer (2019)
Helping students apply knowledge to solve issues (resolution)	Jia et al. (2021)

**Establishing Cognitive Presence:** According to Trenholm et al. (2019), an engagement sub-construct relates to students' level of involvement in learning activities. It is called "cognitive engagement", which suggests that learning happens when students seek comprehension and understanding in strategic learning activities. Jia et al. (2021) also pointed out that "cognitive" would promote student engagement.

The indicators for establishing a cognitive presence can be seen in Table 10.

Table 10 represents the indicators for establishing a cognitive presence, such as trigger, exploration, integration and resolution. The table also highlights the relevant studies on these indicators.

**Questions and Feedback:** It has long been established that student-teacher interaction is vital in increasing student engagement in all learning contexts, including online learning (Abou-Khalil et al., 2021). Any two-way interaction would boost students' engagement in a class by maintaining their interest and motivation in the learning process rather than solely listening to teachers' presentations (Trenholm et al., 2019). The indicators for questions and feedback are listed and described in Table 11.

**Table 11** Indicators for questions and feedback

Indicators	Description	Relevant studies
Addressing students' questions & Providing prompt feedback	Teachers to develop two-way interaction in online classrooms to increase student engagement and motivation. The interactions should be interactive, for example, posing questions or making time for students to make questions, giving answers or feedback to students.	Trenholm et al. (2019)
Asking for questions and feedback	Teachers to invite learners' participation in online learning by asking for their contribution by asking for course-related questions and feedback.	Abou-Khalil et al. (2021)
Clarifying misunderstanding	Teachers to use different strategies to contribute to students' understanding of course concepts and clarify any misunderstandings so that students' interests, motivations and perceptions are emphasised.	Purarjomandlangrudi et al. (2016)

As seen in Table 10, we have identified three indicators of questions and feedback from the mentioned studies. These three indicators have been described as two-way interaction, student contribution through questions and clarification of any misunderstanding.

**Displaying Enthusiasm:** The teachers play a prominent role in planning and conducting online learning with active communication and reliable technology to enhance student engagement. Consequently, students might benefit more from online education if teachers are to show them enthusiasm and motivating and support relationships (Walters et al., 2017). Studies such as McNeill et al. (2019) and Greenberger (2016) described this characteristic with two indicators. The indicators in Table 12 reflect how enthusiasm might be displayed in engaging teaching videos.

Two indicators for displaying enthusiasm have been mentioned in Table 12. The studies suggested that teachers can display enthusiasm by setting clearly defined parameters to motivate the students and displaying consistent positive emotions.

**Establishing Clear Expectations:** Teachers must present themselves professionally and clearly to encourage respectful communication and interaction in any educational context. Teachers are to be clear and detailed in communicating the expectations, roles and responsibilities and be available to respond to requests for information, assistance or feedback. This would help engage students and keep them moving forwards, knowing that instructors are also committed to meeting the course goals (Gina, 2017). Two indicators were identified in the reviewed articles to show how teachers in online education establish expectations through engaging teaching videos.

Table 13 describes two indicators for establishing clear expectations. Ice et al. (2011) stated that expectations could be established by clearly outlining the learning objectives. However, according to Almarghani & Mijatovic (2017), teachers should outline the expectations of students' behaviours and responsibilities.

**Demonstrating Empathy:** According to Greenberger (2016), students' feeling of belonging and being motivated to strive for academic achievement increases when they feel cared for by their teachers or instructors. Interpersonal closeness helps construct

**Table 12** Indicators for displaying enthusiasm

Indicators	Description	Relevant studies
Motivating students	Teachers to create the environment in which they are present, with clearly defined parameters and a focused direction so that students are more motivated, and thus, performance is positively influenced.	McNeill et al. (2019)
Displaying positive emotion	Teachers to display consistent positive emotions to demonstrate their passion for increasing student engagement in online learning activities and positive interpersonal interactions.	Greenberger (2016)

**Table 13** Indicators for establishing clear expectations

Indicators	Description	Relevant studies
Outlining the learning objectives	Teachers to clearly outline and communicate the topics and instructions to increase student engagement in online learning.	Ice et al. (2011)
Outlining teachers' expectations of students' behaviours and responsibilities	Teachers to have students experience appropriate levels of autonomy or independence in online learning by outlining teachers' expectations of students' behaviours and responsibilities.	Almarghani and Mijatovic (2017)

empathy, which in turn optimises teacher-student interaction. (Greenberger, 2016). Table 14 shows the identified indicators and descriptions for demonstrating empathy.

In Table 14, three indicators for demonstrating empathy have been described. For example, according to Johnson et al. (2018), teachers can show empathy by ensuring the student's learning environment is respectful, safe, and supportive.

**Using non-verbal cues:** In distance education, immediacy, like empathy, refers to the interpersonal closeness between online classroom participants and is mediated through verbal and non-verbal cues. By including more of these immediate behaviours, shown below as the indicators, the teachers can ease the physical distance of the online classrooms by increasing student engagement in online learning activities and positive interpersonal interactions (Greenberger, 2016).

Teachers should simulate face-to-face communication to encourage students to be more attentive and engaged in class activities. Moreover, communication is more vivid, fluent and natural if non-verbal language features are included. The indicators for non-verbal language are shown in Table 15.

**Table 14** Indicators for demonstrating empathy

Indicators	Description	Relevant studies
Using appropriate changes in tone of voice	Teachers to read and respond to perceived restlessness by appropriate changes in tone of voice or changes in direction.	Trenholm et al. (2019)
Ensuring the learning environment is a respectful, safe, and supportive one	Teachers motivate student engagement by ensuring the learning environment is a respectful, safe, and supportive one in which learners' learning is scaffolded through each interaction. The satisfactory level is significantly correlated with the level of interactions students have with other individuals (it can be with other students or with teaching staff).	Johnson et al. (2018)
Showing concern	Teachers to ensure their social presence in the class by showing a level of concern and the extent to which they encourage student participation.	Gómez-Rey et al. (2016)

**Table 15** Indicators for using non-verbal cues

Indicators	Relevant studies
<ul style="list-style-type: none"> <li>- facial expressions,</li> <li>- gestures,</li> <li>- eye gazes,</li> <li>- silence.</li> </ul>	Jia et al. (2021) Trenholm et al. (2019)
Intimacy, a fundamental concept of social presence, is a function of factors such as <ul style="list-style-type: none"> <li>- eye contact,</li> <li>- physical proximity,</li> <li>- appropriate body language.</li> </ul>	

Table 15 contains the indicators for using non-verbal cues. The studies mentioned in the table described the significance of non-verbal cues as it simulates face-to-face communication and makes communication more vivid, fluent and natural.

**Demonstrating Professionalism:** According to Richards and Velasquez (2014), it is common for students to hold certain expectations of how teachers engage in the classroom by either presenting themselves or teaching the knowledge. It is investigated that the reviewed articles used indicators listed in Table 16 to inform how teachers should deliver the lecture professionally and appropriately.

In Table 16, the indicators for demonstrating professionalism have been highlighted. According to Gómez-Rey et al. (2016), teachers can demonstrate professionalism by showing in-depth and up-to-date knowledge of the course content. As per Vallade and Kaufmann (2020), teachers can demonstrate professionalism by displaying appropriate behaviour.

**Table 16** Indicators for demonstrating professionalism

Indicators	Description	Relevant studies
Demonstrating in-depth and up-to-date knowledge	Teachers should have in-depth and up-to-date knowledge, linked to the course content or instruction, to increase learners' level of satisfaction and perception of course knowledge.	Gómez-Rey et al. (2016)
Displaying appropriate behaviours	Teachers to avoid the specific behaviours that might interfere with classroom instructions or student learning and are identified into three categories as follows: <ul style="list-style-type: none"> <li>- incompetent behaviours – lack of teaching skills for effective instruction (unclear manner)</li> <li>- indolent behaviours – lack of procedural skills for effective instruction (unprepared, disorganised)</li> <li>- offensive behaviours – lack of interpersonal communication skills for effective instruction (verbal abuse)</li> </ul>	Vallade and Kaufmann (2020)

## Discussion

In this systematic literature review, 11 characteristics that can support teachers in enhancing online student engagement via video conferencing tools have been identified and presented in the result section. These 11 characteristics were categorised into three main themes (teachers' behaviours, teachers' movements, and use of technology), and 47 indicators were established in these articles that they can enhance student engagement in video conferencing.

These identified themes, characteristics and indicators are critical in enhancing student engagement if applied appropriately by teachers in video conferencing. Teachers can use these characteristics and indicators as a benchmark to identify the gap in their teaching performance in online classrooms and improve accordingly. These characteristics and indicators can be applied at the institutional level to enhance and moderate online teaching practice. The educational institute can also use this information to provide professional learning activities for teaching staff to improve their skill in creating engaging teaching videos. In addition, the identified indicators can be measured and contribute to developing a machine learning system that autogenerates a report every time a video (recorded lecture) is processed against the formal behaviours and movements, which is the second part of this study.

Nine characteristics are identified in this systematic literature review under the teacher behaviour theme. The first identified characteristic focuses on encouraging the participation of students in educational activities during video conferencing. Teachers can use different methods to facilitate students' active involvement in the lesson, directly related to students' positive classroom experience in enhancing their learning process. There are six descriptive indicators of encouraging active participation, such as encouraging the students to have meaningful interactions and ask questions. In online learning, teacher presence is vital as it motivates and positively influences the students' performance (McNeill et al., 2019). Establishing teacher presence has been identified as the second characteristic under the teacher behaviour theme. Teachers can use various strategies to maintain their presence and increase the effectiveness of interaction during their online classes. Another characteristic that can enhance student engagement in video conferencing is establishing a social presence. Teachers can establish students' social presence by organising activities that require peer interaction (student-student interaction). Moreover, teachers can also take on multiple roles to demonstrate student engagement and participation.

The fourth characteristic identified under the teacher behaviour theme is establishing a cognitive presence. Teachers can use various methods, such as reflections and discussions, to establish students' cognitive presence in video conferencing. Asking questions and providing feedback is another form of effective student-teacher interaction, as it enhances

student motivation and interest in the learning process (Trenholm et al., 2019). Questions and feedback provide two-way interaction between teachers and students, which is more effective than traditional one-way classroom presentations. Displaying enthusiasm and demonstrating empathy have been considered two crucial characteristics of student engagement in video conferencing under the teacher behaviour theme. By displaying positive emotions such as enthusiasm and empathy, teachers can optimise their interaction with students (Greenberger, 2016). These emotions provide a feeling of belonging and motivation to the students, contributing to their academic achievement.

Teachers should also provide clear and detailed instructions regarding the expected students' behaviours, roles, and responsibilities to enhance student engagement in video conferencing. At the beginning of each video conferencing session, teachers should clearly outline and communicate the learning objectives as it motivates the students to meet their course goals (Ice et al., 2011). Hence establishing clear expectations has been identified as the eighth characteristic under the teacher behaviour theme. The ninth identified characteristic through this systematic literature review is demonstrating professionalism. Teachers need to conduct themselves professionally throughout their teaching, as failure can lead to student disengagement (Vallade & Kaufmann, 2020).

In addition to these above-stated engagement enhancing teacher behaviours, literature has suggested that some non-verbal cues/body movements can also improve student engagement in video conferencing. Physical distance is one of the significant barriers to online learning that affects student engagement (Aladsani, 2021). By using non-verbal cues such as hand gestures, eye gaze, facial expressions, positive body language and appropriate pauses, teachers can make online learning through video conferencing more effective.

The effective use of technology in video conferencing has been identified as another crucial characteristic of enhancing student engagement. As this study focuses on video conferencing, teachers must be fully trained in using relevant technology. With effective use of technology, teachers can find ways to make maximum use of available features of video conferencing. The features such as screen sharing, multiple communication channels, and interactive software tools can make the online classroom environment more engaging (Bolliger & Martin, 2018; Roque-Hernandez et al., 2021).

### **Limitations**

The current study only focuses on higher education, and the identified engaging teaching video characteristics may need to be revised on different levels of education, such as vocational and school education. The researcher only identified the characteristics from peer-reviewed articles written in English, and the characteristics identified may not be as suitable for other languages. The research does not explore the practical component in

detail, and the identified characteristics may not work as effectively in practical learning, workshops, or simulations.

### **Conclusion**

The identified characteristics and indicators can enhance students' learning experience by providing an engaging video conferencing environment. Both teachers and educational institutions can benefit from these characteristics and indicators to improve their teaching practices. Further, the identified characteristics and indicators can assist machine learning engineers in training and developing an instrument that autogenerates a report every time a video (recorded lecture) is processed against the formal behaviours and movements.

### **Implications and future research**

The study will have two broader implications: online learning and teaching using video and to support the design of AI to identify engaging teaching videos. Each is described in the following section:

#### **Teaching and learning online in higher education**

Despite the popularity of online learning in higher education, student engagement has remained a significant concern. The characteristics and indicators of engaging teaching videos identified in this systematic literature review can assist higher education institutions in enhancing student engagement. These characteristics and indicators can be a benchmark for teachers to improve their teaching and learning practices.

#### **AI design to identify engaging teaching videos**

This study will support the creation of an AI instrument based on these identified characteristics and indicators of engaging teaching videos. By applying the characteristics and indicators of engaging teaching videos, researchers can annotate videos to create an AI instrument with the help of open-source project-based annotation software. The AI can be designed based on the deep learning algorithm that will automatically highlight these engaging teaching video characteristics.

#### **Abbreviations**

AI: Artificial intelligence; DBR: Design-based research; NLP: Natural language processing; PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-analyses.

#### **Authors' contributions**

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### **4.3 Links and implications**

The systematic literature review conducted in this phase was instrumental in the research process, providing a methodical and rigorous strategy for collecting, analysing, and synthesising existing knowledge to identify the characteristics and indicators of engaging teaching videos.

The results provide valuable support to higher education institutions in their efforts to enhance online student engagement, an ongoing concern in higher education. The identified themes, characteristics, and indicators are vital in enhancing online student engagement if teachers effectively employ them during video conferencing sessions. These characteristics and indicators serve as a reference point for teachers to identify areas for improvement in their online teaching performance to enhance student engagement. These characteristics and indicators can also be employed at the institutional level to improve and regulate online teaching practices. The educational institutes can utilise this information to offer teaching staff professional development opportunities to improve their skills in creating engaging teaching videos. Examining which videos effectively integrate engaging elements offers insights for enhancing video content and creatively refining teaching methods. Likewise, evaluating the most engaging videos enables teachers to acquire a valuable understanding of what suits best with their students, empowering them to make informed decisions for future learning and improved outcomes. Hence, recognising behaviours and movements that enhance engagement can support teachers in elevating their teaching practices and render their video conferencing sessions more engaging for students.

The importance of the characteristics and indicators has been established above, along with the list and descriptions in Appendix A. These characteristics and indicators can be manually identified from the recorded lecture videos; however, this process can be time-consuming and susceptible to human bias. Thus, this laid the foundation for the next phase, which focused on the development of an AI model capable of generating a report whenever a recorded lecture video undergoes processing through it.

The upcoming chapter, Chapter 5, introduces the subsequent phase of the research, which focuses on the development of an AI model tailored for generating comprehensive reports on engaging teaching videos.

## **CHAPTER 5: PAPER 2 – DESIGNING AN ARTIFICIAL INTELLIGENCE TOOL TO UNDERSTAND STUDENT ENGAGEMENT BASED ON TEACHER’S BEHAVIOUR AND MOVEMENTS IN VIDEO CONFERENCING**

In this chapter, the term “prototype” was used, specifically referring to two distinct models: model 1 and model 2. Following the challenges encountered with Prototype 1 (model 1), a refined iteration, Prototype 2 (model 2), was developed to effectively address these issues, resulting in a successful outcome.

The previous chapter, Chapter 4, explored identifying the characteristics and indicators of engaging teaching videos to support teachers in establishing benchmarks to enhance student engagement in video conferencing. This chapter, Chapter 5, constitutes the second phase of this research focusing on the development of an AI model for generating reports on engaging teaching videos and detailing the approach employed in its creation. Section 5.1 provides the summary of this phase. The paper is embedded in section 5.2 which presents the process of developing the AI model. The development was made feasible through the utilisation of the characteristics and indicators identified in Phase 1. The last section, section 5.3, discusses the implications and links the paper to the final phase.

### **5.1 Introduction**

This paper has been published in “Computers and Education: Artificial Intelligence.” Which is ranked Q1 in three prominent categories: Artificial Intelligence, Computer Science Applications, and Education, as per the Scimago Journal Rank. The full article is accessible via the following link:  
<https://doi.org/10.1016/j.caeai.2023.100187>.

Following the preliminary phase of this research, this subsequent paper aimed at developing an AI model to generate reports of engaging teaching videos employing deep learning as an artificial intelligence methodology.

In this paper, the characteristics and indicators of engaging teaching videos identified in the first phase were applied to create an AI model. Addressing the focused question: To what extent can an AI model be designed to generate a report for indicators and characteristics of engaging teaching videos based on teachers’

behaviours and movements? Twenty-five Zoom-based recorded lecture videos presented to higher education students were annotated manually based on the identified indicators and characteristics of engaging teaching videos. The recorded lecture videos used to train the AI model had 13 female and 12 male presenters, with ethics approval number H20REA185. An AI expert assisted in creating the AI model from the manual annotation reports. This model can detect the behaviours and movements of teachers that enhance engagement in recorded lecture videos. The model also has the capability to automatically generate a report for each processed video, highlighting the identified engagement-enhancing aspects. This phase employed a deep learning model for the classification task of video analysis. Lecture videos of varying quality (poor, average, and good) from various settings were incorporated to train the deep learning model. These videos had durations ranging from 00:59:06 to 01:51:52, with an average duration of 01:28:37. The model was trained with the reports from the manual annotation of videos. Issues related to class imbalance and misleading metrics were identified; thus, to further improve the model's performance, the oversampling technique was implemented. The refined version of the model yielded promising results, achieving an average precision, recall, f1-score, and balanced accuracy of 68%, 75%, 73%, and 79%, respectively, in classifying the annotated videos at the indicator level. These results highlight the effectiveness of oversampling in mitigating imbalanced data distributions and emphasise the potential of the enhanced model to deliver more reliable classifications in real-world scenarios. Additionally, these findings indicate that the CNN model demonstrates superior capability in making precise predictions on novel or unseen data, indicating a more accurate depiction of underlying patterns in the teaching domain. It is crucial to recognise that limitations, such as dataset size and quality, may persist and could potentially affect the reliability of findings.

Answering the research question: How will the AI model improve teaching and learning practices in higher education? The developed AI model efficiently identifies engagement-enhancing teachers' behaviours and movements, processes recorded lecture videos to generate detailed reports, and offers time-saving recommendations for teachers to improve online student engagement. Beyond aiding individual teachers, the model plays a crucial role in assisting educational institutes in ensuring moderation in lecture delivery. By referencing the model's identified characteristics and indicators, institutes can align their lecture delivery with established standards,

promoting fairness, validity, consistency, and reliability. Furthermore, the model extends its application to assess the effective use of technology during video conferencing, contributing to overall teaching improvement. The paper underscores the significance of AI in recognising and evaluating teachers' engagement-enhancing behaviours, ultimately enhancing student engagement. Additionally, it prompts more questions for research, with some particularly addressed in the subsequent research phase, marking a significant outcome of the study.

## 5.2 Published paper

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## Designing an artificial intelligence tool to understand student engagement based on teacher's behaviours and movements in video conferencing

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#### ABSTRACT

Video conferencing is an effective tool that promotes interaction and collaboration, increasing student engagement in online learning. This study is the second phase of design-based research to create a tool to generate a report of engaging teaching videos using deep learning as an artificial intelligence (AI) methodology. In this second phase, the authors have applied the characteristics and indicators of engaging teaching videos identified in the first phase, reported in another study, to develop an Artificial Intelligence enabled tool. Twenty-five recorded lecture videos presented to higher education students were annotated based on the indicators and characteristics of engaging teaching videos. An AI expert has assisted the authors in creating the Artificial Intelligence-enabled tool from the reports generated by this manual annotation. With the assistance of this tool, the engagement enhancing teachers' behaviours and movements can be identified from recorded lecture videos, and a report can be generated on engaging teaching videos. For the classification task of video analysis, the deep learning model is adopted in this research. The model is trained with manually annotated videos and determines class imbalance issues and misleading metrics. The model was further improved by adopting the oversampling technique. The second version of the tool achieved promising outputs with average precision, recall, f1-score, and balanced accuracy of 68, 75, 73, and 79%, respectively, in classifying the annotated videos at the indicator level. The tool can assist the education institutes in creating moderation in the lecture delivery and whether the teachers are utilising the technology effectively. Additionally, this can help teachers recognise the presence or absence of engagement-enhancing behaviours and movements during their video conferencing sessions.

#### 1. Introduction

Over the past few decades, the demand for online learning has significantly increased in higher education, providing students and teachers with more flexible access to educational opportunities. In 2020, due to the global issue of COVID-19, higher education institutes worldwide were compelled to switch their learning mode to online learning (Cucinotta & Vanelli, 2020). This sudden change caused many challenges to teachers and students as they were not prepared for online learning. The research indicates that student engagement in online learning is a significant challenge, and engaging them in online learning is more complex than face-to-face learning (Cesari et al., 2021; Gillett-Swan, 2017; Hew, 2016).

In online learning, technology is crucial in delivering education and

enhancing interaction (Singh & Thurman, 2019). Video conferencing is the most effective technology that assists teachers in offering collaboration and increasing student engagement (Kumar et al., 2015); it is an effective instrument for teaching and communication in online learning (Al-Samarraie, 2019). Several video conferencing platforms are available, such as Zoom, WebEx, Microsoft Teams, GoTo Meeting and Skype for business (Döring et al., 2022). These platforms allow teachers and learners to communicate in real-time via live audio and video (Lieux et al., 2021). This real-time connectivity enhances human connection, permitting educators and students to establish their presence in online learning (Burke et al., 2022). By utilising video conferencing effectively, teachers can provide immediate feedback to students to bridge the psychological and communication distance between them and students (Torrato et al., 2021). Video conferencing also allows wireless screen

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sharing, whiteboard sharing, interactive chat rooms, opinion polls, and discussion platforms.

In their research, Wang et al. (2018) stated that students' engagement is highly needed to successfully utilise video Conferencing tools and conduct online learning. Teachers can use engagement enhancing behaviour and movements to engage students in video conferencing. These behaviours consist of (a combination of) autonomy support, a structure to enhance students' sense of competence, and relatedness support (Aelterman et al., 2019; De Meester et al., 2020). Some of these motivating teachers' behaviour are encouraging active participation, establishing teacher presence, demonstrating empathy, and establishing clear expectations (Authors, 2023). Furthermore, teachers' positive body movements include non-verbal cues, such as facial expressions, gestures, and eye movements (Authors, 2023).

Previous studies have established that these behaviours and movements enhance teachers' presence, increasing student engagement (Cents-Boonstra et al., 2021; Dewan et al., 2019). Therefore, there is a need for an instrument that can measure engaging teaching videos according to teachers' movements and behaviours. The authors have identified these behaviours and movements through a systematic literature review in phase 1, reported in another study (Authors, 2023). Identifying these engaging characteristics and indicators from recorded lecture videos requires a human, and this manual identification and analysis is very time-consuming and expensive (Beaver & Mueen, 2022), and it can also lead to human bias.

To avoid human bias and to measure engaging teaching videos much faster, the authors employed a designed-based research (DBR) approach to create an AI-enabled tool that generates a report for indicators and characteristics of engaging teaching videos. The identified indicators and characteristics in phase 1 of DBR research (Authors, 2023) were applied to 25 Zoom-recorded lecture videos through a manual annotation process. With manual annotation outputs (reports), the AI expert trained the AI-enabled tool. This tool will assist teachers in enhancing the overall quality of online learning. Educational institutes can also utilise this tool to create moderation in their lecture delivery and improve online learning procedures.

The study explored the following research questions.

- (1). To what extent can an AI-enabled tool be designed to generate a report for indicators and characteristics of engaging teaching videos based on teachers' behaviours and movements?
- (2). How will the AI-enabled tool improve teaching and learning practices in higher education?

## 2. Literature review

### 2.1. Online learning in higher education

In today's technology-driven environment, online learning has gained increasing attention. A growing number of students are choosing online learning, leading to online learning in higher education becoming a primary mode of delivery (Salas-Pileo et al., 2022). Further, COVID-19 has created a radical change in education, and higher education worldwide is going through a dramatic transformation in digital technologies (Dwivedi et al., 2020; Krishnamurthy, 2020). Even though the use of technology began several years ago, the abrupt change caused by this pandemic has required higher education institutions worldwide to transition to online learning rapidly. This evolution includes integrating and using technological resources available to teachers and researchers (García-Morales et al., 2021).

### 2.2. Video conferencing and student engagement

In online learning, technology develops a connection between teachers and students and assists in developing the abilities required for online learning. Due to its ability to provide real-time communication

through audio and video calls (Lieux et al., 2021), video conferencing is now an essential tool in online learning (Roth et al., 2020). Several video conferencing tools are available for teachers to digitalise their teaching and learning processes (Mishra et al., 2020). These tools are GoTo Meeting, Microsoft Teams, WebEx, Zoom and Skype (Döring et al., 2022). Although these tools provide various functions to improve online teaching and learning, student engagement is crucial for enhancing teaching quality and video conferencing.

Student engagement is essential for student achievement, academic motivation, performance, and satisfaction (Hu & Li, 2017, pp. 39–43; Kahu et al., 2019). For deep-level learning and retention, engaging students in learning is necessary (Cents-Boonstra et al., 2021; Hu & Li, 2017, pp. 39–43; Kuh et al., 2008). However, the lack of student engagement is a significant issue in online learning (Dembereldorj, 2021), which results in non-completion, withdrawal, and unsatisfactory learning experiences (Bergdahl, 2022).

Video conferencing can assist in engaging students in online learning by offering features such as whiteboard sharing, screen sharing, discussion platforms, chat rooms, and polls. Video conferencing facilitates the connectivity of people, allowing teachers and students to gain access to online learning opportunities (Burke et al., 2022). Video conferencing assists in overcoming the communication and psychological distance between learners and teachers and allows them to interact and participate (Torrato et al., 2021). Therefore, teachers should utilise technology efficiently in online learning by leveraging all the engaging video features during video conferencing sessions to increase student engagement.

### 2.3. Teachers' movements and behaviour in video conferencing

Teachers' movements and behaviours in video conferencing significantly impact student engagement. According to Aelterman et al. (2019), teachers' motivating behaviours positively affect student engagement and feelings of competence. Teachers' behaviours provide autonomy support, students' sense of competence, and relatedness support (Aelterman et al., 2019; De Meester et al., 2020). These motivating behaviours include asking questions, encouraging problem-solving, providing constructive feedback, and developing mutually positive relationships with students (Aelterman et al., 2019; Haerens et al., 2013).

In addition to the aforementioned teacher behaviours that enhance engagement, previous research has indicated that certain body movements and non-verbal cues can also improve student engagement during video conferencing. One of the main obstacles to online learning that affects student engagement is the physical distance (Aladsani, 2021). Teachers use non-verbal cues such as eye gazing, silence, appropriate facial expressions, and appropriate body language to make video conferencing more effective (Jia et al., 2021; Trenholm et al., 2019).

An instrument is required to measure the engaging teaching videos according to teachers' movements and behaviours. However, most instruments currently available to measure student engagement are developed for face-to-face learning environments (Lee et al., 2019). Few researchers have investigated student engagement in online learning and developed assessment tools. Halverson and Graham (2019) stated that with clear indicators, student engagement could be measured and recommended a framework by providing indicators for cognitive and emotional engagement. Lee et al. (2019) also highlighted the importance of indicators and recognised them as an essential factor that positively affects learning and engagement. They emphasised the necessity of having an appropriate measurement tool for student engagement to ensure the quality of education. They developed an instrument with six factors with 24 items on a five-point Likert scale.

In the above section, the authors have established the importance of teachers' behaviours and movements in video conferencing and indicators to measure student engagement; however, no detailed list of characteristics and indicators of engaging teaching videos before the

Authors (2023) identified those in their previous study (phase 1). A systematic literature review was performed where authors identified 11 characteristics that can provide aid for enhancing student engagement via video conferencing. As shown in Table 1, the identified characteristics of engaging teaching videos have descriptive indicators and are categorised into three themes: Teachers' behaviours, movements, and use of technology). These identified indicators and characteristics are essential in improving student engagement.

Authors (2023) strongly believe that the characteristics and indicators stated in Table 1 above can be used as a benchmark to increase teachers' performance in online learning. Educational institutes can implement these indicators and characteristics of engaging teaching videos to enhance and regulate online teaching practices. This information can also be used by institutes around the world to create and provide training for teachers to enhance their skills in creating teaching videos in such a way that it enhances their students' engagement. In addition, Artificial Intelligence (AI) instruments can be used to identify the characteristics of student engagement in the online learning environment and later improve the teaching video qualities to incorporate engagement indicators.

2.4. AI and education

AI has been widely adopted in different applications, such as healthcare (Shaik, Tao, Higgins, et al., 2022; Tao et al., 2021) and education, with its ability to read and analyse text and videos (Shaik, Tao, Li, et al., 2022). In their study, Leisner et al. (2020) discussed three different learning conditions and explored the influence of in-video quizzes to annotate learning success and interest. The study was conducted on 78 students from four classes delivered by the same physics teacher. Wróblewska et al. (2022) proposed a framework to assess academic lectures based on quantitative features and provide objective feedback to help lecturers improve their didactic behaviours or course contents. In another study, the researchers (Liu et al., 2023) presented bidirectional encoder representations from transformers (BERT) model for cognitive presence identification. This AI model revealed the evolution and differences in MOOC learners' cognitive presence levels. The authors adopted AI methods such as computer vision and deep learning to process and annotate video lecture recordings. Gholamrezaie et al. (2022) proposed an intelligent system AI-EVL for effective learning by searching and enriching YouTube videos. The system visually informs the user about the contents of the video before watching it and then segments the video based on time slots and displays subtitles and annotated information.

Advancements in deep learning have fast-forwarded the process of image or video classification. Deep learning models include recurrent neural networks (RNN) (Jeong & Cho, 2022), convolutional neural networks (CNN) (Vrskova et al., 2020), and transformers (Liu et al., 2022). These models are a kind of neural network architecture that is effective in natural language processing tasks but has also been applied to computer vision tasks such as object detection and image recognition, which have the potential to learn the videos in the form of images and classify the videos. The technology field is abuzz with the latest development of ChatGPT, an AI-based tool created by OpenAI for generating text. This tool is designed to provide relevant responses and comprehend natural language to user queries. Within two months of its launch, it garnered a massive user base of over 100 million, prompting OpenAI to announce a subscription plan for unrestricted access and faster response times (Halaweh, 2023).

While ChatGPT can revolutionise educational activities, it poses certain concerns regarding potential bias (Navigli et al., 2023), privacy (Ali et al., 2023), job loss (Grassini, 2023), and academic integrity (Cotton et al., 2023; Perkins, 2023). The authors argue that teachers and learners must develop competencies to understand technology, limitations and unexpected vulnerabilities to incorporate large language models (Kasneji et al., 2023). ChatGPT is a versatile educational tool,

**Table 1**  
Main theme, characteristics, and indicators of engaging teaching videos (Authors, 2023, p. 11, p.11).

Main theme	Characteristics	Indicators
Teachers' Behaviours	Encourage Active Participation	<ul style="list-style-type: none"> <li>Encouraging students' participation in discussion</li> <li>Encouraging students to share their knowledge and ideas</li> <li>Encouraging students to ask questions</li> <li>Encouraging collaborative learning activities</li> <li>Encouraging meaningful interaction</li> <li>Encouraging students to turn on their webcams</li> </ul>
	Establishing Teacher Presence	<ul style="list-style-type: none"> <li>Clear and concise explanations of information</li> <li>Recognising and considering learners' Individual differences</li> <li>Using an appropriate style of presentation</li> <li>Allowing sufficient time for students' information processing</li> <li>Providing Learning resources</li> <li>Giving clear instructions</li> <li>Using a range of teaching strategies</li> <li>Appropriate speed of lecture delivery</li> </ul>
	Establishing Social Presence	<ul style="list-style-type: none"> <li>Maintaining constant teacher-student interaction</li> <li>Encouraging student-student interaction (Peer collaboration)</li> <li>Active and constructive communication</li> </ul>
	Establishing Cognitive Presence	<ul style="list-style-type: none"> <li>Taking on multiple roles</li> <li>giving students a sense of puzzlement (trigger)</li> <li>providing opportunities for students to reflect (exploration)</li> <li>leading students to think and learn through discussion with others (integration)</li> <li>helping students apply knowledge to solve issues (resolution)</li> </ul>
	Questions and Feedback	<ul style="list-style-type: none"> <li>Addressing students' questions &amp; Providing prompt feedback</li> <li>Asking for questions and feedback</li> <li>Clarifying misunderstanding</li> </ul>
	Displaying Enthusiasm Establishing Clear Expectations	<ul style="list-style-type: none"> <li>Motivating students</li> <li>Displaying positive emotion</li> <li>Outlining the learning objectives</li> <li>Outlining teachers' expectations of students' behaviours and responsibilities</li> </ul>
Teachers' Movements	Demonstrating empathy	<ul style="list-style-type: none"> <li>Using appropriate changes in tone of voice</li> <li>Ensuring the learning environment is a respectful, safe, and supportive one</li> <li>Showing concern</li> </ul>
	Demonstrating Professionalism	<ul style="list-style-type: none"> <li>Demonstrating in-depth and up-to-date knowledge</li> <li>Displaying appropriate behaviours</li> </ul>
Use of Technology	Using non-verbal cues	<ul style="list-style-type: none"> <li>facial expressions</li> <li>gestures</li> <li>eye gazes</li> <li>silence</li> <li>eye contact</li> <li>physical proximity</li> <li>appropriate body language</li> </ul>
	Using technology effectively	<ul style="list-style-type: none"> <li>Screen sharing &amp; Enabling Chat, Camera, and Microphone</li> <li>Varying the presentation media</li> <li>Providing technical support to students</li> <li>Providing multiple communication channels</li> <li>Providing interactive software tools</li> <li>Enabling class recording for later review</li> </ul>

offering teachers intelligent assistance in grading and language support while providing learners with an interactive and adaptive learning experience that fosters creativity and engagement. Careful implementation is required to navigate ethical concerns and potential biases, and the integration of ChatGPT should complement traditional teaching methods to ensure a comprehensive educational experience. A pedagogical approach that prioritises critical thinking and fact-checking and a well-defined strategy within educational systems are essential to incorporate and fully leverage the capabilities of extensive language models in teaching and learning settings.

In this context, Zhai (2022) suggests adjusting learning goals to include using AI tools for subject-domain tasks, emphasising creativity and critical thinking, and designing AI-based learning tasks to assist students in solving problems. Furthermore, there is a need for new assessment formats that focus on skills that AI cannot replace. The latest version of ChatGPT, GPT-4, has multimodal learning and generation capabilities, including the ability to analyse videos.

Mubarak, Cao, and Ahmed (2020) conducted sequential temporal classification by analysing video clickstream data, which can predict the performance of learners and address their issues to improve the educational process. The authors deployed a variant of the RNN model known as long short-term memory (LSTM) on characteristics derived from video data to forecast weekly learner performance and assist teachers in setting measures for timely intervention. The LSTM model outperforms the other baseline models' logistic regression (LR), artificial neural networks (ANN), and support vector machine (SVM) with an accuracy rate of 93%. Hieu et al. (2021) proposed an automated system that allows schools to capture entire sessions and summarise students' behaviour in the classroom. The authors used the deep neural networks (DNN) model and trained it with 1.2 million images, achieving an accuracy of 88.9%. Mubarak, Cao, Zhang, and Zhang (2020) proposed an LSTM model-based visualisation tool to address the research question, "How does learners' behaviour in videos impact their performance in the MOOC course?". The deep learning was trained with Massive Open Online Courses (MOOCs) course videos as a time series sequence. The model achieved an accuracy of 90% in predicting the learners' performance and enabling teachers to take timely actions for intervention.

Bhatti et al. (2021) provided a feedforward learning model that can assess the facial expressions of an instructor in a classroom. The authors extracted features using the CNN model and employed the Regularized Extreme Learning Machine (RELM) model to classify five different expressions as amusement, awe, confidence, disappointment, and neutral of the instructor within the classroom. The proposed model can achieve the best performance of 96.8% compared to other baseline models.

In conclusion, numerous studies have concluded that teachers should utilise appropriate behaviours and movements in online learning to increase their presence, which enhances student engagement (Cents-Boonstra et al., 2021; Dewan et al., 2019). The identified teachers' behaviours and movements could aid in training deep learning algorithms. Nonetheless, a notable research gap exists in the field of AI, as there is currently no AI instrument capable of identifying the indicators of engaging teaching videos. The development of an AI tool proficient in discerning these specific engaging indicators is an unexplored opportunity. This tool has the potential to greatly aid educators and educational institutions in enhancing the effectiveness of learning and enriching the overall educational journey for students.

### 3. Research gaps

Drawing from the analysis of existing literature, a conspicuous research gap emerges. Presently, no established video annotation procedure exists to assist AI engineers in training AI-enabled tools that can support in improving the teaching and learning process. Moreover, a notable absence persists in terms of an AI tool capable of generating comprehensive reports on the indicators and characteristics of engaging teaching videos.

## 4. Methodology

The authors have employed a designed-based research (DBR) approach to develop an AI tool that generates a report whenever a video recording is analysed for teachers' behaviours and movements.

Researchers (Barab & Squire, 2004; Oh & Reeves, 2010; Van et al., 2006) used various terms such as design experiments, development research, educational design research, and design research; however, design-based research became the dominant one used for the research paradigm that is used for creating educational technologies (Miah et al., 2020). The usage of DBR increased significantly, mainly with technological innovation and interventions in education (Anderson & Shattuck, 2012). This approach allows researchers to produce tools, approaches, and theories (McKenney & Reeves, 2018).

The authors structured this study in three phases to design an Artificial Intelligence tool. The first phase (Authors, 2023) identified the teachers' behaviours and movements in video conferencing as characteristics and indicators of engaging teaching videos. In this study, the authors identified 47 indicators and 11 characteristics categorised into three main themes (see Table 1).

This current study focuses on the second phase of DBR (prototyping), which involves video annotation to create an AI-enabled tool. Authors have applied the identified indicators and characteristics of engaging teaching videos to recorded lecture videos using Zoom to design an AI-enabled that autogenerate a report on engaging teaching videos. The tool is designed through two prototypes. This study also explains how these indicators and characteristics were applied in training deep learning algorithms, which is a classification tool for annotating videos. In this stage, an AI expert has assisted in creating an AI-enabled instrument. In the last phase of the DBR research, which will be reported in another study, the authors will compare the performance of the AI methodology annotation to manual annotation and evaluate the entire process to further enhance the deep learning instrument.

### 4.1. Data collection and analysis

The process of designing the AI-enabled tool is illustrated in Fig. 1, which outlines the process starting from the video collection process and manual annotation using the VIA tool. With the assistance of an AI expert, the annotated videos are pre-processed through several tasks, including splitting the videos into chunks, converting chunks into images, labelling images, and dividing them into training and evaluating data for deep learning model training and evaluation. The next step involves implementing prototype 1 for modeling, evaluating, and classification results from an educational and AI perspective. The challenges identified in data and modeling led to the development of prototype 2, which oversamples the data to overcome these challenges. This section presents two sets of results, one for each prototype in the result section.

### 4.2. Video collection process

The authors gathered the recorded lecture videos, which are recordings of lectures presented by a regional university of Australia's teachers to higher education students. The lecturers have used Zoom as the video conferencing software while presenting their lectures. Based on the discussion with the experts in AI, a data size of 25 recorded lecture videos has been selected. These recorded lecture videos have been presented to higher education students and cover health, law, business, education, engineering, sciences, and arts disciplines. The video duration ranges from 00:59:06 to 01:51:52 with an average time of 01:28:37. In the selection process, the authors ensured to select various presenter settings such as presenter location on the top right corner, middle, and bottom right corner. We included poor, average, and good-quality videos to train the deep learning model in various settings. The authors also paid attention to other variabilities while selecting the videos, such as videos where students also turned on their cameras and

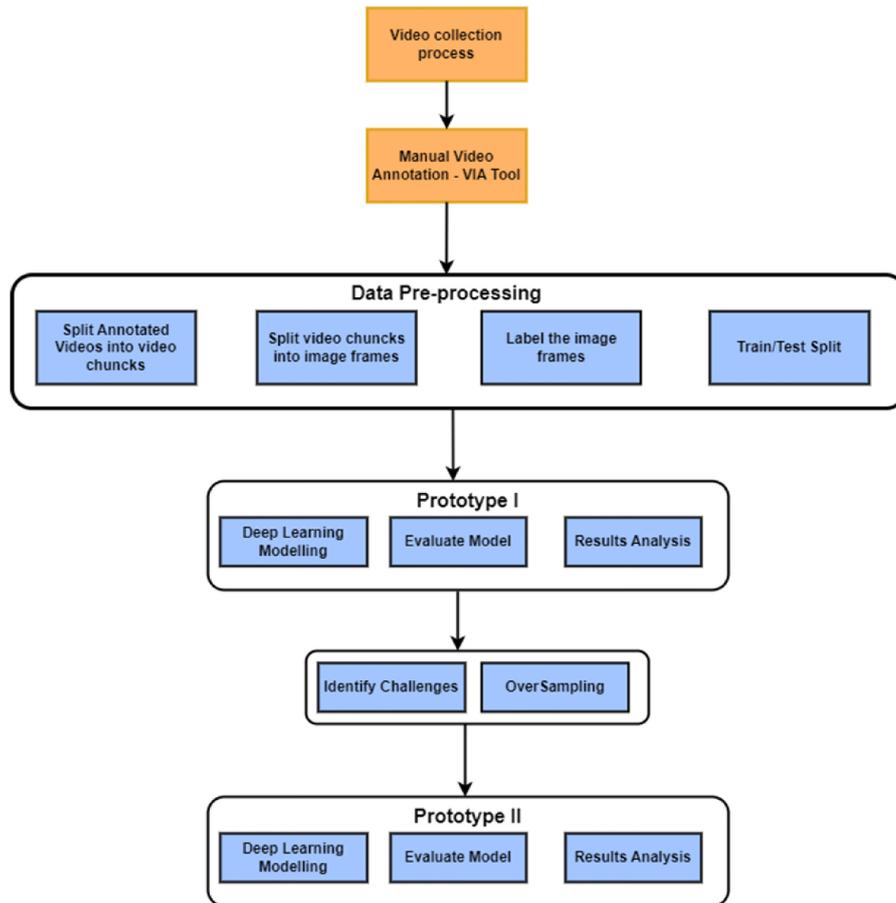


Fig. 1. Experimental design of the proposed methodology.

videos where the presenter’s camera location changed while presenting. The authors gathered and stored the data (lecture videos) in cloud storage (OneDrive) and categorised it into demographics, with 13 female and 12 male presenters. The authors have ethics approval from the University of Southern Queensland with ethics approval number H20REA185. The authors have not gathered information regarding the lecturers’ age, location and academic background.

4.3. Manual annotation of videos

The authors manually annotated 25 recorded lecture videos individually. In this manual annotation process, the authors have used VGG Image Annotator (VIA) software to annotate zoom-based lecture recordings. VIA is an open-source project-based annotation software for annotating images, audio, and videos available at [https://www.robots.ox.ac.uk/~vgg/software/via/app/via\\_video\\_annotator.html](https://www.robots.ox.ac.uk/~vgg/software/via/app/via_video_annotator.html). The manual annotation has been performed for each video on the indicator level. All indicators, characteristics and their main themes are shown in Table 1, and deep learning has been trained on the indicators level. The exported reports from this manual annotation assisted the AI engineer in

training the AI tool. The processes of manual annotation is attached separately to this paper.

4.4. Involvement of AI expertise

The authors enlisted the support of an AI expert to develop an AI tool capable of producing a report based on certain indicators and

Table 2  
AI expert involvement.

Process	Involvement
AI process	Extracting temporal coordinates from videos and transforming them into image frames to train convolutional neural networks (CNN) model
Data pre-processing	Captured the annotated image frames for the convolution layer of the deep learning model
Deep learning model	Developed the CNN model as a deep learning approach
Model evaluation	Collaborating with the other authors in performing the Model evaluation

characteristics of engaging teaching videos. The AI expert played a role in the processes mentioned in Table 2, further described in the subsequent section.

4.5. AI process

In AI methodology, the authors focused on creating a deep learning model to learn a teacher’s actions in a recording with the support of an AI expert. This is achieved by recording the temporal coordinates extracted from the tool’s manual video annotation. Temporal coordinates are markers in the video timeline that help identify specific points in time. Selected lecture videos split based on these coordinates and transformed them into a stack of image frames, as depicted in Fig. 2. The pre-processed frames were then labelled with corresponding teaching indicators and prepared the data model for training. Next, the data was split into two sets - train and test - for model training and evaluation. The training set was used to make the deep learning model learn the frames and corresponding labels. The testing set was used to evaluate how well the model was learned. An AI expert fed the train set to the CNN model to learn the actions in image frames and their corresponding label. Finally, the test set was used to assess the effectiveness of the CNN model.

4.6. Data pre-processing

During the data pre-processing step, the AI expert captured the temporal coordinates provided by the video annotation tool. For example, suppose a lecture recording displays the teaching indicator “Clear and concise explanation of information” at the temporal coordinates (3051.315, 3053.256). In that case, the recorded lecture was divided into video segments highlighting and extracting the teaching indicator. Then, each video was split into segments into image frames and annotated each frame with the “Clear and concise explanation of information” teaching indicator. These annotated image frames are represented as 3D matrices and serve as input for the convolution layer of the deep learning model, as described in the subsequent subsection.

4.7. Deep learning model

The AI expert utilised and developed the CNN model as deep learning to classify images that contain three-dimensional (3-D) data, encompassing width, height, and colour channels (such as RGB). CNN model

was selected for this study due to its ability to automatically and adaptively learn spatial hierarchies of features from the input data, making them particularly suitable for our study involving video classification, where spatial features play a vital role. CNNs have consistently demonstrated state-of-the-art performance in various image and video recognition tasks, providing strong motivation for their application in our study (Hasnine et al., 2021; Pabba & Kumar, 2021; Sharma et al., 2022). The flexible architecture of CNNs allowed us to design and optimise the network to suit best the specific characteristics and challenges of the teaching behaviours we aimed to classify. Additionally, CNNs are scalable to larger datasets, allowing for future expansion of the research should more data become available. The strength of the CNN model lies in its ability to manage the high dimensionality of images by preserving essential information while compacting the overall data structure. Fig. 3 portrays the learning workflow of the CNN model. Initially, the pre-processed input image frames, containing both spatial dimensions and colour information, are sent to a two-dimensional (2D) convolution layer. This layer applies various filters to break down the image into smaller sub-images, allowing the model to examine specific features within these sections. Following the convolution process, the pooling layer receives the output, selecting the most significant value from each feature group and crafting a down-sampled representation of the features. This down-sampling technique aids in reducing computational complexity and enhancing model robustness. The pooled features are then flattened into a 2D array to be further processed in the CNN’s output layer. This final layer computes a probability for each potential classification label, and a specific threshold can be set to translate these probabilities into definitive class labels.

4.8. Model evaluation

The AI expert collaborates with the other authors in the model evaluation. The evaluation process considered six metrics, and each is described below.

**Accuracy:** This measures the proportion of labels accurately generated by the model compared to all the labels.

**Precision:** This measures the proportion of labels precisely generated by the model among all labels generated by the model.

**Recall:** This measures the proportion of labels accurately generated by the model among all the labels present in the video.

**F1-score:** This is a combined measure of precision and recall and is commonly used to assess the overall performance of the model.

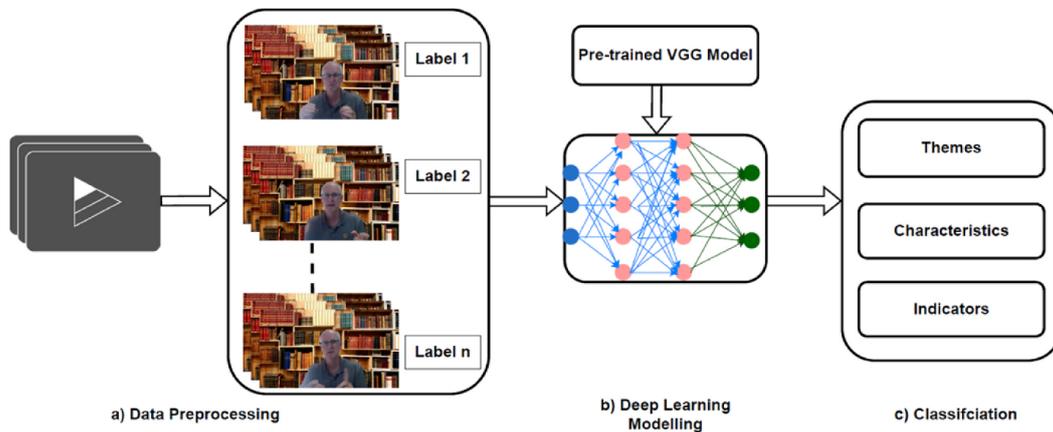


Fig. 2. Proposed AI methodology for video annotation.

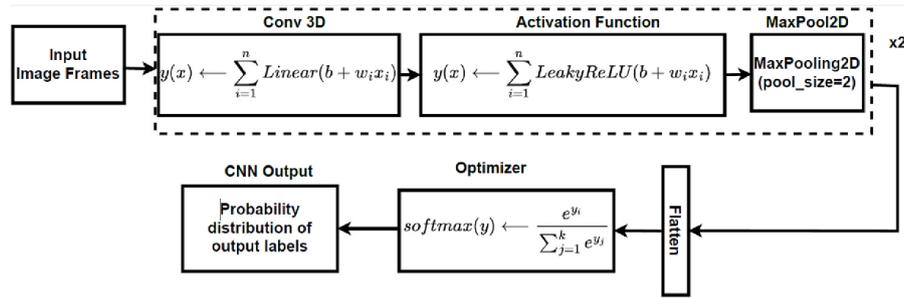


Fig. 3. Proposed CNN model learning process.

**Cohen’s Kappa:** Cohen’s Kappa measures the agreement between two raters, adjusting for the probability of random agreement. It ranges from  $-1$  (complete disagreement) to  $1$  (complete agreement), with  $0$  indicating agreement by chance.

**Area Under the Curve (AUC):** AUC represents the area under the curve, providing a threshold-independent evaluation of a binary classifier’s ability to distinguish between classes. It ranges from  $0$  to  $1$ , with  $0.5$  representing no discrimination and  $1$  representing perfect discrimination.

5. Results

In this section, the authors present the outcomes of prototype 1, where a model is built and prototype 2, where the model is refined further. Firstly, the authors discuss the challenges identified in prototype 1, which facilitated its improvement and the subsequent development of prototype 2. Additionally, the authors thoroughly examined prototype 2 as a potential key to these challenges and discussed the results obtained.

5.1. Model building: prototype 1

In this study, the video annotation is conducted at different levels of labels on the pre-processed videos. The labels are categorised into themes, characteristics, and indicators. In this case, the themes are Teachers’ behaviours, Teachers’ movements, and the use of technology. Six evaluation methods are used to report the results where precision measures the true positive predictions (i.e., when the model correctly identifies a video as belonging to a certain theme) among all positive predictions. If the precision is high, it signals that the model is making many false positive predictions. Recall measures the true positive predictions, and a high recall means that the instrument correctly identifies most of the videos that belong to a certain theme. The F1-score is a metric of a model’s accuracy that considers both precision and recall and is a commonly used metric for classification tasks. Balanced accuracy is the average recall obtained in each class. This metric looks at the recall for each class individually and gives an overall accuracy score. Cohen’s Kappa is used to measure the agreement between two raters, adjusting for the probability of random agreement. Area Under the Curve (AUC) represents the area under the curve, providing a threshold-independent evaluation of a binary classifier’s ability to distinguish between classes.

Table 3 Theme-Level performance of the CNN model.

Themes	Precision	Recall	F1-Score	Balanced Accuracy	Cohen’s Kappa	AUC
Teachers’ Behaviours	0.74	0.74	0.74	0.75	0.73	0.85
Teachers’ Movements	0.78	0.74	0.76	0.79	0.75	0.81
Use of Technology	0.64	0.76	0.70	0.95	0.68	0.93

Table 3 comprehensively evaluates three themes: Teachers’ Behaviours, Teachers’ Movements, and Use of Technology in the context of video classification. For Teachers’ Behaviours, the model shows a balanced performance with precision, recall, and F1-score, all at  $0.74$ , indicating a consistent ability to identify this theme accurately. The Balanced Accuracy of  $0.75$  and Cohen’s Kappa score of  $0.73$  reinforce this balanced performance, while the AUC of  $0.85$  demonstrates excellent discriminatory power. The theme Teachers’ Movements shows slightly improved precision at  $0.78$  but maintains a similar recall at  $0.74$ , resulting in an F1-score of  $0.76$ . The Balanced Accuracy and Cohen’s Kappa values are  $0.79$  and  $0.75$ , respectively, indicating good overall classification and substantial agreement. The AUC value of  $0.81$  further illustrates a strong capability to differentiate classes. Use of Technology, on the other hand, exhibits a lower precision of  $0.64$  but compensates with a higher recall of  $0.76$ , reflecting a tendency to accurately capture positive instances at the potential expense of false positives. The F1-score of  $0.70$ , the exceptional Balanced Accuracy of  $0.95$ , and the AUC of  $0.93$  indicate the model’s superior ability to classify and discriminate this theme despite its lower precision. Cohen’s Kappa score of  $0.68$  denotes substantial inter-rater agreement.

Table 4 presents the classification performance across various

Table 4 Characteristic-Level performance of the CNN model.

Characteristics	Precision	F1-Score	Recall	Balanced Accuracy	Cohen’s Kappa	AUC
Encourage Active Participation	0.77	0.76	0.77	0.85	0.74	0.83
Establishing Teacher Presence	0.67	0.75	0.70	0.82	0.66	0.79
Establishing Clear Expectations	0.60	0.67	0.63	0.79	0.58	0.74
Demonstrating Empathy	0.61	0.28	0.39	0.76	0.45	0.71
Using Non-verbal Cues	0.75	0.86	0.80	0.81	0.73	0.82
Using Technology Effectively	0.78	0.61	0.68	0.87	0.71	0.88

educational characteristics. In encouraging active participation, the model performs well with precision, recall, and F1-score, all around 0.76–0.77 and an AUC of 0.83. Establishing teacher presence has fair outcomes with precision at 0.67, an F1-score of 0.75, and an AUC of 0.79, although the small data distribution may affect reliability. The model struggles more with establishing clear expectations and demonstrating empathy, with inconsistencies in precision, recall, and F1-scores and lower Cohen’s Kappa values, reflecting moderate agreement. However, it excels in using non-verbal cues and technology effectively, especially in the high AUC values of 0.82 and 0.88, respectively. Overall, the model exhibits varying success across different characteristics, performing strongly in some areas while facing challenges in others, and the different data distributions might also impact the generalizability of these results.

Table 5 shows performance results for various teaching indicators in a multi-label classification task. The indicators are listed in the first column, and the corresponding results for precision, recall, f1-score, balanced accuracy, Cohen’s Kappa, AUC and data distribution are shown in the following columns. The data distribution column shows the number of instances each indicator is present in the data used to analyse the performance of the multi-label classifier. The precision of an indicator is correctly predicted positive instances divided by the sum of true positive instances and incorrectly predicted positive instances (false negative instances). The recall of an indicator is the number of true positive instances divided by the sum of true positive instances and false negative instances (incorrectly predicted negative instances). The f1-score is a weighted average of precision and recall and is a frequently used metric for evaluating the performance of multi-label classifiers. The balanced accuracy is the average for each class, considering both the positive and negative classes. Cohen’s Kappa measures the agreement between two raters, adjusting for the probability of random agreement. It ranges from –1 (complete disagreement) to 1 (complete agreement), with 0 indicating agreement by chance. AUC represents the area under the ROC curve, providing a threshold-independent evaluation of a binary classifier’s ability to distinguish between classes. It ranges from 0 to 1, with 0.5 representing no discrimination and 1 representing perfect discrimination.

The zero metrics indicate a critical issue rooted in data distribution and have significant implications for AI models. This phenomenon arises when there is a severe class imbalance, where certain classes have a disproportionately smaller number of instances compared to others within the training dataset. In our case, the data distribution column reflects this smaller number of instances issue. This class imbalance issue is widely recognised in the field of machine learning and has been extensively studied due to its far-reaching consequences (Johnson & Khoshgoftaar, 2019).

From the results, it can be seen that the teaching indicators with higher f1-scores, precision, recall, AUC, and Cohen’s Kappa values are:

“Encouraging students to share their knowledge and ideas” (f1-score: 0.75, precision: 0.7, recall: 0.79, AUC: 0.8, Cohen’s Kappa: 0.7), “Outlining the learning objectives” (f1-score: 0.63, precision: 0.61, recall: 0.65, AUC: 0.75, Cohen’s Kappa: 0.6), and “appropriate body language” (f1-score: 0.73, precision: 0.72, recall: 0.75, AUC: 0.81, Cohen’s Kappa: 0.74). The model has effectively predicted these indicators. On the other hand, indicators with zero scores in precision, recall, f1-score, Cohen’s Kappa, and AUC of 0.5, such as “Encouraging students’ participation in discussion,” “Enabling class recording for later review,” “Providing Learning resources,” “Encouraging students to ask questions,” “Encouraging collaborative learning activities,” “eye contact,” “Varying the presentation media,” and “Encouraging meaningful interaction,” have not been well-predicted by the multi-label classifier. These categories failed due to limited data availability or possibly challenges inherent in classifying these specific behaviours.

5.2. Identifying challenges

The analysis of prototype 1 revealed two major issues: an imbalanced dataset and misleading metrics. Addressing these issues is essential for developing an accurate tool for classifying teaching videos. To overcome these challenges, the AI expert developed a prototype, prototype 2, which implemented solutions to both issues.

Table 6 provides a detailed explanation of each problem and outlines the solutions employed by the AI expert to resolve them. The challenges faced in training the prototype 1 are listed in the first column. A detailed explanation of the challenges is stated in the second column, and the solution adopted by the AI expert in the last column.

Table 6 Challenges identified in prototype 1 and the solution adopted.

Challenge	Explanation	Solution Adopted
Imbalanced dataset	An imbalanced dataset is one where the number of instances in the target classes is unequal, leading to an unequal distribution of the target variable. This can lead to a biased model that is successful for the majority but less for the minority.	Oversampling addresses this problem by duplicating samples from the underrepresented class in the dataset until the class distribution is balanced.
Misleading Metrics	Oversampling aims to address this problem by duplicating samples from the underrepresented class in the dataset until the class distribution is balanced.	Alternative evaluation metrics are adopted to overcome this issue.

Table 5 Indicator-level performance of the CMN model.

Indicators	precision	recall	f1-score	Balanced Accuracy	Cohen’s Kappa	AUC	Data Distribution
Encouraging students’ participation in discussion	0.00	0.00	0.00	0.50	0.00	0.50	7
Enabling class recording for later review	0.00	0.00	0.00	0.50	0.00	0.50	5
Providing Learning resources	0.00	0.00	0.00	0.50	0.00	0.50	2
Giving clear instructions	0.41	0.69	0.52	0.70	0.40	0.65	37
Encouraging students to share their knowledge and ideas	0.70	0.79	0.75	0.82	0.70	0.80	152
Encouraging students to ask questions	0.00	0.00	0.00	0.49	0.00	0.50	19
Outlining the learning objectives	0.61	0.65	0.63	0.80	0.60	0.75	36
Using appropriate changes in tone of voice	0.55	0.50	0.52	0.75	0.53	0.72	94
Facial expressions	0.52	0.24	0.33	0.73	0.35	0.64	57
Encouraging collaborative learning activities	0.00	0.00	0.00	0.49	0.00	0.50	10
Eye contact	0.00	0.00	0.00	0.50	0.00	0.50	1
Appropriate body language	0.72	0.75	0.73	0.78	0.74	0.81	293
Encouraging meaningful interaction	0.00	0.00	0.00	0.50	0.00	0.50	4
Screensharing & Enabling Chat, Camera, and Microphone	0.41	0.52	0.46	0.69	0.45	0.68	86
Varying the presentation media	0.00	0.00	0.00	0.50	0.00	0.50	5

5.3. Model refinement: prototype 2

The outcomes of the second prototype are described in this section, developed after identifying the challenges encountered in prototype 1 and taking appropriate measures to overcome them in prototype 2. Prototype 2 is the refined version of prototype 1. The pre-processed data was fed into the deep learning model, and training and evaluation were conducted. The outcomes of prototype 2 are presented and analysed in this section.

5.4. Theme level results

The authors evaluate and compare the performance of the artificial intelligence model on the three different themes before and after the improvements in data.

As shown in Table 7, the evaluation of three distinct themes in teaching—Teachers’ Behaviours, Teachers’ Movements, and Use of Technology—reveals significant insights into the model’s performance. For the theme of Teachers’ Behaviours, the model exhibits a precision of 0.81, recall of 0.82, F1-score of 0.84, balanced accuracy of 0.85, Cohen’s Kappa of 0.82, and AUC of 0.87. In the case of Teachers’ Movements, the metrics are even higher, with precision, recall, F1-score, balanced accuracy, Cohen’s Kappa, and AUC values of 0.82, 0.83, 0.85, 0.89, 0.84, and 0.89, respectively. Finally, for the theme of Use of Technology, the values are 0.75 for precision, 0.86 for recall, 0.81 for F1-score, 0.88 for balanced accuracy, 0.78 for Cohen’s Kappa, and 0.86 for AUC. Comparing the two tables indicates that the improved results have higher values for all evaluation metrics across all three themes. This improvement suggests that the refined model or hyperparameters have enhanced the dataset’s accuracy and ability to classify these themes. However, it is essential to note that the data distribution for each theme is uniform at 361, which might impact the interpretation of these results. In scenarios where data distribution varies significantly, it may affect the model’s performance, especially if the dataset is imbalanced.

5.5. Characteristic level results

Table 8 presents the characteristic-level performance of the improvised CNN model, detailing the precision, recall, F1-score, Cohen’s Kappa, AUC, balanced accuracy, and data distribution for six different characteristics related to teaching.

The performance for “Encourage Active Participation” is notable with a precision of 0.81, recall of 0.87, F1-score of 0.82, Cohen’s Kappa of 0.82, AUC of 0.86, and balanced accuracy of 0.86. Similarly, “Establishing Teacher Presence” shows strong results, particularly in precision (0.82) and AUC (0.84). “Establishing Clear Expectations” demonstrates a promising F1-score of 0.76, while “Demonstrating Empathy” has an impressive precision of 0.84. The characteristics “Using Non-Verbal Cues” and “Using Technology Effectively” also display robust outcomes, with the latter achieving a remarkable AUC of 0.85.

A significant observation from this table is the consistent data distribution across all characteristics (351 for each). This uniform distribution indicates that the dataset has been balanced, likely through oversampling or other data-level enhancements. The balanced distribution and improvements across multiple evaluation metrics signal that the model performs better in classifying these teaching characteristics. This improvement enhances the model’s accuracy and reliability. It

suggests that the CNN model is now better poised to make predictions on new or unseen data, reflecting a more faithful representation of the underlying patterns in the teaching domain.

5.6. Indicator level results

Similarly, balancing the data appears to have refined the overall performance of the indicators (see Table 9), as indicated by the increased precision, recall, F1 score, Cohen’s Kappa, and AUC across almost all indicators (see Table 10).

In summary, prototype 2 achieved better performance than prototype 1 by addressing the identified challenges. It demonstrated improved efficiency in classifying videos based on three levels of labelling: themes, characteristics, and indicators.

6. Baseline model comparisons

In this section, we present a comprehensive comparison between the proposed CNN architecture and traditional baseline models, including the k-Nearest Neighbors (k-NN) Classifier (Bourguet et al., 2020), Decision Tree (Zaletelj & Košir, 2017), and Support Vector Machine (SVM) (Thomas & Jayagopi, 2017). The comparison aims to demonstrate the efficacy of the proposed CNN model against conventional algorithms in classifying teaching behaviours.

The results of the classification models applied to identify teacher behaviours in video classification present a clear comparison of their effectiveness. Among the baseline models, the k-NN classifier shows a balanced performance with a precision of 0.72, recall of 0.7, and F1-score of 0.71. Its Cohen’s Kappa score of 0.42 and AUC of 0.71 further highlight a reasonable level of agreement and discriminatory power. The Decision Tree model performs slightly worse, with all metrics around the 0.68 mark, reflecting a more modest performance in classification. Cohen’s Kappa score of 0.36 also indicates a lower level of agreement between raters. The SVM model shows an improvement, especially in precision (0.75) and AUC (0.75), showing a better balance between classifying the positive and negative classes. However, our proposed CNN model significantly outperforms all the baseline models in all the metrics. With a precision of 0.82, recall of 0.8, and F1-score of 0.81, it demonstrates a superior balance between sensitivity and specificity in classifying teacher behaviours. Cohen’s Kappa score of 0.62 signifies a substantial agreement, and the AUC of 0.82 indicates the excellent ability to distinguish between different teacher behaviours. The CNN model’s robust performance explains its effectiveness in recognising and categorising teacher behaviours in video data. It is a promising tool for enhancing the analysis and understanding of pedagogical practices.

7. Discussion

This study has developed an AI-enabled tool to identify the teachers’ behaviours and movements in engaging teaching videos. Teachers should use engagement-enhancing behaviours and movements in video conferencing to improve student engagement in online education settings. The authors have identified these teachers’ behaviours and movements in phase 1 of the DBR project and established their importance in enhancing students’ engagement. However, there is a need for an AI-enabled instrument to identify the indicators and characteristics of engaging teaching videos and generate a report. Thus, an instrument is

Table 7 Theme-Level performance of the improvised CNN model.

Themes	Precision	Recall	F1-Score	Balanced Accuracy	Cohen’s Kappa	AUC	Data Distribution
Teachers’ Behaviours	0.81	0.82	0.84	0.85	0.82	0.87	361
Teachers’ Movements	0.82	0.83	0.85	0.89	0.84	0.89	361
Use of Technology	0.75	0.86	0.81	0.88	0.78	0.86	361

**Table 8**  
Characteristic-Level performance of the improvised CNN model.

Characteristics	Precision	Recall	F1-Score	Cohen's Kappa	AUC	Balanced Accuracy	Data Distribution
Encourage Active Participation	0.81	0.87	0.82	0.82	0.86	0.86	351
Establishing Teacher Presence	0.82	0.75	0.79	0.81	0.84	0.84	351
Establishing Clear Expectations	0.71	0.7	0.76	0.75	0.81	0.82	351
Demonstrating Empathy	0.84	0.65	0.62	0.78	0.80	0.8	351
Using Non-Verbal Cues	0.79	0.87	0.88	0.84	0.86	0.83	351
Using Technology Effectively	0.82	0.78	0.72	0.79	0.85	0.86	351

**Table 9**  
Indicator-Level performance of the improvised CNN model.

Indicators	Precision	Recall	F1-Score	Balanced Accuracy	Cohen's Kappa	AUC	Data Distribution
Encouraging students' participation in discussion	0.68	0.70	0.71	0.86	0.71	0.85	293
Enabling class recording for later review	0.70	0.75	0.69	0.81	0.72	0.80	293
Providing Learning resources	0.65	0.75	0.75	0.68	0.70	0.75	293
Giving clear instructions	0.61	0.75	0.60	0.75	0.67	0.76	293
Encouraging students to share their knowledge and ideas	0.75	0.82	0.85	0.86	0.79	0.87	293
Encouraging students to ask questions	0.65	0.69	0.71	0.85	0.70	0.83	293
Outlining the learning objectives	0.62	0.85	0.83	0.82	0.73	0.84	293
Using appropriate changes in tone of voice	0.65	0.70	0.60	0.75	0.67	0.77	293
facial expressions	0.62	0.72	0.80	0.79	0.70	0.80	293
Encouraging collaborative learning activities	0.68	0.69	0.71	0.78	0.70	0.79	293
eye contact	0.75	0.78	0.68	0.72	0.74	0.76	293
appropriate body language	0.78	0.85	0.83	0.80	0.79	0.82	293
Encouraging meaningful interaction	0.65	0.75	0.65	0.80	0.70	0.80	293
Screensharing & Enabling Chat, Camera, and Microphone	0.61	0.75	0.66	0.82	0.68	0.81	293
Varying the presentation media	0.78	0.69	0.81	0.82	0.76	0.83	293

The balanced accuracy has also improved significantly, indicating better overall model performance distinguishing between the two classes.

**Table 10**  
Baseline models comparison.

Model	Precision	Recall	F1-Score	Balanced Accuracy	Cohen's Kappa	AUC
k-NN	0.72	0.70	0.71	0.71	0.42	0.71
Decision Tree	0.68	0.67	0.67	0.68	0.36	0.68
SVM	0.75	0.73	0.74	0.74	0.48	0.75
CNN (Ours)	0.82	0.80	0.81	0.81	0.62	0.82

required to reflect the teachers' behaviours and movements in engaging teaching videos.

7.1. Exploration of research findings

In this research, the authors identified that most instruments currently available to monitor student engagement are designed for in-person learning environments. Only a few instruments are available that can predict student engagement in online learning settings; however, they do not provide clear indicators for engaging teaching videos. The authors strongly believe that indicators are required to observe and measure engaging teaching videos. Researchers (Halverson & Graham, 2019; Lee et al., 2019) have developed instruments with indicators to predict student engagement in online learning environments; however, the indicators measuring student engagement are broad and do not measure it based on teachers' behaviours and movements. Therefore, the authors have performed a systematic literature review in phase 1 of this DBR research project and identified 11 characteristics and 47 descriptive indicators (Authors, 2023). These behaviours and movements are essential to enhance student engagement (Aelterman et al., 2019; Aladsani, 2021; De Meester et al., 2020; Jia et al., 2021). Prior use of instruments to measure student engagement required ongoing manual human analysis, which is inherently biased, so this paper has presented a method that uses artificial intelligence to reduce such bias. With the assistance of an AI expert, the authors created an AI-enabled

instrument that can automatically identify the indicators and characteristics of engaging teaching videos and generate a report.

In the current study, the authors employed the DBR methodology to design the AI-enabled tool, as this approach is suitable for technological interventions. Video analysis with Artificial Intelligence was employed to address the gap, specifically using a deep learning model called convolutional neural networks (CNN). The model was applied to video features to classify teaching characteristics, themes, and indicators. This approach aims to assist teachers in identifying areas for timely intervention.

Following the guidelines for DBR, the tool is designed through two prototypes. An AI expert assisted in creating the prototypes, where the authors observed two issues in the results of prototype 1. The first issue was an imbalanced dataset where the number of instances in the target classes was unequal, leading to an unequal distribution of the target variable. This can result in a bias, where the model might be able to perform successfully for the majority class but unsatisfactory for the minority class. Based on the results discussed in the prototype I, the classification model can perform at themes and characteristic levels of the data due to the availability of more data. However, at the indicator level, the model performance is poor. The data distribution column in Tables 4 and 6 show the imbalance in the number of records among the labels. An oversampling technique is adopted in data modeling to overcome the data imbalance issue. Oversampling is a technique used in artificial intelligence to balance class distribution in the dataset (Shaik, Tao, Li, et al., 2022). In a multi-class classification problem, class imbalance occurs when one class has significantly more samples than the others. This can cause the classifier to perform poorly on the underrepresented class as it may be biased towards the majority class. Oversampling addresses this problem by duplicating samples from the underrepresented class in the dataset until the class distribution is balanced. This process improved the performance of the classifier as it is now trained on a more balanced dataset. By having more samples of the underrepresented class, the classifier can learn better the characteristics of this class, which can lead to improved accuracy and less bias. Another identified issue is balanced accuracy, which is sometimes misleading

because it does not consider the class distribution in the data. In a multi-class classification problem with imbalanced data, a model may achieve highly balanced accuracy by making correct predictions for the majority class and mostly incorrect predictions for the minority class. This can result in a misleading evaluation of the performance of the model, as it is not accurately reflected that the model can make correct predictions for the minority class, which is often the class of interest in imbalanced data scenarios. To overcome this issue, alternative evaluation metrics such as recall, F1-score, and precision are used in imbalanced data scenarios to evaluate the model's performance more accurately. This study has adopted the same metrics.

In relation to RQ1: To what extent an AI-enabled tool can be designed to generate a report for indicators and characteristics of engaging teaching videos based on teachers' movements and behaviours? The results show that a deep learning model can be trained with the indicators and characteristics of engaging teaching videos based on teachers' movements and behaviours. The AI-enabled model achieved the results with average precision, recall, f1-score, and balanced accuracy of 68%, 75%, 73%, and 79%, respectively, in classifying the annotated videos at the indicator level. The findings in this research will also assist future researchers in creating a similar AI-enabled instrument, as the authors have also provided the procedure of manual video annotation (Please refer to the attachment).

The study highlights the importance of fine-grained labelling, dataset rebalancing, and appropriate evaluation metrics in developing accurate and efficient systems for analysing teaching behaviours in educational videos. While the findings are promising, further exploration and refinement are needed, including collecting a more balanced and comprehensive dataset and incorporating additional features or modalities to enhance the system's capability (Ding et al., 2022).

In conclusion, the study focused on developing a video annotation and classification system for analysing teaching behaviours. The prototypes addressed challenges related to imbalanced datasets and misleading metrics, demonstrating improvements in performance and reliability. The findings emphasise the importance of fine-grained labelling, dataset rebalancing, and appropriate evaluation metrics in developing accurate systems for analysing teaching behaviours. Integrating AI into education has the potential to enhance online teaching effectiveness, but considerations regarding bias, privacy, job displacement, and academic integrity must be taken into account. Adjusting learning goals and leveraging AI tools can further support teaching and learning in online environments.

### 7.2. Implication for teaching and learning

To answer RQ2: How will the AI-enabled tool improve teaching and learning practices in higher education? This study can have at least four implications for teaching in higher education involving video conferencing. First, the AI-enabled tool developed in this study will identify the engagement enhancing teachers' behaviours and movements in the form of characteristics and indicators of engaging teaching videos and generate a report every time a recorded lecture video is processed. The AI system will efficiently analyse engaging video elements and provide recommendations, thus saving teachers considerable time recreating engaging videos. This, in turn, can yield improved student learning outcomes. The report from the AI system will highlight the timestamps of characteristics and indicators present or missing in the teaching using bar charts. These characteristics and indicators enhance students' sense of competence and connectedness, facilitate learning, and increase students' engagement. For example, if teachers encourage active participation in their video conferencing, it positively affects students' devotion to the academic experience.

Similarly, when teachers demonstrate empathy in their sessions, students feel motivated to strive for academic achievement. On the other hand, the absence of these characteristics and indicators can disengage the students. For example, if establishing teacher presence is missing in

video conferencing, it can disengage the students as they develop feelings of isolation. AI reports identifying engaging video characteristics also offer teachers valuable assistance in multiple ways, including time-saving, enhanced learning, professional development support, and fostering continuous teaching improvement. Regarding professional development and ongoing improvement, AI reports help teachers identify both the strengths and weaknesses of their videos in terms of engagement. Analysing which videos successfully incorporate engaging elements provides insights for enhancing video content and innovatively refining teaching practices. Similarly, by assessing the most engaging videos, teachers gain valuable insights into what resonates best with their students, enabling informed decisions for future learning and better outcomes. Therefore, this identification of engagement enhancing behaviours and movements can assist teachers in improving their teaching and making their video conferencing more engaging for students.

Second, this AI-enabled tool can assist the institutes in creating moderation in their lecture delivery. To create moderation, the institutes can refer to the characteristics and indicators the AI-enabled tool can identify. The report generated by the AI-enabled tool can be compared for the teachers to ensure the lecture delivery is aligned with the standards and is fair, valid, consistent and reliable. Thirdly, this tool can identify the effective use of technology during video conferencing. Using technology while video conferencing, such as enabling class recording for later review, sharing screen, enabling chat function, using a microphone and camera, and varying the presentation media can increase student satisfaction levels. Lastly, this research highlights AI's importance in identifying the gaps and increasing student engagement and provides suggestions and procedures to create similar AI tools that can improve teaching. The attached manual video annotation procedure can assist future researchers in developing similar tools to improve learning and teaching.

### 7.3. Future research

In the last phase of this research, the proposed methodology will undergo evaluation and comparison with the understanding of educational experts. This evaluation aims to ensure that the tool is free from internal bias. To accomplish this, a new set of videos will be annotated and classified using the model presented in this study, with the resulting data being recorded for later analysis. The same videos will then be provided to educational experts for manual classification. Subsequently, the two sets of results will be compared to assess the accuracy and effectiveness of the artificial intelligence model in video classification. After the validation process, the authors will make this tool available for educational institutes, where institutes can use this to create moderation in their lecture delivery via video conferencing. This tool will also be made available for teachers who would like to identify their behaviours and movements that are present and those who are missing while presenting their lectures on video conferencing tools.

### 8. Limitations

The recorded lecture videos used in training the AI-enabled tool have English language teachers; for that reason, the tool may not be able to identify the indicators and characteristics of engaging teaching in other language videos. The authors trained the deep learning model with only 25 recorded lecture videos; therefore, the deep learning model is not trained with all the characteristics and indicators identified in phase 1.

### 9. Conclusion

This study adds to the existing knowledge of engaging teaching videos through the development of an AI-enabled tool. The tool generates a report by identifying the indicators and characteristics of engaging teaching videos where the importance of teachers' movements

and behaviours in fostering student engagement has already been established in phase 1. With the help of this tool, educational institutes can create moderation in online lecture delivery. The procedure to build an AI-enabled tool can assist future researchers in creating similar tools to improve student engagement in online learning. The teachers can utilise the report from this tool to identify the gap in their teaching, and by addressing those gaps, they can make their teaching more effective and engaging.

#### Statements on open data and ethics

This research was carried out with ethical guidelines in mind. 25 recorded lecture videos were annotated to train the AI-enabled tool from a larger preexisting data set under ethical approval. The videos were from teachers from the University of Southern Queensland (a regional university of Australia) presenting the lecture to students online using Zoom (a video conferencing tool). The authors have ethics approval from the University of Southern Queensland with ethics approval number H20REA185.

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#### Author contributions

**Navdeep Verma:** Conceptualization, Methodology, Formal analysis, Writing - Original Draft and Review and editing.

**Seyum Getenet:** Conceptualization, Writing - Original Draft and Review and editing.

**Christopher Dann:** Conceptualization, Writing - Original Draft and Review and editing.

**Thanveer Shaik:** AI methodology, Formal analysis, Review and editing.

#### Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

#### Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.caeai.2023.100187>.

#### Acronyms

DBR	Design Based Research
AI	Artificial Intelligence
BERT	Bidirectional Encoder Representations from Transformers
MOOC	Massive Open Online Course
RNN	Recurrent Neural Networks
CNN	Convolutional Neural Networks
LSTM	Long short-term memory
LR	Logistic Regression
ANN	Artificial Neural Networks
SVM	Support Vector Machine
DNN	Deep Neural Networks
VIA	VGG Image Annotator

3-D	Three-Dimensional
RGB	Red Blue Green
2-D	Two-Dimensional
AUC	Area Under the Curve
KNN	K-Nearest Neighbors

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### **5.3 Links and Implications**

The developed AI model can identify teachers' engagement-enhancing behaviours and movements and generate a report every time a video is processed through it. The model will analyse engagement-enhancing teachers' behaviours and movements effectively and offer recommendations, thereby saving teachers a significant amount of time that would otherwise be spent on recreating engaging videos. Additionally, the AI model can support educational institutes in creating moderation in their lecture delivery. By referencing the characteristics and indicators identified by the AI model, institutes can ensure their lecture delivery is reliable, fair, consistent, and valid. The application of the AI model goes beyond identifying teachers' engagement-enhancing behaviours and movements. It also allows for assessing the effective use of technology during video conferencing sessions. This assessment can lead to enhancements as needed, contributing to the overall teaching and learning improvement. Furthermore, this paper underscores the significance of AI in recognising the presence or absence of engagement-enhancing teachers' behaviours and movements during video conferencing sessions, thereby enhancing student engagement. Additionally, it offers recommendations and methodologies for developing similar AI models aimed at enhancing online student engagement. The findings will also assist future researchers in creating similar AI models, as the procedure of manual video annotation has also been provided.

Although the results are promising, it has been previously discussed that the model has been trained with only twenty-five recorded lecture videos; thus, it lacks exposure to the full spectrum of the characteristics and indicators identified through manual annotation. This deficiency has implications for the accuracy and impartiality of the outcomes, which may be addressed by evaluating the tool that paves the way for the final phase of this research.

The next chapter, Chapter 6, presents the final phase of this research focused on evaluating the AI model developed in the previous phase and detailing the evaluation procedure that can be used for evaluating similar AI models for enhancing online student engagement.

## **CHAPTER 6: PAPER 3 – EVALUATING ARTIFICIAL INTELLIGENCE-ENABLED TOOL IDENTIFYING ENGAGEMENT ENHANCING TEACHER’S BEHAVIOURS AND MOVEMENTS IN VIDEO CONFERRENCING**

The preceding chapter, Chapter 5, elaborated on the development of an AI model that has the capacity to generate reports on engaging teaching videos. In this chapter, Chapter 6, the final phase of this research is unveiled. The evaluation methodology crafted to assess the developed model is outlined in section 6.1. The paper is embedded in section 6.2 which presents the evaluation procedure designed to systematically measure various aspects of the developed model’s performance, such as its accuracy in generating reports and its impartiality. The implications of the final phase are summarised in the concluding section, section 6.3.

### **6.1 Introduction**

This paper was submitted for publication 1<sup>st</sup> of March 2024, to the “International Journal of Educational Technology in Higher Education” which holds a Q1 rank in the Scimago Journal Rank and currently under review.

In the previous phase, an AI model was developed that processes and interprets teachers’ behaviours and movements in engaging teaching videos. It is necessary to conduct an evaluation to ensure that the AI-generated reports are accurate and free from any internal bias; however, there is a scarcity of available evaluation methods specifically tailored for assessing AI tools in education. This final phase presents an evaluation methodology designed for assessing the developed AI model and similar models used in educational settings to enhance online student engagement.

During the evaluation, the AI model processed a set of two videos, while the two human experts performed manual analysis of the same videos to identify the indicators of engaging teaching videos. The outcomes produced by the AI model and the human experts were assessed on three levels which included tallying the total number of indicators identified by both the AI model and human experts, assessing the consistency of their recognition of the indicators across multiple video segments, and subsequently comparing their findings to establish similarity scores. While the

first two levels produced positive results, the similarity scores obtained in the third level between the AI reports and the experts' manual analyses were significantly low which revealed significant discrepancies between the AI reports and the experts' analyses. This finding directly addresses the research question: How accurately can an AI model generate a report for indicators and characteristics of engaging teaching videos based on teachers' behaviours and movements? The notable differences observed in the similarity scores indicate that the AI model's ability to generate accurate reports is limited. Three main factors contributed to these discrepancies. Firstly, the distinct interpretation of indicators by human experts can lead to varying conclusions, highlighting the importance of establishing standardised definitions to foster a shared understanding. Secondly, while human experts' knowledge evolves over time, the AI model's static nature can result in outdated analyses, highlighting the necessity for ongoing training to align with the expanding expertise of human experts. Lastly, the current limitations of the AI model, stemming from its training on a limited dataset, hinder its ability to generate accurate reports, underlining the necessity of training the AI model on a larger dataset. These factors point out the importance of continuous refinement in AI models to enhance their reliability and effectiveness.

## 6.2 Paper submitted for publication

**International Journal of Educational Technology in Higher Education**  
**Evaluating Artificial Intelligence-enabled tool identifying engagement enhancing**  
**teacher's behaviours and movements in video conferencing**  
 --Manuscript Draft--

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<b>Abstract:</b>	Due to the continued increase in the popularity of online learning, addressing challenges such as student engagement becomes crucial to ensure an effective online learning environment. This can be addressed through technology integration and engagement-enhancing teachers' behaviours and movements. This study concludes a design-based research (DBR) project by evaluating the Artificial Intelligence (AI) tool developed in the previous phases. The evaluation occurred across three levels using two recorded lecture videos presented to higher education students. The evaluation aimed to assess the tool's ability to consistently recognise indicators of engaging teaching behaviours and movements in videos and compare its performance to human experts. Percentage calculation was employed to quantify the degree of similarities between the findings of the tool and those of the two experts. The results demonstrated promising performance by the AI tool, as it successfully recognised 50% of indicators in level 1 and efficiently identified recurring indicators in level 2, aligning closely with human experts' capabilities. However, in level 3, the similarity scores between the tool and experts were relatively low, indicating the necessity for further refinement. This paper provides an evaluation method to validate the effectiveness of AI-enabled tools developed to enhance online student engagement.
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## Evaluating Artificial Intelligence-enabled tool identifying engagement enhancing teacher's behaviours and movements in video conferencing

### Abstract:

Due to the continued increase in the popularity of online learning, addressing challenges such as student engagement becomes crucial to ensure an effective online learning environment. This can be addressed through technology integration and engagement-enhancing teachers' behaviours and movements. This study concludes a design-based research (DBR) project by evaluating the Artificial Intelligence (AI) tool developed in the previous phases. The evaluation occurred across three levels using two recorded lecture videos presented to higher education students. The evaluation aimed to assess the tool's ability to consistently recognise indicators of engaging teaching behaviours and movements in videos and compare its performance to human experts. Percentage calculation was employed to quantify the degree of similarities between the findings of the tool and those of the two experts. The results demonstrated promising performance by the AI tool, as it successfully recognised 50% of indicators in level 1 and efficiently identified recurring indicators in level 2, aligning closely with human experts' capabilities. However, in level 3, the similarity scores between the tool and experts were relatively low, indicating the necessity for further refinement. This paper provides an evaluation method to validate the effectiveness of AI-enabled tools developed to enhance online student engagement.

**Keywords:** AI, video conferencing, AI evaluation, Online student engagement, Teachers' behaviours, Teachers' movements

## 1. Introduction

Over the past decade, online learning has grown significantly in higher education institutions. This growth is due to its flexibility, accessibility, and cost efficiency (Castro & Tumibay, 2021; Dhawan, 2020). Further, COVID-19 has forced higher education institutes worldwide to transition to online learning (Xie et al., 2021). Due to this sudden change, teachers face significant challenges in adapting to online learning, the biggest of which is student engagement (Alenezi et al., 2022). Studies have highlighted that engaging students in online learning is more complex than face-to-face learning (Gillett-Swan, 2017; Hew, 2016).

In online learning, technology is a crucial component for enhancing student engagement. Video conferencing is an effective tool that enhances student engagement by allowing teachers to collaborate and communicate (Al-Samarraie, 2019; Kumar et al., 2015). Past research in online learning established that teachers' behaviours and movements could develop and enhance their presence, leading to increased student engagement (Authors, 2023a; Cents-Boonstra et al., 2021; Dewan et al., 2019). Although the research highlighted the importance of engagement-enhancing teachers' behaviours and movements, no instrument can identify these human characteristics from lecture videos. Therefore, the authors employed designed-based research (DBR) to design an instrument that can identify teachers' behaviours and movements in the form of characteristics and indicators of engaging teaching videos. In the first phase of this DBR, the authors performed a systematic literature review and identified the characteristics and indicators of engaging teaching videos (Authors, 2023a). However, a manual annotation of recorded lecture videos was required to identify these characteristics and indicators.

In the second phase of the DBR, the authors, with the guidance of an AI expert, trained an AI-enabled tool to replace manual annotation of engaging teaching videos based on teachers' behaviours and movements, which expedites the process as manual annotation was identified as time-consuming (Beaver & Mueen, 2022). The identified characteristics and indicators were then applied to train the AI-enabled instrument using deep learning as an AI methodology. The instrument has achieved promising outputs with average precision, recall, f1-score, and balanced accuracy of 68%, 75%, 73%, and 79% in classifying the annotated videos at the indicator level (Authors, 2023b).

In phase 3, the current study, the authors seek to evaluate the tool created in phase 2 by analysing the AI-generated reports and the human experts' findings after processing and

1 annotating the same set of videos. This evaluation aims to ensure that the tool is free from  
2 human bias and that the autogenerated reports are accurate. Additionally, the evaluation  
3 method used in this study can be utilised to validate similar instruments designed to enhance  
4 online student engagement. This study aims to address the following research question.  
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7 *"How accurately can an AI-enabled instrument generate a report for indicators and*  
8 *characteristics of engaging teaching videos based on teachers' behaviours and movements?"*  
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## 10 11 12 **2. Background**

13 This section consists of three main sections. Section 2.1 presents the three distinct phases of  
14 the DBR, with a special focus on the current phase. Moving on to Section 2.2, existing  
15 studies on evaluation methods in the field of education are explored. Finally, Section 2.3  
16 delves into studies that discuss evaluation methods within the realm of AI. Each section  
17 provides valuable insights and analysis into these important topics, shedding light on their  
18 significance and implications in their respective domains.  
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### 25 **2.1 Previous Phases**

26 This study is the third phase of a DBR, where authors evaluate the AI-enabled instrument to  
27 ensure it is free from internal bias. In the first phase, the authors performed a systematic  
28 literature review to identify the characteristics and indicators of engaging teaching videos.  
29 The authors have reviewed 34 studies and identified 11 characteristics that are critical in  
30 enhancing student engagement in video conferencing based on teachers' behaviours and  
31 movements (Authors, 2023a). Further, the authors identified 47 indicators that can describe  
32 each characteristic. The identification and categorisation of indicators into the 11 main  
33 characteristics are supported by the significant findings in the reviewed study and research  
34 concerning teaching video engagement. These characteristics were grouped into three broad  
35 areas: Teachers' behaviours, movements, and use of technology. Appendix 1 represents the  
36 main theme, characteristics, and indicators of engaging teaching videos.  
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49 Researchers have shown great interest in the impact of teachers' behaviours and  
50 movements on student engagement in online learning (Cents-Boonstra et al., 2021; Ma et al.,  
51 2015). Authors (2023a) strongly believe that the characteristics and indicators stated in  
52 Appendix 1 can be used as a benchmark to increase teachers' performance in online learning.  
53 Educational institutes can implement these indicators and characteristics of engaging teaching  
54 videos to enhance and regulate online teaching practices. Educational institutes worldwide  
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can also use this information to create and provide training for teachers to enhance their skills in creating teaching videos in such a way that it enhances their students' engagement. However, identifying these engaging characteristics and indicators from recorded lecture videos requires human involvement, and this manual identification and analysis is very time-consuming and expensive (Beaver & Mueen, 2022). Additionally, this approach may introduce human bias into the analysis. Therefore, to avoid human bias and to identify engaging teaching videos efficiently, the authors, with the assistance of an AI expert, created an AI-enabled tool in phase 2 that generates a report for indicators and characteristics of engaging teaching videos (Authors, 2023b).

In the second phase, the authors manually annotated 25 lecture recordings by utilising the identified characteristics and indicators. The recorded lecture videos were presented to higher education students by lecturers from a university in Australia. The videos encompass a range of fields, including health, law, business, education, sciences, and arts, with an average length of 01:28:37. There were 13 female and 12 male speakers featured in the videos, and the authors secured ethical approval from the local university under the ethics approval number H20REA185. The manual annotation of these videos was performed individually using the Visual Geometry Group (VGG) Image Annotator (VIA) tool available at [https://www.robots.ox.ac.uk/~vgg/software/via/app/via\\_video\\_annotator.html](https://www.robots.ox.ac.uk/~vgg/software/via/app/via_video_annotator.html). The manual annotation was carried out at the indicator level. Through the manual annotation of 25 recorded lecture videos, the authors have identified 7 characteristics and 15 descriptive indicators, as detailed in Table 1. Based on the outcomes of this manual annotation, an AI expert supported the authors in training an AI-enabled tool designed to identify the characteristics and indicators of engaging teaching videos each time a video is processed through it.

**Table 1** Characteristics and Indicators identified in manual annotation (Authors, 2023b, p.7)

Characteristics	Indicators
Encourage Active Participation	<ul style="list-style-type: none"><li>• Encouraging students' participation in discussion</li><li>• Encouraging students to share their knowledge and ideas</li><li>• Encouraging students to ask questions</li><li>• Encouraging collaborative learning activities</li><li>• Encouraging meaningful interaction</li></ul>
Establishing Teacher Presence	<ul style="list-style-type: none"><li>• Providing Learning resources</li><li>• Giving clear instructions</li></ul>

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Establishing Clear Expectations	<ul style="list-style-type: none"><li>• Outlining the learning objectives</li></ul>
Demonstrating Empathy	<ul style="list-style-type: none"><li>• Using appropriate changes in tone of voice</li></ul>
Using Non-verbal Cues	<ul style="list-style-type: none"><li>• Facial expressions</li><li>• Eye contact</li><li>• Appropriate body language</li></ul>
Using Technology Effectively	<ul style="list-style-type: none"><li>• Enabling class recording for later review</li><li>• Screen sharing &amp; Enabling Chat, Camera, and Microphone</li><li>• Varying the presentation media</li></ul>

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The engaging characteristics and indicators identified through manual video annotation were utilised to train prototype 1. Recognising challenges like class imbalance and misleading metrics, the model underwent refinement in prototype 2 by implementing the oversampling technique. By adopting the oversampling technique, the tool was further improvised and achieved promising outputs with average precision, recall, f1-score, and balanced accuracy of 68%, 75%, 73%, and 79%, respectively, in classifying the annotated videos at the indicator level.

The developed tool has the potential to support higher education institutions in creating moderation in lecture delivery. Moreover, it can significantly influence teaching and learning by providing teachers with reports on their technology utilisation effectiveness and identifying engagement-enhancing behaviours and movements present or lacking during their lecture delivery. With a primary objective of ensuring the tool's accuracy and impartiality, the current study introduces an AI evaluation method that can be used to verify the tool's accuracy and impartiality in report generation.

**2.2 Evaluation methods in education**

To evaluate the available instruments in education, researchers (Apicella et al., 2022; Giang et al., 2022; Shekhar et al., 2018) have used various evaluation methods to validate the available instruments.

Giang et al. (2022) conducted a validation of their proposed model to measure student engagement, which includes four sub-components, emotional engagement, cognitive engagement, participatory engagement, and agentic engagement, by employing a qualitative analysis approach, conducting interviews and focus group sessions as part of their data collection process. An interview in research is a data collection method where a researcher asks participants questions to gather information about their experiences, opinions, and perspectives (Kyale, 1996). Frequently, interviews are combined with other data collection

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methods to ensure a comprehensive and diverse range of information for analysis purposes (Turner, 2010).

In their recent study, Apicella et al. (2022) carried out an experimental case study to verify the effectiveness and validity of the tool they introduced to assess and monitor student engagement. A case study is commonly defined as a thorough and methodical examination of an individual, group, community, or another entity where the researcher carefully analyses detailed information about various factors or variables (Heale, 2018).

Shekhar et al. (2018) employed a mixed-method approach, integrating both quantitative and qualitative methods, to assess the effectiveness and validity of the instruments they developed for observing active learning, instructor participation, student resistance, and student engagement. This combination of methods allowed for the validation of broader frameworks through qualitative analysis and the identification of specific items to include in quantitative instruments during the developmental stage, as Sandelowski (2000) suggested.

Chiu (2021) applied questionnaires in his study and adopted a quantitative analysis method to evaluate the model he provided, where he invoked digital support to satisfy the needs of autonomy, competence, and relatedness, which results in students being actively engaged in online learning. A questionnaire is a structured technique for collecting primary quantitative data in the literature. It is generally a series of written questions for which the respondents must provide answers (Bell, 1999).

Lee et al. (2019) have incorporated expert opinions and conducted validity and reliability analyses to ensure the accuracy and consistency of the model they proposed to enhance student engagement in e-learning environments. Expert opinion refers to a judgment by an individual with superior knowledge in a specific domain. It encompasses two key components: expertise and domain specificity (Pingenot & Shanteau, 2009).

### 2.3 Evaluation Methods in AI

Several studies have explored using Deep Learning and Computer Vision techniques to evaluate AI-enabled tools that identify engagement-enhancing teacher behaviours and movements in video conferencing. Ma et al. (2021) proposed a deep learning-based approach to recognise student engagement in online learning environments using a combination of convolutional and recurrent neural networks. They analysed facial expressions, body movements, and gaze patterns to predict engagement levels.

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Behera et al. (2020) focused on automatically analysing teachers' nonverbal behaviours in online learning settings. They employed computer vision techniques such as face detection, tracking, gesture recognition, and body pose estimation to extract meaningful features from video data. AI algorithms were applied to classify nonverbal behaviours and assess their impact on student engagement. In their research, Weng et al. (2023) conducted a systematic literature review on video-based learning analytics in online education. The review highlighted the importance of utilising computer vision techniques to analyse teachers' behaviours and their impact on student engagement and learning outcomes. Ashwin and Guddeti (2019) explored the application of deep learning techniques for automatic emotion recognition in educational videos. They used convolutional neural networks and recurrent neural networks to analyse teachers' and students' facial expressions and body movements, demonstrating the potential of deep learning models in capturing emotional cues and evaluating their impact on student engagement.

These studies (Ashwin & Guddeti, 2019; Behera et al., 2020; Ma et al., 2021; Weng et al., 2023) highlight the use of Deep Learning and Computer Vision techniques in evaluating AI-enabled tools for identifying engagement-enhancing teachers' behaviours and movements in video conferencing. They provide valuable insights into the potential of these techniques for enhancing student engagement and improving the quality of online learning experiences.

Existing research in education lacks evaluation methods specifically designed for measuring student engagement in online learning environments using AI-enabled tools (Huang et al., 2023). Previous studies have focused on developing instruments and models for traditional face-to-face settings, utilising methods such as interviews, case studies, mixed-method approaches, and questionnaires. The evaluation methods used to validate the instruments in education might not be suitable for the AI-enabled tool created by the authors as these methods require humans to analyse, which can lead to bias (Heeg & Avraamidou, 2023).

This paper seeks to validate the AI-enabled tool developed in the preceding phase to identify teachers' engagement-enhancing behaviours during video conferencing. It aims to contribute to the advancement of evaluation methodologies for AI-enabled tools by introducing an evaluation method tailored for assessing AI-enabled tools to enhance online student engagement. The integration of this method can elevate the performance of AI-

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enabled tools and their impact on student engagement, thus enhancing the overall quality of online learning experiences.

### 3. Methods

The authors utilised a DBR approach to create an AI tool that generates reports on teachers' behaviours and movements whenever it processes a recorded lecture video. The DBR methodology has gained recognition in educational research, with many researchers highlighting its ability to support the development of practical research processes (Tinoca et al., 2022). Based on the principles of the DBR approach, the research was conducted in 3 phases. The phases of the DBR process are summarised in Figure 1.

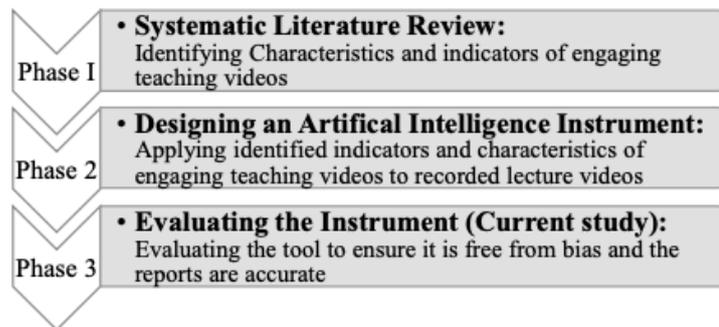


Figure 1: Research Phases

As shown in Figure 1, this present study focuses on the third phase of DBR, where authors have evaluated the AI-enabled instrument to ensure it is accurate and free from internal bias. The authors have used an AI evaluation method to ensure that the instrument is bias-free and the reports it generates are accurate. As part of the evaluation process, the tool processed two recorded lecture videos and then generated results, identifying indicators of engaging teaching videos. Meanwhile, human experts who are well-versed in the domain independently analysed the same set of videos and provided their findings. Based on the AI reports and the human experts' analysis outcomes, the authors evaluated the instrument by tallying the total number of indicators identified by the AI tool and two human experts, determining their consistency in recognising the same indicators across multiple video segments and comparing their findings to establish similarity scores.

### 3.1 Data Collection

The evaluation of the AI-enabled tool's ability to identify teachers' engagement-enhancing behaviours and movements in video conferencing involved the participation of two human experts who manually annotated two videos and the AI-generated reports. The results obtained from the AI tool and the two human experts were carefully analysed at three levels during the evaluation process.

Two videos of varying durations were utilised, one lasting 49 minutes and 3 seconds with 11 segments and the other lasting 58 minutes and 40 seconds with 23 segments, featuring presenters with different camera settings. The research was conducted with ethics approval from the University of Southern Queensland (ethics approval number H20REA185). However, demographic information about the lecturers, such as age, location, and academic background, was not collected.

### 3.2 Video Analysis

This section delves into two distinct approaches for processing and analysing a set of videos to identify teachers' engagement-enhancing behaviours and movements. It highlights the annotation process carried out by human experts and the use of AI tools designed by the authors in the previous phase to achieve a similar objective.

#### *Expert Involvement*

The two human experts conducted an annotation process guided by the 7 characteristics and 15 descriptive indicators of engaging teaching videos identified in the previous phase (refer to Table 1). The Visual Geometry Group Image Annotator (VIA) tool was used to carry out the manual annotation process (refer to Appendix 2).

#### *AI Reports*

The AI tool employed a deep learning model known as Convolutional Neural Networks (CNN) to process the same set of recorded lecture videos. Its main goal was also to identify the teachers' engagement-enhancing behaviours and movements based on the list of characteristics and indicators it had been trained with, similar to what the human experts utilised for manual annotation. By examining visual cues and patterns, the tool generated detailed reports highlighting the teachers' behaviours and movements that enhance student engagement.

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### 3.3 Data Analysis

The analysis was conducted across three levels. In the first level, the study determined the total number of indicators identified by the tool and the two human experts individually. In the second level of data analysis, the indicators identified by both the AI tool and Expert 1, the AI tool and Expert 2, and both experts in the same segments of the video were examined to determine the ability of the AI tool and the two human experts to identify these indicators in the video in multiple distinct segments of the videos. Lastly, in the third level, the outcomes for each video were compared in three distinct scenarios. The first scenario matched the AI-generated results with Expert 1's findings, while the second scenario compared the automated outcomes with Expert 2's findings. The third and final scenario compared the findings of Expert 1 with those of Expert 2. Percentage calculation served as the statistical analysis method employed to determine the similarity percentage, measuring the level of agreement between the AI tool's identification of indicators and those of human experts across various scenarios. Percentage was calculated by dividing the number of identical indicators identified by the total number of listed indicators and then multiplying the result by 100. The formula used for the calculation was  $(\text{value}/\text{total value}) \times 100$ . Timestamps corresponding to the identification of identical indicators were also provided, specifying the segments that refer to the specific parts of the video recording where each indicator was recognised.

### 4. Results

Tables 2 and 3 serve as invaluable resources, offering a clear outline of the analyses conducted on each video and facilitating a deeper understanding of the comparative evaluations undertaken by both human experts and the AI tool. The explanation of the results consists of three levels, where the findings from both the AI and experts were analysed.

#### Explanation of findings

The analysis findings for the two distinct videos at each level are presented in this section. Tables have been included to showcase the outcomes of AI processing and expert analysis, forming the foundation for further exploration and discussion.

### Video analysis 1

Table 2 highlights video 1 segments (0 to 11) and the results obtained from the AI tool and experts 1 and 2. Expert 2 has not identified any indicators in segments 6 to 11 that significantly influenced the similarity score.

Table 2. AI and experts' findings of video 1

Video 1	AI tool	Expert 1	Expert 2
Segment 0	1	1	14
Segment 1	6	8	6
Segment 2	6	8	6
Segment 3	14	8	14
Segment 4	1	14	8
Segment 5	15	7	15
Segment 6	7	7	No identified indicator
Segment 7	5	9	No identified indicator
Segment 8	2	8	No identified indicator
Segment 9	5	9	No identified indicator
Segment 10	9	9	No identified indicator
Segment 11	5	9	No identified indicator

Further, the video 1 analysis results are presented in levels showing the total number of indicators identified by both the AI tool and the human experts, the frequency of identical indicators identified by all parties across various video segments, and the similarity scores derived from comparing findings between the AI tool and the human experts in three distinct scenarios.

#### *Level 1 Results*

The results provide a positive implication of an advantage of utilising the AI tool as it was able to identify 8 unique identifiers out of the 15 indicators listed in this study. The indicators uniquely identified by the AI tool yielded 53% of the total indicators listed, while the indicators identified by both experts only yielded 33%, which was 5 out of the 15 indicators listed. This indicates that the AI tool was able to process and identify more unique identifiers from the various segments in the first video than the two human experts.

#### *Level 2 Results*

Based on the findings outlined in the table above, among the identified indicators, the AI tool managed to identify three unique indicators more than once. The AI tool identified a range of indicators, including encouraging students' participation in discussions and providing learning resources, each occurring twice. Additionally, the tool noted the encouraging meaningful interaction, which was observed three times. Expert 1 identified giving clear

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instructions twice, as well as outlining the learning objectives and using appropriate changes in tone of voice, each occurring four times. On the other hand, Expert 2 recognised indicators such as providing learning resources and screen sharing, & enabling chat, camera, and microphone, each occurring twice.

**Level 3 Results**

As per the findings outlined in Table 2, comparing outcomes between the AI tool and the assessments conducted by Expert 1 reveals that both sources independently identified three common indicators of engaging teaching videos. These shared indicators were identified within the common segments of the video, resulting in a 25% similarity score. The commonly recognised indicators encompassed Encouraging students' participation in discussion (video segment 0), Giving clear instructions (video segment 6), and Using appropriate changes in tone of voice (video segment 10). Furthermore, in the comparison between the AI tool and Expert 2, it was recognised that both entities identified four common indicators of engaging teaching videos, resulting in a similarity rate of about 33%. The mutually recognised indicators were Providing learning resources (video segments 1 and 2), screen sharing and enabling Chat, Camera, and Microphone (video segment 3), and Varying the presentation media (video segment 5). Contrarily, upon comparing the outcomes obtained by the two human experts, it was determined that no shared indicators were mutually identified, signifying a complete absence of similarity in their findings, with a similarity score of 0%.

**Video analysis 2**

Further, Table 3 presents video 2 segments (0 to 23) and the results from the AI tool and experts 1 and 2. Similar to the outcomes observed in the analysis of video 1, expert 2 has also not detected any indicators within segments 11 to 23 that impacted the similarity score.

Table 3. AI and experts' findings of video 2

Video 2	AI tool	Expert 1	Expert 2
Segment 0	1	14	15
Segment 1	10	8	15
Segment 2	5	7	5
Segment 3	5	4	5
Segment 4	1	7	2
Segment 5	12	12	4
Segment 6	5	7	2
Segment 7	10	12	10
Segment 8	5	7	7

1	Segment 9	7	12	7
2	Segment 10	1	12	1
3	Segment 11	1	12	No identified indicator
4	Segment 12	5	9	No identified indicator
5	Segment 13	1	12	No identified indicator
6	Segment 14	1	12	No identified indicator
7	Segment 15	9	7	No identified indicator
8	Segment 16	5	7	No identified indicator
9	Segment 17	14	15	No identified indicator
10	Segment 18	5	12	No identified indicator
11	Segment 19	14	12	No identified indicator
12	Segment 20	1	9	No identified indicator
13	Segment 21	14	15	No identified indicator
14	Segment 22	1	1	No identified indicator
15	Segment 23	5	12	No identified indicator

Additionally, the analysis results for video 2 are presented in levels, illustrating the total count of indicators identified by both the AI tool and the human experts, the frequency of shared indicators identified across different segments of the video, and the similarity scores generated by comparing the findings of the AI tool and the human experts in three scenarios.

#### ***Level 1 Results***

The unique indicators identified by the AI tool and the two human experts were slightly close in differences of percentages from the total indicators listed. The AI tool was able to identify 7 out of 15 unique indicators, which comprise 47% of the total indicators listed. This percentage also coincides with the percentage analysed from the results obtained in Expert 2's analysis. Meanwhile, expert 1 was able to identify 8 unique indicators in video 2, garnering 53% as the overall total.

#### ***Level 2 Results***

From the indicators identified by the AI tool and the two human experts from the second video, all of them were able to identify four distinct indicators that appeared frequently from the various video segments presented. The AI tool detected several indicators during the observation. These included encouraging students' participation in discussion and encouraging meaningful interaction, each occurring 8 times. Additionally, the facial expressions indicator was noted twice, while screen sharing and enabling chat, camera, and microphone were observed three times. Expert 1 recognised indicators such as giving clear instructions, using appropriate changes in tone of voice, and appropriate body language, with

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frequencies of 6, 2, and 10 occurrences, respectively. Varying the presentation media was also noted twice. Expert 2 identified indicators including encouraging students to share their knowledge and ideas, encouraging meaningful interaction, giving clear instructions, and varying the presentation media, each occurring twice.

**Level 3 Results**

As presented in Table 3, the comparison of the AI tools and Expert 1's analyses explains that both identified two common indicators of engaging teaching videos. These indicators were found in the same video segment, accounting for about 8% similarity in their findings. The mutually recognised indicators were Encouraging students' participation in discussion (video segment 22) and Appropriate body language (video segment 5). Furthermore, after analysing the outcomes from both the AI instrument and expert 2, it was observed that they identified five shared indicators of engaging teaching videos, resulting in an approximately 21% similarity in their findings. The indicators recognised by both parties were Encouraging meaningful interaction (video segments 2 and 3), Facial expressions (video segment 7), Giving clear instructions (video segment 9), and Encouraging students' participation in discussion (video segment 10). Moreover, upon comparing the results of Expert 1's and Expert 2's analyses, it was discovered that they both identified one common indicator of engaging teaching videos. This indicator was identified as Giving clear instructions (video segment 8), demonstrating a similarity of findings of around 4%.

**Overall Analysis Result (Video 1 & 2)**

In the first level of analysis, the tool's capacity to detect indicators was determined. It successfully identified 50% of the indicators, while Expert 1 recognised 43% and Expert 2 identified 40%. In the second level, both the AI tool and experts repeatedly identified the same indicators in the lecture video. This demonstrates the tool's ability to consistently identify and highlight indicators when detected in the video. Moving on to the third level, a comparison was made between the AI-generated reports and those of the experts. The similarity between AI and Expert 1 was around 17%, and between AI and Expert 2, it was 27%. The similarity between expert 1 and expert 2 was approximately 2%. These results indicate that further training and improvements are needed for the tool to better align with the analysis carried out by human experts.

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## 5. Discussion

Researchers (Apicella et al., 2022; Giang et al., 2022; Shekhar et al., 2018) have developed various evaluation methods such as interviews, case studies, mixed-method approaches, and questionnaires to validate the instruments and ensure their effectiveness in education.

However, existing research in education lacks evaluation methods specifically designed for measuring student engagement in online learning environments using AI-enabled tools (Heeg & Avraamidou, 2023; Huang et al., 2023). Therefore, the authors developed an evaluation method to analyse an AI-enabled tool used to enhance student engagement in online learning. The proposed evaluation methodology ensures that the AI tool is accurate and internally bias-free. The evaluation method was employed to evaluate the AI-enabled tool developed in the second phase of this study based on the characteristics and indicators of engaging teaching videos identified in the first phase.

### 5.1. Exploration of research findings

The research has revealed the absence of a standardised evaluation method for assessing AI tools used to enhance online student engagement (Heeg & Avraamidou, 2023; Huang et al., 2023). To address the research gap, this study has introduced an innovative evaluation approach that effectively measures the accuracy and impartiality of an AI-enabled tool. This approach involved annotating and classifying a set of videos for evaluation purposes, with the outcomes being recorded for later analysis. The same videos were provided to educational experts for manual classification. Subsequently, the results were analysed across three levels to assess the accuracy and effectiveness of the AI model in video classification.

In relation to the RQ: How accurately can an AI-enabled instrument generate a report for indicators and characteristics of engaging teaching videos based on teachers' behaviours and movements? Based on the level 1 analysis findings, the authors discovered that the AI-enabled tool outperformed human experts in recognising indicators. Specifically, the tool successfully identified 50% of the indicators, whereas Expert 1 recognised 43% and Expert 2 identified 40%. Moving on to the level 2 analysis, it was revealed that the tool consistently identified and highlighted indicators multiple times, showcasing its capability to do so based on their occurrence in the video. However, in the level 3 analysis, there are some discrepancies in the results between the AI instrument and the human experts. The difference in results between the AI tool, Expert 1, and Expert 2 can be attributed to three main factors. Firstly, human experts might interpret indicators differently, which can lead to different

1 conclusions. Riding et al. (2010) highlighted that individuals are likely to process identical  
2 information in varying manners, engaging distinct brain regions based on their cognitive  
3 style. Even when the experts are utilising an identical set of indicators as the foundation,  
4 variations in their interpretation of these indicators may arise. For instance, in video segment  
5 3 in Table 3 Video Analysis 2, Expert 1 identified the indicator as "Encouraging collaborative  
6 learning activities", while Expert 2 identified it as "Encouraging meaningful interaction."  
7 Although these indicators may seem similar in meaning, they are distinct indicators with  
8 different implications. It should be acknowledged that even slight variations in the identified  
9 indicators can significantly impact the overall analysis and conclusions. Therefore, it is  
10 essential to establish standardised and more precise definitions for the indicators to ensure  
11 that experts have a common understanding and reference point. The process of  
12 standardisation is essential, as it establishes a shared vocabulary, terminology, credibility,  
13 facilitated implementation, and a foundation for benchmarking (Idris & Durmuşoğlu, 2021).  
14 Secondly, experts are consistently expanding their understanding and expertise with these  
15 indicators within the evolution of the human mind. Butz and Kutter (2017) emphasised that  
16 such evolution is propelled by social interactions and coordinated cooperation. As a result of  
17 this ongoing human mind evolution, the pre-existing knowledge programmed into the AI tool  
18 becomes outdated and surpassed. Lastly, the discrepancy in results was because of the small  
19 data set (with only 25 recorded videos) used to train the AI tool. Due to this constraint, the  
20 tool lacks exposure to different variations of indicators, ultimately impairing its capacity to  
21 generate accurate and reliable reports. A substantial volume of data is necessary to train an AI  
22 model effectively, allowing it to identify patterns, make predictions, and refine its  
23 performance over time (Aldoseri et al., 2023). Thus, it would be necessary to train the AI tool  
24 using a larger dataset encompassing a wide range of variations.  
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## 46 **5.2. Implications**

47 This study holds significant implications for the field of education, particularly in the context  
48 of online learning and the utilisation of AI-enabled tools. First, this three-phase research  
49 project provides the characteristics and indicators of engaging teaching videos that can  
50 improve student engagement in video conference settings. These characteristics and  
51 indicators can help teachers and educational institutions to enhance their pedagogical  
52 approaches.  
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Secondly, although the researchers successfully identified those characteristics and indicators, performing manual analysis poses challenges in terms of time consumption and cost, and there is also the risk of potential human bias. Therefore, this research also provides an AI tool that analyses engaging video elements and provides recommendations effectively, saving teachers a great deal of time and money. One of the multifaceted benefits of AI is its ability to automate processes, leading to increased efficiency in terms of both time and cost (Rahayu, 2023).

Moreover, the AI-generated reports identifying the characteristics of engaging teaching videos provide teachers with significant support in various aspects, such as saving time, enhancing learning, and reinforcing professional development. When it comes to professional development and ongoing improvement, AI reports play a crucial role in assisting teachers in identifying both the strengths and weaknesses of their lecture delivery in terms of engagement. Similarly, processing engaging recorded lecture videos using the AI tool provides teachers with valuable insights into what resonates most effectively with their students. This empowers them to make well-informed decisions for future learning experiences, ultimately resulting in improved teaching and learning outcomes. Further, this research also provides a manual annotation procedure that can assist AI engineers in developing similar AI tools.

Lastly, the evaluation method provided in this study will assist researchers in evaluating similar AI tools created for education to ensure their accuracy and impartiality. Aldoseri et al. (2023) highlighted that inaccurate, biased, or irrelevant outcomes derived from low-quality data can have adverse effects on decision-making processes grounded in AI outputs, emphasising the importance of validation to enable AI systems to generate dependable and valuable outcomes. Thus, employing the proposed evaluation method can reinforce trust within local educational institutes regarding the reliability of AI tools used in educational settings. The AI-generated outcomes can be harnessed by educational institutes to ensure moderation in lecture delivery and will also facilitate the process of continuous improvement in teaching practices by ultimately helping teachers adopt different teaching strategies in their instructional approach to online learning.

**6. Limitations and future directions**

While the authors aimed to design an AI-enabled tool to understand student engagement based on teachers' behaviours and movements in video conferencing, certain limitations have

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been recognised. Firstly, significant differences in outcomes have been identified, attributed to factors such as human bias, human evolution, and the limited training of AI tools with a small dataset containing few indicators and variations. These factors underscore the necessity to enhance the AI tool's performance to better align with the analysis conducted by human experts. Secondly, the evaluation methodology, which solely compares expert reports with AI-generated ones, fails to consider alternative scenarios, such as having experts assess AI-generated reports or facilitating peer evaluation among experts, which could offer deeper insights for aligning the AI tool's performance with human experts' analytical capabilities. Finally, the reliance on a small dataset for evaluation highlights the need for assessments on larger datasets by processing and analysing more lecture videos to comprehensively evaluate the tool's performance.

In future research, the findings from this final phase and addressing the identified limitations may be incorporated for improvement. One potential avenue is to develop a comprehensive manual outlining the process of identifying indicators in education. This manual may include detailed descriptions of each indicator and its characteristics, along with sub-indicators and examples defining each indicator in different scenarios. Standardising the evaluation process in this manner would ensure consistent and reliable assessments across different contexts. Additionally, enhancing the AI tool by upgrading its capabilities is crucial. Currently trained with only 15 indicators due to a small dataset, manual annotation is limited to these indicators. To overcome this, the AI tool needs training with a broader range of indicators, encompassing variations within each category. Annotating a larger dataset would provide the necessary diversity for comprehensive training. These approaches would significantly improve the quality and accuracy of the evaluation process, advancing education research. Furthermore, alternative scenarios, such as having experts assess AI-generated reports or facilitating peer evaluation among experts, should be considered. Implementing these methods would offer diverse perspectives, aiding in understanding the AI tool's performance compared to human experts' analytical capabilities. Lastly, expanding the dataset by analysing more lecture videos would enable a comprehensive evaluation of the AI tool's performance across various contexts. Utilising a larger dataset enhances the generalisability of findings and insights, thereby strengthening the validity and applicability of the AI tool in online learning environments. By implementing these approaches, the overall quality and accuracy of the evaluation process can be significantly improved, leading to advancements in the field of education research.

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## 7. Conclusion

As detailed in the explanation of findings, the differences in outcomes between the AI tool and the two human experts can be ascribed to three main factors: the distinct interpretation of indicators by human experts can lead to varying conclusions, highlighting the importance of establishing standardised definitions to foster a shared understanding, the AI tool's static knowledge becomes outdated as human experts' minds evolve, emphasising the need for ongoing training to keep pace with the expanding expertise of human experts, and the current limitations of the AI tool, stemming from its training on a limited dataset, hinder its ability to generate accurate reports, underlining the necessity of training the AI tool on an extensive dataset. By considering these factors, further research and development can enhance the AI tool's performance and promote greater alignment with human expert analysis.

### List of Abbreviations

Abbreviation	Definition
AI	Artificial Intelligence
CNN	Convolutional Neural Network
COVID-19	Coronavirus Disease 2019
DBR	Design-based Research
VIA	VGG Image Annotator

### Declarations

#### Availability of data and materials

Please contact the authors for a data request.

#### Competing interests

The authors declare that they have no competing interests.

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#### Authors' contributions

**Navdeep Verma:** Conceptualisation, Methodology, Formal analysis, Writing - Original Draft

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and Review and editing.

**Seyum Getenet:** Conceptualisation, Writing - Original Draft and Review and editing.

**Christopher Dann:** Conceptualisation, Writing - Original Draft and Review and editing.

**Thanveer Shaik:** AI methodology, Formal analysis, Review, and editing.

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## 9. Appendices

### Appendix 1

Main theme, characteristics, and indicators of engaging teaching videos (Authors, 2023, p.11)

Main theme	Characteristics	Indicators
Teachers' Behaviours	Encourage Active Participation	<ul style="list-style-type: none"> <li>• Encouraging students' participation in discussion</li> <li>• Encouraging students to share their knowledge and ideas</li> <li>• Encouraging students to ask questions</li> <li>• Encouraging collaborative learning activities</li> <li>• Encouraging meaningful interaction</li> <li>• Encouraging students to turn on their webcams</li> </ul>
	Establishing Teacher Presence	<ul style="list-style-type: none"> <li>• Clear and concise explanations of information</li> <li>• Recognising and considering learners' Individual differences</li> <li>• Using an appropriate style of presentation</li> <li>• Allowing sufficient time for students' information processing</li> <li>• Providing Learning resources</li> <li>• Giving clear instructions</li> <li>• Using a range of teaching strategies</li> <li>• Appropriate speed of lecture delivery</li> </ul>
	Establishing Social Presence	<ul style="list-style-type: none"> <li>• Maintaining constant teacher-student interaction</li> <li>• Encouraging student-student interaction (Peer collaboration)</li> <li>• Active and constructive communication</li> <li>• Taking on multiple roles</li> </ul>
	Establishing Cognitive Presence	<ul style="list-style-type: none"> <li>• giving students a sense of puzzlement (trigger)</li> <li>• providing opportunities for students to reflect (exploration)</li> <li>• leading students to think and learn through discussion with others (integration)</li> <li>• helping students apply knowledge to solve issues (resolution)</li> </ul>
	Questions and Feedback	<ul style="list-style-type: none"> <li>• Addressing students' questions &amp; Providing prompt feedback</li> <li>• Asking for questions and feedback</li> <li>• Clarifying misunderstanding</li> </ul>
	Displaying Enthusiasm	<ul style="list-style-type: none"> <li>• Motivating students</li> <li>• Displaying positive emotion</li> </ul>
	Establishing Clear Expectations	<ul style="list-style-type: none"> <li>• Outlining the learning objectives</li> <li>• Outlining teachers' expectations of students' behaviours and responsibilities</li> </ul>
	Demonstrating empathy	<ul style="list-style-type: none"> <li>• Using appropriate changes in tone of voice</li> <li>• Ensuring the learning environment is a respectful, safe, and supportive one</li> <li>• Showing concern</li> </ul>

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	Demonstrating Professionalism	<ul style="list-style-type: none"><li>• Demonstrating in-depth and up-to-date knowledge</li><li>• Displaying appropriate behaviours</li></ul>
Teachers' Movements	Using non-verbal cues	<ul style="list-style-type: none"><li>• facial expressions</li><li>• gestures</li><li>• eye gazes</li><li>• silence</li><li>• eye contact</li><li>• physical proximity</li><li>• appropriate body language</li></ul>
Use of Technology	Using technology effectively	<ul style="list-style-type: none"><li>• Screen sharing &amp; Enabling Chat, Camera, and Microphone</li><li>• Varying the presentation media</li><li>• Providing technical support to students</li><li>• Providing multiple communication channels</li><li>• Providing interactive software tools</li><li>• Enabling class recording for later review</li></ul>

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## Appendix 2

### Manual Video Annotation Procedure

VGG Image Annotator (VIA) software has been used in this manual video annotation process to annotate zoom-based lecture recordings. VIA is an open-source project-based annotation software for annotating images, audio, and videos available at [https://www.robots.ox.ac.uk/~vgg/software/via/app/via\\_video\\_annotator.html](https://www.robots.ox.ac.uk/~vgg/software/via/app/via_video_annotator.html).

In this project, the researchers have used the following to annotate the videos:

**Step 1: Creating a new project:** Open the VIA annotation tool by clicking the link above. Add the project name on the top left-hand side (refer to Figure 1). The project name should be the same as the recorded lecture name.

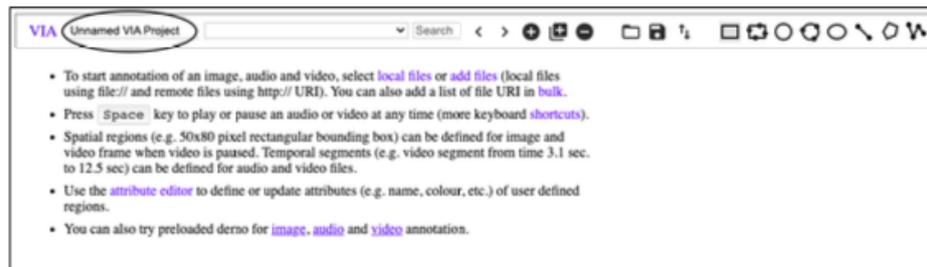


Figure 1. Create a new project

**Step 2: Add a video file:** The second step is to add a video by clicking the plus icon (refer to Figure 2). Select the video to be annotated from the desktop or cloud storage.



Figure 2. Add a video

**Step 3: Define the attributes:** Once the video is added, define the attributes by clicking on 1 (refer to Figure 3).

In this step, two attributes have been created by typing the attribute name in 2 (refer to figure 3) and clicking Create. In this project, the first attribute was created to identify the engaging teaching video indicators and the second to highlight the presenter's location in the video.

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Figure 3. Define the attributes

While defining the attributes, the following information has been inserted (refer to Figure 4):

**Attribute 1:** The name of the first attribute is "Engaging teaching video indicators". The anchor is set to "Temporal Segment in Video or Audio" as researchers identified the indicators in small video segments. The text function is selected for the input type.

**Attribute 2:** The name of the second attribute is "Presenter location". The attribute is created to signal the presenter's location in the video. The anchor is set to "Spatial region in a video frame" as an area is highlighted to indicate the presenter's location. The input type is set as Select. In the options section, the researchers have typed "presenter" to

**Name** = Presenter location

**Anchor** = Spatial region in a video frame

**Input Type** = Select

Options = \*Presenter (Note: if there are multiple presenters in a video, we can add \*presenter 1, presenter 2)

Id	Name	Anchor	Input Type	Description	Options	Default Value	Preview
1	Engaging teaching vi	Temporal Segment in V	TEXT		-	-	
2	Presenter location	Spatial Region in a Vid	SELECT		Presenter	Not Defined	Presenter

Figure 4. Attribute 1 and 2

**Step 4: Adding indicators to Attribute 1 (engaging teaching video indicators):** After defining the attributes, the next step is adding the indicators. The researchers added the indicators at the bottom left-hand side by writing the indicator name and then clicking Add (refer to Figure 5). The following indicators have been added:

Indicators	Description
1. Encouraging students' participation in discussion	Teachers to engage students in discussions or debates to yield their interest and motivate a deeper understanding
2. Encouraging students to share their knowledge and ideas	Teachers to ask for students' participation in active learning methods by sharing their perceptions, knowledge, and ideas
3. Encouraging students to ask questions	Teachers to create a safe and open environment that allows students to ask their questions to enhance the student interaction experience
4. Encouraging collaborative learning activities	Teachers to create opportunities for students to interact with each other through group activities or collaborative work
5. Encouraging meaningful interaction	Teachers construct a welcoming and efficient online learning environment by fostering regular and meaningful communication with students,) and providing meaningful answers to students' enquiries.
6. Providing Learning resources	Teachers to provide students with various learning resources, videos, etc., to increase students' active participation
7. Giving clear instructions	Teachers to be clear and detailed in communicating the instructions, expectations, roles and responsibilities to show commitment to meeting the course goals
8. Outlining the learning objectives	Teachers to clearly outline and communicate the topics and instructions to increase student engagement in online learning
9. Using appropriate changes in tone of voice	Teachers to read and respond to perceived restlessness by appropriate changes in tone of voice or changes in direction
10. Facial expressions	Teachers to maintain appropriate facial expressions such as smiling and nodding
11. Eye contact	Teachers to maintain eye contact with students in online learning.
12. Appropriate body language	Teachers to maintain appropriate body language in

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	the online classroom.
13. Enabling class recording for later review	Teachers to increase the value of the online learning experience by enabling class recording, which allows students access to classroom sessions from the comfort of their home and if they want to review afterwards
14. Screensharing & Enabling Chat, Camera, and Microphone	Teachers to assure students of their presence and positively impact student engagement and satisfaction by communicating in real-time through chat, camera, microphone and screen-sharing
15. Varying the presentation media	Teachers to vary the presentation media (e.g. videos, slides, note sharing, etc.) to capture student attention and foster engagement

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Figure 5. Adding indicators

**Step 5: Drawing boundary box to signal presenter location (Attribute 2: presenter location):** The researchers drew a boundary box to indicate the presenter's location.

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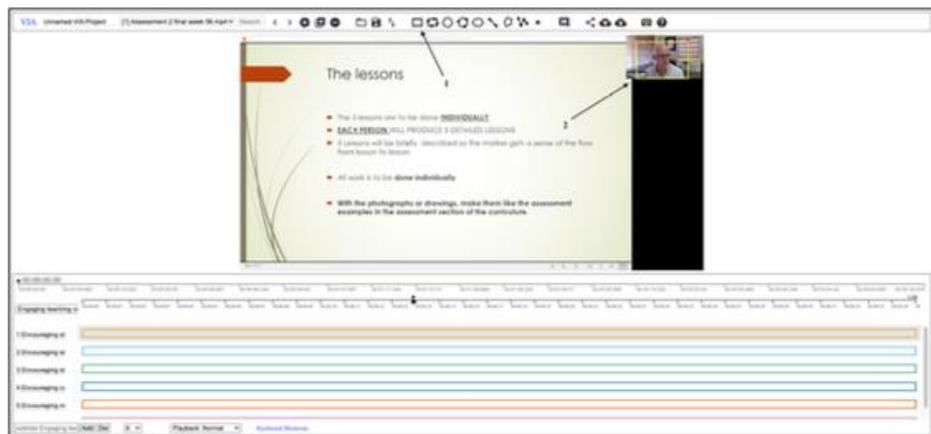


Figure 6. Drawing boundary box

Step 6: Identifying the indicators from the video: A manual annotation is performed after defining the attributes and indicating the presenter's location. In this process, the video is played, and indicators are identified in small segments. To start the temporal segment, click "a", and to stop, click "Shift" + "a".

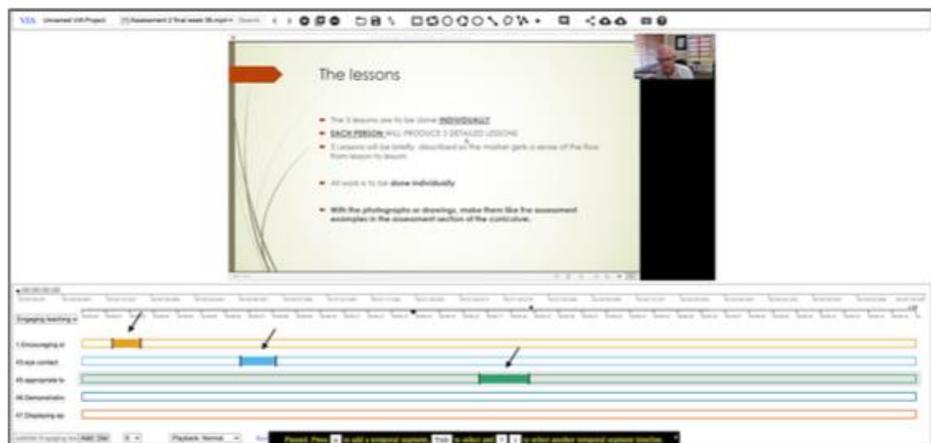


Figure 7. Identifying the indicators

Step 7: Saving and Exporting the Project for Machine Learning: Once the annotation is complete, save the project by clicking on one and selecting the project's location. Similarly, click on 2 to export the project.

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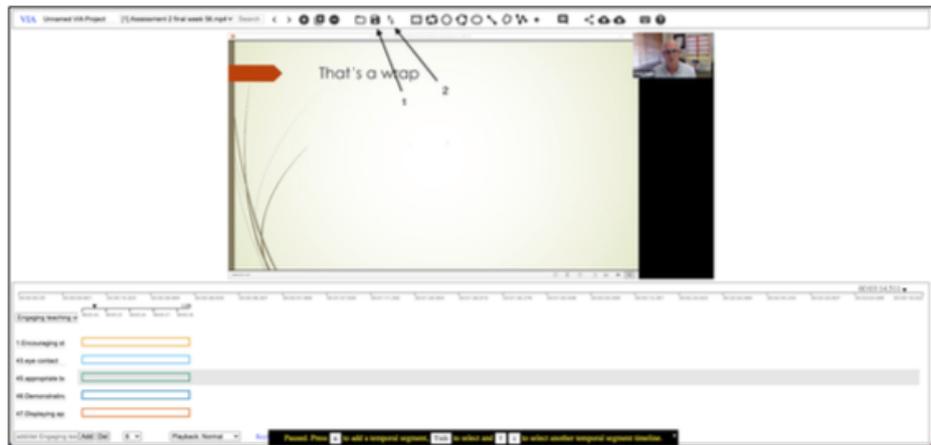


Figure 8. Save and export

## **Evaluating Artificial Intelligence-enabled tool identifying engagement enhancing teacher's behaviours and movements in video conferencing**

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### **Author contributions:**

**Navdeep Verma:** Conceptualization, Methodology, Formal analysis, Writing - Original Draft and Review and editing.

**Seyum Getenet:** Conceptualization, Writing - Original Draft and Review and editing.

**Christopher Dann:** Conceptualization, Writing - Original Draft and Review and editing.

**Thanveer Shaik:** AI methodology, Formal analysis, Review and editing

### **6.3 Links and Implications**

This phase provides implications in education, particularly in online learning context and the use of AI systems. The evaluated AI model offers valuable support to teachers in multiple areas, such as timesaving, improved learning, and professional development. The evaluation method designed in this phase will assist researchers in assessing similar AI models designed for online student engagement to ensure its accuracy and fairness. As a result, educational institutions can entirely rely on the outcomes generated by these systems and use them to enhance their teaching methods. These outcomes will contribute to the continuous improvement of teaching practices by enabling teachers to adopt various instructional strategies in online learning. It also highlights the importance of educators' involvement in the development and evaluation of AI models to enhance online student engagement.

Based on the evaluation results, additional research and development efforts are essential to improve the performance of the AI model and ensure better alignment with human expert analysis. One potential approach for enhancement involves creating a comprehensive manual that outlines the process of identifying indicators in education. This manual will provide detailed descriptions of each indicator and its characteristics. It could further specify them by incorporating sub-indicators and examples that clearly illustrate their application in various scenarios. Standardising the evaluation process in this way would enable consistent and reliable assessments across different contexts.

Additionally, upgrading the capabilities of the AI model is an implicit strategy for improvement. The model has only been trained with a small dataset with 25 recorded lecture videos, as this was what could be achieved within the research program. As a result, during annotation, only those 15 indicators could be identified. To overcome this limitation, training the AI model with a broader range of indicators, including different variations within each category, would be beneficial. This can be accomplished by annotating a larger dataset, which would provide the necessary diversity for comprehensive training. By implementing these approaches, the overall quality and accuracy of the evaluation process can be significantly enhanced, leading to significant advancements in the field of education research and changes to the learning environments.

The next chapter, Chapter 7, synthesises the key insights such as the study's pedagogical and research implications, limitations, recommendations for educators and future research, and a summary of the findings.

## **CHAPTER 7: DISCUSSION AND CONCLUSION**

This chapter serves as the culmination of the study, weaving together essential insights obtained throughout. The findings of each phase are further discussed in this chapter. Section 7.1 discusses the roadmap of the study by elaborating and linking the three phases. Section 7.2 delves into the pedagogical and research implications of the findings. A reflective examination of the study's limitations is presented in section 7.3. Section 7.4 extends the practical recommendations for educators and educational institutions, while also delineating pathways for future research. The chapter ends with the presentation of conclusions in section 7.5.

### **7.1 Discussion**

This research comprises of three phases to design an AI model focused on improving online student engagement based on teachers' behaviours and movements during video conferencing sessions in higher education. This section synthesises key insights and implications from each phase, highlighting the potential transformative impact of the developed AI model on educational practices in online learning environments.

The initial phase involved a systematic literature review. The studies incorporated in the review were collected from seven databases and selected based on inclusion/exclusion criteria aligned with the Preferred Reporting Items for Systematic Reviews guidelines. Initially, 1,170 peer-reviewed articles were identified, with 70 duplicates promptly removed during screening. Subsequently, after examining titles and abstracts, 1,037 articles were excluded in the initial screening phase. The remaining 63 articles underwent further evaluation, leading to the exclusion of 29 based on secondary exclusion criteria. Eventually, 34 studies met the criteria and were included in the review. From the selected studies, 11 characteristics and 47 associated indicators were identified, categorised, and explained. These findings directly relate to the first research question guiding this study: What are the characteristics and indicators of engaging teaching videos? The identified characteristics and their corresponding indicators (refer to Appendix A) form a robust foundation for enhancing online student engagement. Noteworthy teacher behaviours include encouraging active participation, establishing presence (both social and

cognitive), giving clear instructions, and demonstrating professionalism (Ice et al., 2011; Jia et al., 2021; Lim et al., 2021; Trenholm et al., 2019; Vallade & Kaufmann, 2020). Non-verbal cues and effective use of technology were also emphasised (Almutairi & White, 2018; Gina, 2017; McNeill et al., 2019; Richards & Velasquez, 2014). To increase the scalability and avoid any form of human bias, the study incorporated AI to automate the process.

In relation to the second guiding question: How will the AI model improve teaching and learning practices in higher education? The insights from Phase 1 guided the development of an AI model in Phase 2, designed to identify teachers' behaviours and movements in engaging teaching videos, with support from an AI expert. The developed AI model identifies engagement-enhancing teacher behaviours and movements, processes recorded lecture videos to generate detailed reports and offers recommendations for improving online student engagement. It supports individual teachers and helps educational institutions ensure moderated lecture delivery by aligning with established standards of fairness and reliability. The model also evaluates technology use during video conferencing, contributing to overall online teaching and learning improvement.

To develop the AI model, the AI expert used the Python programming language to develop the AI model for data preprocessing, modeling, and visualization. The AI expert employed various libraries such as pandas, numpy, sklearn, keras, and moviepy to facilitate these tasks. A detailed Python script with explanatory comments for each code block is provided in Appendix D, offering transparency and clarity in our computational methodology.

The Convolutional Neural Network (CNN) model was adopted to train the model. CNN is a deep learning model that learns directly from data and has the ability to handle spatial features in video classification tasks (Yamashita et al., 2018). However, challenges related to imbalanced datasets were identified in Prototype 1 (model 1). An imbalanced dataset occurs when there's an unequal distribution of instances among target classes, leading to an uneven representation of the target variable (Kunakorntum et al., 2020). Prototype 1 (model 1) exhibited an average precision, recall, f1-score, and balanced accuracy of 26%, 28%, 26%, and 62%, in categorising the annotated videos at the indicator level. This underscores the presence of a data imbalance, highlighted by the unequal distribution of indicators related to engaging teaching videos. For example, the indicator "appropriate body

language” has been identified 293 times, whereas “eye contact” was identified only once during the manual annotation.

The application of oversampling techniques addressed this data imbalance, highlighting the significance of dataset preparation in AI model training. Oversampling aimed to address the issue by replicating samples from the underrepresented class (Indicators of engaging teaching videos) in the dataset until the class distribution was balanced (Kunakorntum et al., 2020; Vairetti et al., 2024). After oversampling, the issue was resolved which significantly improved the tool’s overall performance. Prototype 2 (model 2) then demonstrated an average precision, recall, f1-score, and balanced accuracy of 68%, 75%, 73%, and 79%, respectively, in classifying the annotated videos at the indicator level. Despite the promising results, further evaluation was necessary to ensure the model’s accuracy and freedom from internal bias.

The final phase introduced a comprehensive evaluation procedure explicitly designed to assess the developed AI model and similar models used to enhance online student engagement. This step is crucial to ensuring the accuracy and impartiality of AI-generated results and addressing concerns related to internal bias. The evaluation process comprised three levels: firstly, tallying the identified indicators by the model and two human experts individually; secondly, assessing the tool’s and experts’ proficiency in recognising indicators multiple times based on their presence in the video; and thirdly, comparing the outcomes across three scenarios: AI versus Expert 1, AI versus Expert 2, and Expert 1 versus Expert 2. Similarity percentages were calculated using the formula  $(\text{value}/\text{total value}) \times 100$ , indicating agreement between the AI model and human experts. Timestamps denoting the segments of video where identical indicators were recognised were also provided.

In the initial level of analysis, the model’s efficacy in detecting indicators was assessed. It successfully identified 50% of the indicators, while Expert 1 recognised 43%, and Expert 2 identified 40%. In the subsequent level, both the AI model and experts consistently detected the same indicators in the lecture video, demonstrating the model’s reliability in consistently highlighting indicators upon detection in the video. Transitioning to the final phase, a comparison was drawn between the AI-generated reports and those of the experts. In relation to the third guiding question: How accurately can an AI model generate a report for indicators and characteristics of engaging teaching videos based on teachers’ behaviours and movements? The

findings revealed that the similarity between AI outcomes and Expert 1 analysis was approximately 17%, and between AI and Expert 2, it stood at 27%. Both figures are relatively low, likely due to three main factors. First, human experts may interpret indicators differently, which can lead to different conclusions. Second, experts are consistently expanding their understanding and expertise with these indicators overtime, whereas the knowledge of the AI model remains the same. Lastly, the AI was trained on a limited dataset of only 25 recorded videos, which may have constrained its learning and performance. This underscores the necessity for further training and enhancements to ensure the model's accuracy and efficacy through the closer alignment of its outcome with the analysis conducted by human experts.

The results convey the importance of thorough evaluation in AI models, as proper assessment is crucial in establishing reliable models that will drive improvements in the education field. The procedure employed during the model evaluation promotes the responsible integration of AI in education by facilitating the identification of inconsistencies, ensuring the accuracy of AI models and precision in reports, and fostering a positive impact on resolving issues in teaching and learning, such as enhancing online student engagement.

Despite the valuable insights this research provides into enhancing online student engagement, particularly the potential contributions of the developed AI model, there are several limitations in the chosen education metrics that could affect the accuracy and depth of the model's performance. One such limitation is the research's emphasis on teacher-centred behaviours and movements in the metrics. Although teacher's presence is indeed key to student engagement where their expertise and commitment ensure quality learning and establish a strong connection with students, this study does not explore the other factors, such as the role of students themselves in their engagement. Additionally, the model created in this research study identifies the effective use of technology, but it is solely based on video conferencing tools, and has not explored other technologies like learning management systems. Furthermore, the evaluation of the model relies only on quantitative metrics like precision, recall, and F1-score. While these metrics provide a deeper, more balanced evaluation of model performance, particularly when dealing with imbalanced data, it would also be beneficial to incorporate qualitative aspects of engagement such as the emotional tone or relational dynamics between teacher and student.

## **7.2 Implications**

This section presents the implications of the study for teaching, learning, and research, emphasising the transformative potential of AI models in revolutionising teaching practices and enhancing online student engagement.

### ***7.2.1 Implication for teaching and learning***

In online learning, a distinguished challenge is the lack of student engagement. Research shows that engaging students in online learning is more complex than face-to-face learning (Cesari et al., 2021; Gillett-Swan, 2017; Hew, 2016). Teachers can address this issue by effectively integrating technology and incorporating engagement-enhancing behaviours and movements during video conferencing. The characteristics and indicators identified through a systematic literature review in the first phase of this research can assist teachers in establishing a benchmark and identifying areas of improvement in their online teaching performance. Moreover, these findings served as the foundation for the development and training of the AI model.

The researchers (Davies et al., 2020; Holmes & Tuomi, 2022; Nguyen et al., 2022; Tahiru, 2021) have established the importance of the integration of AI to revolutionise teaching and learning. The AI model developed in this study's second phase can automatically identify engagement-enhancing teachers' behaviours and movements whenever a video is processed through it. The AI system's report highlights the bar charts denoting timestamps of characteristics and indicators whether present or absent in the teaching (refer to appendix C). The AI model categorises the reports into three themes: teachers' behaviours, teachers' movements, and use of technology. Teachers' motivating behaviours are crucial for enhancing student engagement, feelings of competence, and relatedness support (Aelterman et al., 2019). These behaviours encompass a synthesis of autonomy support, structured approaches to enhance students' sense of competence, and relatedness support (Aelterman et al., 2019; De Meester et al., 2020). Some of the stimulating teachers' behaviours are conveying students' interests or judgment through questions, offering choices, cultivating independent problem-solving, providing support and constructive feedback, and exhibiting warmth and regard to nurture mutually positive relationships with students (Aelterman et al., 2019; Haerens et al., 2013).

Further, the report will highlight teachers' movements during video conferencing. These visual motions are non-verbal cues, similar as facial articulations, gestures, and eye movements (Aladsani, 2021). The presence of these movements helps boost tremendous immediacy, social presence, and a sense of connectedness, facilitating learning and broadening learners' engagement (Olitsky, 2007). Lastly, this report will highlight how effectively the teachers utilise technology during video conferencing, such as screen sharing, enabling camera, enabling recordings for later review, providing interactive software tools, and providing interactive software tools.

In teaching practices, the development of AI models holds promise in revolutionising teaching methodologies (Cheng & Wang, 2023). Regarding professional growth and ongoing enhancement, AI reports play a crucial role in assisting teachers in identifying both the strengths and weaknesses of their lecture delivery in terms of engagement (Kamalov et al., 2023). This study also helps bridge the gap between educators and AI by establishing the importance of teachers' involvement in developing AI models to enhance online student engagement. This research highlights the importance of educators in AI model development to ensure that the models align closely with pedagogical needs, further optimising their impact on enhancing online student engagement.

Given their expertise in education, teachers' continual involvement in the refinement of the AI model for enhancing online student engagement is given emphasis as the findings pinpointed the static nature of the model's knowledge, highlighting the risk of it becoming outdated over time. Therefore, their persistent involvement is required to ensure the AI model remains aligned with human experts' constantly evolving knowledge and expertise. Similarly, their active involvement in evaluating AI models holds immense potential for building confidence in such technologies. Additionally, the evaluation procedure presented in this DBR project contributes to establishing standards for assessing similar AI models in educational settings, which reinforces their credibility.

### ***7.2.2 Implication for research***

DBR research approach is employed in this research study to design an AI model to enhance student engagement during video conferencing by identifying the engagement-enhancing teachers' behaviours and movements. This study establishes

that integrating DBR and AI offers a systematic approach to designing and refining the model to promote online student engagement. Combining the two can transform the educational environment, envisioning a scenario where tools previously considered futuristic become essential components of the teaching and learning process.

Further, AI-driven education holds significant benefits, and AI is currently being acknowledged as a potential remedy for perceived challenges in the field of education (Davies et al., 2020; Nguyen et al., 2022). Therefore, the AI model's development in this study marks a significant advancement, translating research findings into practical applications. The model's potential to analyse teachers' behaviours and movements in engaging teaching videos holds promise for improving online student engagement. The manual annotation procedure provided in this research will aid researchers in the future in creating similar AI models to enhance online student engagement (refer to Appendix B).

Moreover, the AI model ensure the efficient processing of a larger volume of videos. The challenges, such as imbalanced datasets and model performance issues, highlight the importance of continuous refinement in AI systems. Also, as the human mind evolves, the AI model's static knowledge risks becoming outdated. Hence, ongoing training is essential to ensure that AI models keep pace with the expanding expertise of human experts.

Moreover, the research indicates that there is a lack of evaluation methods to validate the AI models in education (Huang et al., 2023), and the available ones require humans to analyse, which can lead to bias (Heeg & Avraamidou, 2023). Therefore, the study's emphasis on evaluation metrics specifically designed to evaluate the AI models in education and the need for a more balanced dataset contributes to the ongoing discourse on responsible AI integration in educational settings.

Lastly, the research signifies the importance of including large data sets while training an AI model. This ensures that the model is trained with multiple variances and scenarios. A substantial volume of data is necessary to train an AI model effectively, allowing it to identify patterns, make predictions, and refine its performance over time (Aldoseri et al., 2023).

### 7.3 Limitations

The study acknowledges several limitations that merit consideration. First, its focus on higher education may restrict the generalisability of findings to other educational levels, such as vocational or school education, justifying a need for revisions to the identified characteristics and indicators of engaging teaching videos. This study has also not considered the ethical implications of using the AI model in online learning with minors.

Moreover, the research lacks a detailed exploration of practical learning, potentially compromising the effectiveness of identified characteristics in practical learning settings such as workshops and simulations. Further, the model was trained using only 25 recorded lecture videos, resulting in a limited dataset with few indicators and variations. This raises concerns about its ability to capture all identified characteristics, thus potentially affecting its performance.

Additionally, the AI model's training solely on English-language teacher lecture videos may limit its ability to recognise indicators and characteristics in videos of other languages. Like the language, the body language differs from culture to culture. Each culture has its own facial expressions, gestures, eye movements, and other body movements. However, the model is trained with the videos presented by higher education teachers from a regional university in Australia; therefore, the model may not work as effectively in identifying the body language from the videos where the presenters are from different cultures.

. Moreover, while human experts utilised an annotation manual and a list of characteristics and indicators to guide their annotations, the study did not thoroughly investigate the potential for human bias during the manual annotation process. These gaps highlight the need for a more comprehensive approach to understanding both human and machine limitations in evaluation.

Also, only two Prototypes (model 1 and model 2) were created to design the AI model, whereas it can be refined through multiple models by addressing issues and feeding more data to the machine. Additionally, in the evaluation process, the comparison made between AI-generated reports and experts' manual analyses failed to consider alternative scenarios such as having experts assess the AI-generated reports or facilitating peer-evaluation among experts, which could provide deeper insights to better align the AI model's performance with human experts' analytical capabilities.

Further, the evaluation was performed on a single stage, relying on a small dataset. This highlights the need for a larger dataset by processing and analysing more lecture videos to evaluate the model's performance more effectively. Additionally, the evaluation relied solely on percentage calculations as the statistical analysis to measure the agreement between the AI model's identification of indicators and those of human experts. Using only this metric may not provide a comprehensive assessment of the model's performance that more in-depth statistical methods can offer. Moreover, it is important to consider that the human mind continually evolves. The experts have gained more knowledge and experience regarding the indicators, surpassing the knowledge initially programmed into the AI model. In contrast, the tool's knowledge remains static and becomes outdated over time

Lastly, due to the limited financial resources, the AI model developed in this research is not yet available to the public. Due to the model's complexity and system requirements, only an AI expert can use it to process the videos and generate reports on engaging teaching videos based on their behaviours and movements during video conferencing.

Addressing these limitations would enhance the study's robustness and applicability, resulting in a more accurate AI model. The appropriate utilisation of this model will assist in improving online teaching and learning.

## **7.4 Recommendations**

In this section, recommendations are put forward for teachers, educational institutes, and future research to utilise the findings, address the acknowledged limitations of the research and maximise the potential of AI models in education.

### ***7.4.1 Recommendations for Teachers and Educational Institutes***

The recommendations derived from this research emphasise practical implementation for teachers and educational institutes. Educators are encouraged to actively integrate the 11 identified characteristics and 47 indicators (refer to Appendix A) into their online teaching practices, using them as a basis for self-assessment and improvement identification regarding student engagement. These characteristics and indicators specifically target video conferencing, which is the most critical technology used in online learning to develop the connection between teachers and students and assist in developing the abilities required for online learning.

In addition to integrating the characteristics and indicators of engaging teaching videos in their online teaching methodologies, teachers must be involved in developing AI models to enhance online student engagement. Their profound understanding of education and invaluable expertise enable them to assist in tailoring AI models to generate efficient reports. Moreover, the impact of AI on teacher autonomy is an essential aspect to consider. Teachers must feel empowered in their professional roles, free from undue influence stemming from AI support.

The AI model significantly increases the scalability as it can process the videos faster and auto-generate a report. Therefore, educational institutes are advised to extend this integration to an institutional level, developing guidelines and frameworks to enhance online teaching practices. Educational institutes should also spread awareness of AI in education to their educators so that they can quickly adapt to the education world of the future.

Further, organising professional learning activities becomes crucial to enhance teachers' skills in creating engaging teaching videos. Moreover, the AI model may be integrated into video conferencing sessions, employing its ability to identify teachers' behaviours and movements as soon as the session is finished. The reports assist in the identification of effective strategies for utilising technology and consistently integrating specific teachers' behaviours and body movements that play a significant role in enhancing engagement during video conferencing. To ensure teachers have a clear understanding of AI model functionalities and advantages, it is necessary to train them on how AI-enabled systems function. Further, they should receive training or instructions on how to interpret the AI-generated reports to implement necessary changes based on the recommendations. For educational institutes using AI models, implementing the proposed evaluation methodology is essential for maintaining accuracy and reliability. A continuous focus on improving and refining AI models, including exploring additional features, remains a priority. In conclusion, these recommendations guide teachers and educational institutions in effectively utilising identified characteristics and indicators of engaging teaching videos. The awareness of AI and the effective use of AI models are essential to address challenges associated with technology adoption in education and in enhancing online student engagement.

#### **7.4.2 Recommendations for Future Research**

In future research, it is valuable to consider the insights obtained from this study while also addressing the acknowledged limitations. One potential avenue for future research could be to standardise the process of identifying characteristics and indicators of engaging teaching videos in education. This can be achieved by designing a structured step-by-step process that includes detailed descriptions of each indicator and its characteristics, along with sub-indicators and examples. Providing clear definitions and visually recorded video snippets for each indicator in various scenarios will increase the consistency of the manual annotation. Also, providing concrete examples of teaching behaviours and movements in such ways will benefit both the AI system and the institution. These definitions and video snippets foster collaborative dialogue among educators and administrators, promoting continuous improvement in teaching practices. Moreover, they support targeted feedback and evaluation processes, enhancing overall teaching quality and student learning outcomes. Other than standardising the manual annotation process for consistency, future research could also focus on identifying potential biases in human annotations and explore strategies for mitigating these biases. Given that these annotations serve as the AI model's foundation, any inherent bias can affect the model's performance and accuracy. Thus, addressing these biases is crucial to ensure the model produces reliable and precise results.

Furthermore, researchers can explore enhancing the capabilities of the AI model. Currently, the designed AI model is trained with only 15 indicators due to the small dataset used for training. To overcome this constraint, the model needs to be trained with a larger dataset that encompasses all the identified indicators. This approach will provide the necessary diversity for comprehensive training. Implementing these approaches promises significant improvements in the overall quality and accuracy of the AI model and the evaluation process, thereby advancing the field of education research.

Moreover, researchers can identify specific characteristics and indicators of engaging teaching videos presented to other educational level students, such as vocational and school students. Based on the different characteristics and indicators, the researcher can revise the AI model to ensure it effectively indicates the engagement enhancing teachers' behaviours and movement in all levels of education.

Researchers can further modify the AI model to ensure it effectively identifies the engagement enhancing behaviours and movement from recorded lecture videos in different languages. The model should be able to recognise differences in body language from culture to culture and generate reports accordingly.

Additionally, testable hypotheses could be formulated to predict the designed AI model's behaviour in real-life scenarios. Following this, software based on the evaluated model could be developed and made publicly accessible for educators worldwide to generate reports on engaging teaching videos based on their behaviours and movements during video conferencing.



**Figure 4.** Stages of software development around the AI model

The figure above describes the stages for developing software around the AI model. The stages highlighted in green have already been achieved in this research project, and the ones highlighted in grey indicate the future research required. Ethics approval was obtained in the first stage to access and utilise the data (recorded lecture videos). The second stage focused on video selection for manual annotation to train the AI model. In the subsequent data pre-processing stage, the temporal coordinates provided by the tool were captured during manual video annotation. In the next stage, the AI model was trained by opting CNN, a powerful tool in video or image processing. After training the model, the results were classified into three levels: themes, characteristics, and indicators. In the next stage, the model was evaluated across three levels to assess its ability to consistently recognise indicators of engaging teaching behaviours and movements in videos.

Since the model developed in this study is an early prototype and the feedback interface from the model was not thoroughly tested, a separate study is required. Additionally, further refinements and reproductions are necessary before any empirical work can be undertaken in the real world, particularly in the form of publicly available software. The software will be user-friendly, and anyone with access will be able to generate a report on engaging teaching videos based on teachers' behaviours and movements. In the last stage, the software will be made available to the public, where teachers and educational institutes worldwide will be

able to use it to generate reports that can lead to enhancements as required, contributing to overall teaching and learning improvements. With ethical and organisational permission, the software can be applied to live online teaching sessions (videoconferencing). Once the software is publicly available, future work could involve a longitudinal study to measure the actual impact of the AI-generated reports on teacher behaviour and movements, consequently, on student engagement. This would provide empirical evidence of the model's effectiveness in real-world educational settings.

In future research, the annotation procedure used in this study can be applied to develop similar models using different metrics to enhance online teaching and learning. For instance, an AI model could be trained using the online engagement framework proposed by Redmond et al. (2018), which identifies five key elements of online learning: social, cognitive, behavioural, collaborative, and emotional engagement. The indicators associated with these elements can be utilised to train the AI model for the automatic identification.

Apart from using the evaluation method used in this study, the evaluation of AI models in future work could involve multiple metrics to assess the agreement and consistency between the findings of an AI tool and two human experts in evaluating specific segments of video data. For example, Cohen's Kappa can be used to measure the inter-rater agreement for categorical items, considering the possibility of agreement occurring by chance. Bland-Altman analysis can further explore the agreement between the AI model and the experts by analysing the differences between their assessments. The Intraclass Correlation Coefficient (ICC) can assess the reliability and agreement of the quantitative measurements between the AI tool and both experts. Finally, the Pearson and Spearman correlation coefficients can be used to measure the linear and rank-order relationships between the AI model's assessments and those of the experts.

Beside the aforementioned recommendations for future research, it is crucial to address ethical concerns before developing, training, and using the model. This includes ensuring the privacy of teachers and students, obtaining informed consent for data usage, and mitigating potential biases in AI models. Teachers and students, as research participants, should be informed about how their data is collected and utilised, ensuring they have a voice in the process. Researchers must also be vigilant in identifying and mitigating potential biases within the AI models to ensure fair and

accurate assessments of teaching effectiveness. Incorporating these considerations into future research will enhance the credibility of AI applications in education and will maintain a respectful and supportive environment for teachers.

## **7.5 Conclusion**

This study highlights the significant role that teachers play in enhancing online student engagement. Their motivating teaching behaviours positively influence online student engagement. Additionally, it discusses the significance of specific gestures and non-verbal cues in enhancing student engagement during video conferencing sessions. Therefore, it is crucial to identify the characteristics and indicators of engaging teaching videos based on teachers' behaviours and movements.

The findings of this research encompass four main components. First, Phase 1 provides a list of the characteristics and indicators of engaging teaching videos derived from an extensive review of relevant literature, laying the foundation for enhancing online student engagement and informing AI model algorithms. In Phase 2, an AI model was designed to expedite the processing of lecture videos while ensuring a bias-free approach. In the same phase, a manual annotation procedure was established and implemented during the development of the AI model. This procedure can also serve as a valuable resource for future researchers aiming to design similar models. Lastly, Phase 3 introduces an evaluation methodology intended to assess the AI model's performance in online settings, ensuring its accuracy and impartiality.

Overall, by integrating the outcomes from all three phases, this research presents an AI model that generates reports on the characteristics and indicators of engaging teaching videos based on teachers' behaviours and movements. The AI-generated reports can help teachers identify areas to improve their teaching, making learning more effective and engaging. The evaluation procedure created in the research project established the importance of educators' involvement in developing and testing AI models in education. The evaluation process will help educational institutions increase local trust in AI models to improve the online learning environment. This research project breaks the barriers between AI scientists and educators. By fostering more collaborative approaches inspired by the outcomes of this research, the overall teaching and learning can be greatly improved.

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## APENDIX A. MAIN THEME, CHARACTERISTICS, AND INDICATORS OF ENGAGING TEACHING VIDEOS

Main theme	Characteristics	Indicators
Teachers' Behaviours	Encourage Active Participation	<ul style="list-style-type: none"> <li>• Encouraging students' participation in discussion</li> <li>• Encouraging students to share their knowledge and ideas</li> <li>• Encouraging students to ask questions</li> <li>• Encouraging collaborative learning activities</li> <li>• Encouraging meaningful interaction</li> <li>• Encouraging students to turn on their webcams</li> </ul>
	Establishing Teacher Presence	<ul style="list-style-type: none"> <li>• Clear and concise explanations of information</li> <li>• Recognising and considering learners' Individual differences</li> <li>• Using an appropriate style of presentation</li> <li>• Allowing sufficient time for students' information processing</li> <li>• Providing Learning resources</li> <li>• Giving clear instructions</li> <li>• Using a range of teaching strategies</li> <li>• Appropriate speed of lecture delivery</li> </ul>
	Establishing Social Presence	<ul style="list-style-type: none"> <li>• Maintaining constant teacher-student interaction</li> <li>• Encouraging student-student interaction (Peer collaboration)</li> <li>• Active and constructive communication</li> <li>• Taking on multiple roles</li> </ul>
	Establishing Cognitive Presence	<ul style="list-style-type: none"> <li>• giving students a sense of puzzlement (trigger)</li> <li>• providing opportunities for students to reflect (exploration)</li> <li>• leading students to think and learn through discussion with others (integration)</li> <li>• helping students apply knowledge to solve issues (resolution)</li> </ul>

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	Questions and Feedback	<ul style="list-style-type: none"> <li>• Addressing students' questions &amp; Providing prompt feedback</li> <li>• Asking for questions and feedback</li> <li>• Clarifying misunderstanding</li> </ul>
	Displaying Enthusiasm	<ul style="list-style-type: none"> <li>• Motivating students</li> <li>• Displaying positive emotion</li> </ul>
	Establishing Clear Expectations	<ul style="list-style-type: none"> <li>• Outlining the learning objectives</li> <li>• Outlining teachers' expectations of students' behaviours and responsibilities</li> </ul>
	Demonstrating empathy	<ul style="list-style-type: none"> <li>• Using appropriate changes in tone of voice</li> <li>• Ensuring the learning environment is a respectful, safe, and supportive one</li> <li>• Showing concern</li> </ul>
	Demonstrating Professionalism	<ul style="list-style-type: none"> <li>• Demonstrating in-depth and up-to-date knowledge</li> <li>• Displaying appropriate behaviours</li> </ul>
Teachers' Movements	Using non-verbal cues	<ul style="list-style-type: none"> <li>• facial expressions</li> <li>• gestures</li> <li>• eye gazes</li> <li>• silence</li> <li>• eye contact</li> <li>• physical proximity</li> <li>• appropriate body language</li> </ul>
Use of Technology	Using technology effectively	<ul style="list-style-type: none"> <li>• Screen sharing &amp; Enabling Chat, Camera, and Microphone</li> <li>• Varying the presentation media</li> <li>• Providing technical support to students</li> <li>• Providing multiple communication channels</li> <li>• Providing interactive software tools</li> <li>• Enabling class recording for later review</li> </ul>

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## APPENDIX B. MANUAL VIDEO ANNOTATION PROCEDURE

VGG Image Annotator (VIA) software has been used in this manual video annotation process to annotate zoom-based lecture recordings. VIA is an open-source project-based annotation software for annotating images, audio, and videos available at [https://www.robots.ox.ac.uk/~vgg/software/via/app/via\\_video\\_annotator.html](https://www.robots.ox.ac.uk/~vgg/software/via/app/via_video_annotator.html).

In this project, the researchers have used the following to annotate the videos:

**Step 1: Creating a new project:** Open the VIA annotation tool by clicking the link above. Add the project name on the top left-hand side (refer to Figure 1).

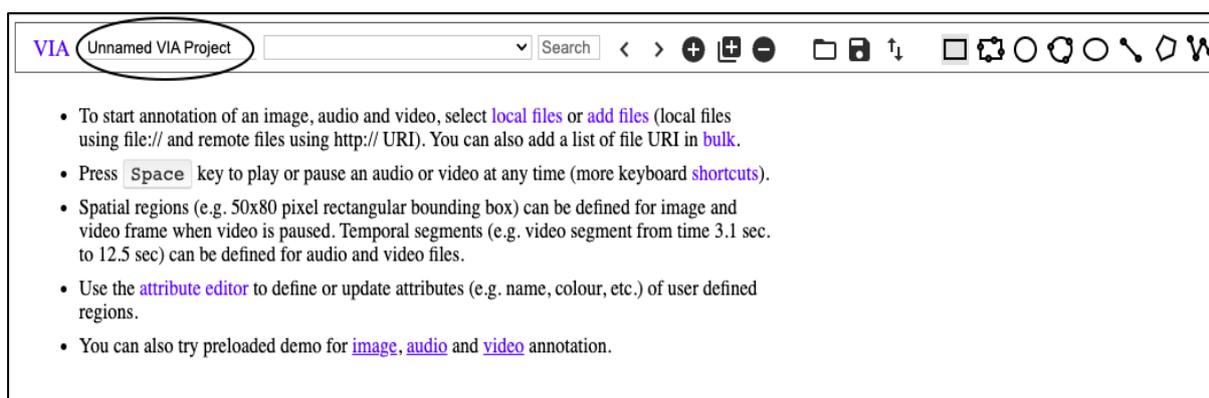


Figure 5. The process of creating a new project

**Step 2: Add a video file:** The second step is to add a video by clicking the plus icon (refer to Figure 2). Select the video to be annotated from the desktop or cloud storage.

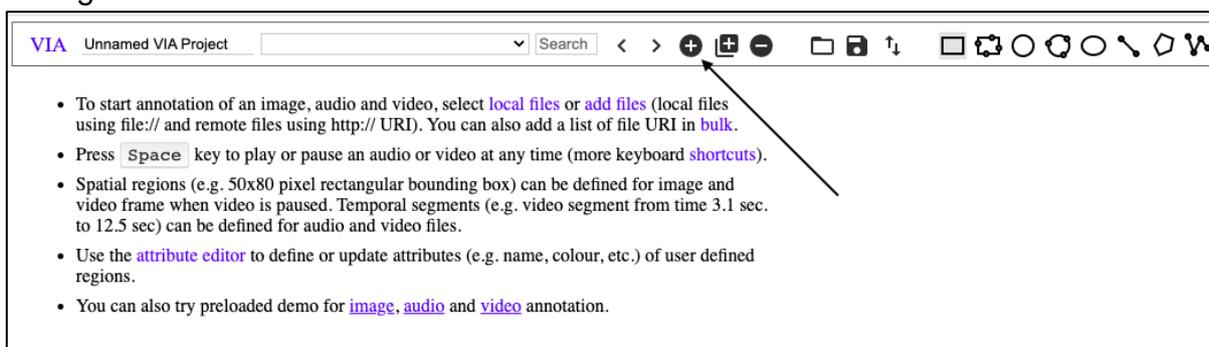
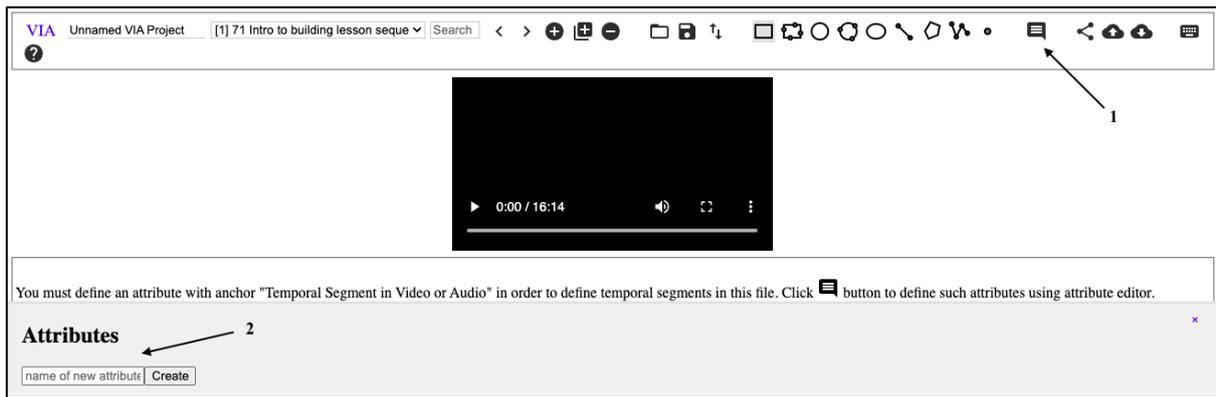


Figure 6. Adding a video to the project

**Step 3: Define the attributes:** Once the video is added, define the attributes by clicking on 1 (refer to Figure 3). In this step, two attributes have been created by typing the attribute name in 2 (refer to figure 3) and clicking Create. In this project, the first attribute was created to identify the engaging teaching video indicators and the second to highlight the presenter's location in the video.



**Figure 7.** Defining the attributes

While defining the attributes, the following information has been inserted (refer to Figure 4):

**Attribute 1:** The name of the first attribute is "Engaging teaching video indicators". The anchor is set to "Temporal Segment in Video or Audio" as researchers identified the indicators in small video segments. The input type is selected for to text function.

**Attribute 2:** The name of the second attribute is "Presenter location". The attribute is created to signal the presenter's location in the video. The anchor is set to "Spatial region in a video frame" as an area is highlighted to indicate the presenter's location. The input type is set as Select. In the options section, the researchers have typed "presenter" to

**Name** = Presenter location

**Anchor** = Spatial region in a video frame

**Input Type** = Select

**Options** = \*Presenter (Note: if there are multiple presenters in a video, we can add \*presenter 1, presenter 2)

You must define an attribute with anchor "Temporal Segment in Video or Audio" in order to define temporal segments in this file. Click button to define such attributes using attribute editor.

**Attributes**

name of new attribut

	Id	Name	Anchor	Input Type	Description	Options	Default Value	Preview
	1	Engaging teaching vi	Temporal Segment in V	TEXT	<input type="text"/>	-	-	<input type="text"/>
	2	Presenter location	Spatial Region in a Vide	SELECT	<input type="text"/>	Presenter	Not Defined	Presenter

**Figure 8.** Attributes 1 and 2

#### Step 4: Adding indicators to Attribute 1 (engaging teaching video indicators):

After defining the attributes, the next step is adding the indicators. The researchers added the indicators at the bottom left-hand side by writing the indicator name and then clicking Add (refer to Figure 5).

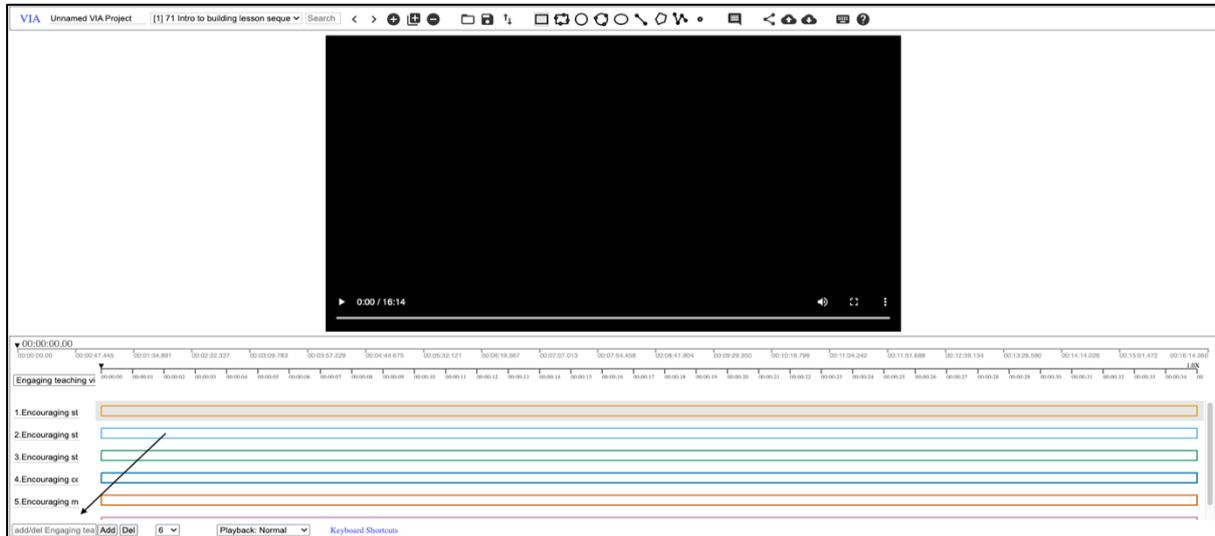


Figure 9. Adding indicators of engaging teaching videos

#### Step 5: Drawing boundary box to signal presenter location (Attribute 2: presenter location):

The researchers drew a boundary box to indicate the presenter's location.

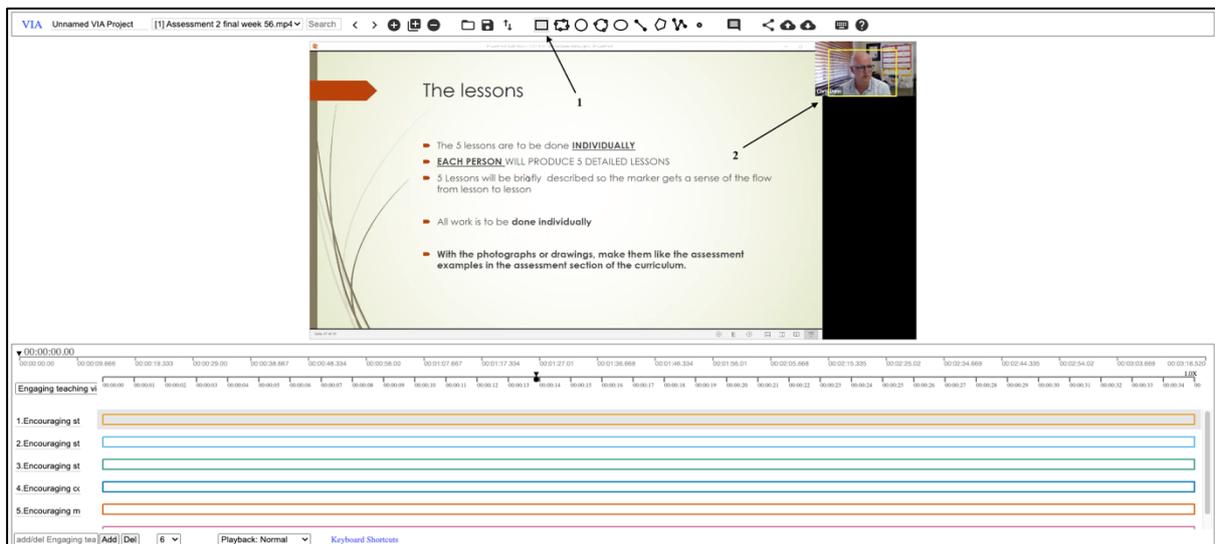
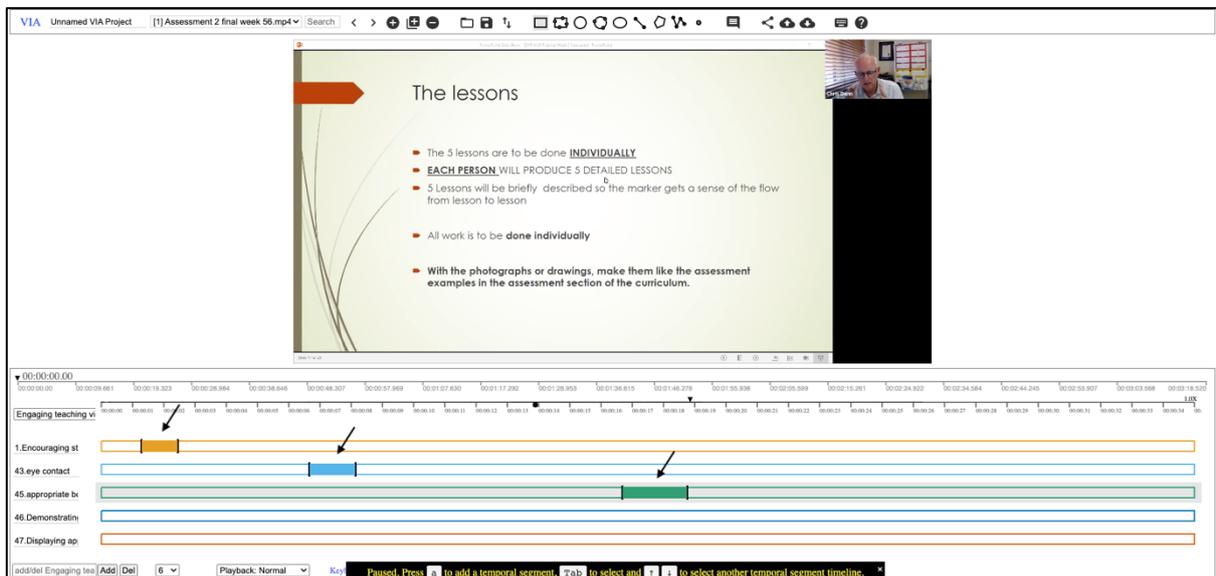


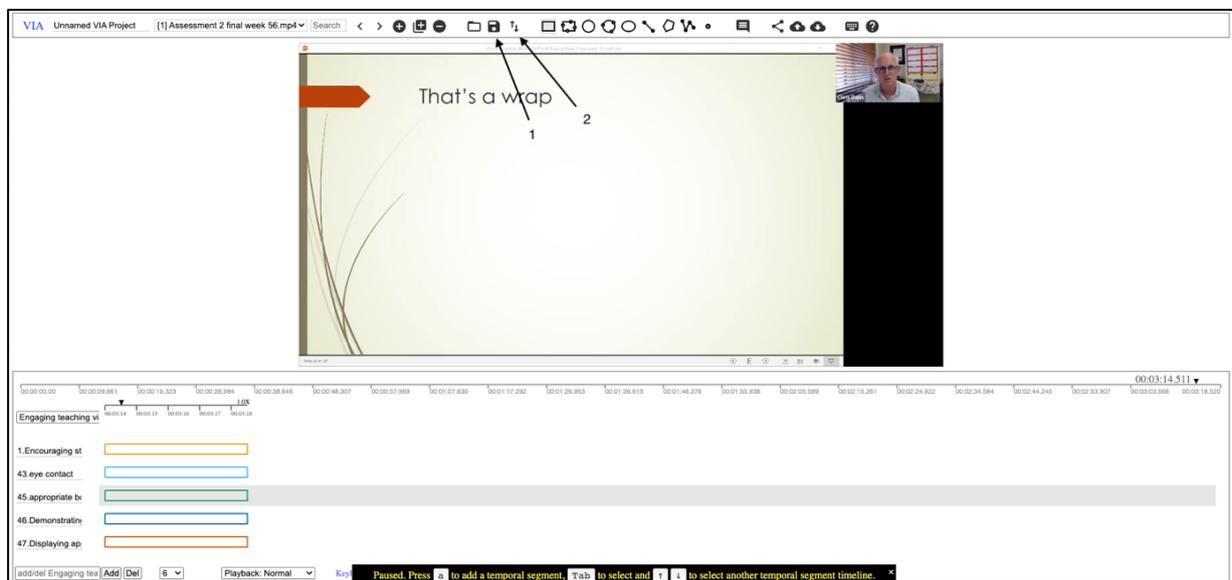
Figure 10. Drawing boundary box around the presenter location

**Step 6: Identifying the indicators from the video:** A manual annotation is performed after defining the attributes and indicating the presenter's location. In this process, the video is played, and indicators are identified in small segments.



**Figure 11.** Identifying the indicators from the recorded lecture video

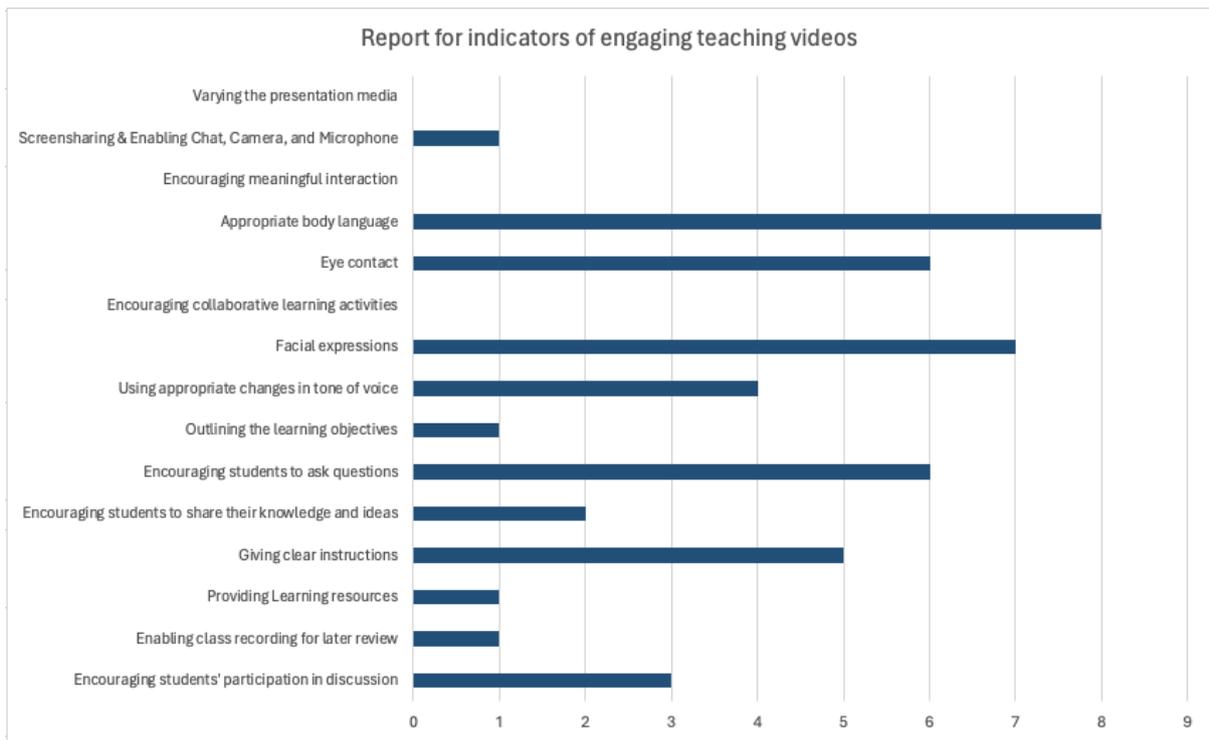
**Step 7: Saving and Exporting the Project for Machine Learning:** Once the annotation is complete, save the project by clicking on one and selecting the project's location. Similarly, click on 2 to export the project.



**Figure 12.** Saving the project and exporting the data for AI Model development

## APPENDIX C. AI-enabled tool report for indicators of engaging teaching videos

**Graphical representation:** The graph below summarises the findings of the AI-enabled tools. It highlights the indicators present and absent during the video conferencing. The graph also provides information on the number of times a particular indicator was present during lecture delivery.



**Overall Summary:** The table below provides a detailed explanation of each indicator presented during the video conferencing. The first column states the indicator, the second column highlights the video segment, and the last timestamp of the indicator presents during the lecture delivery.

Indicator	Video Segment	Timestamp
Encouraging students' participation in discussion	Segment 5	00:06:52 - 00:06:57
	Segment 11	00:19:27 - 00:19:32
	Segment 38	01:11:55 - 01:12:01
Enabling class recording for later review	Segment 2	00:02:05 - 00:02:10

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Providing Learning resources	Segment 45	01:25:06 - 01:25:12
	Segment 4	00:04:18 - 00:04:26
	Segment 8	00:14:20 - 00:14:26
Giving clear instructions	Segment 12	00:21:08 - 00:21:13
	Segment 18	00:32:11 - 00:32:17
	Segment 21	00:37:33 - 00:37:37
Encouraging students to share their knowledge and ideas	Segment 16	00:28:02 - 00:28:08
	Segment 40	01:15:09 - 01:15:16
	Segment 24	00:48:06 - 00:48:11
	Segment 28	00:54:19 - 00:54:26
Encouraging students to ask questions	Segment 30	00:59:01 - 00:59:07
	Segment 31	01:02:27 - 01:02:33
	Segment 33	01:05:55 - 01:06:04
	Segment 34	01:06:44 - 01:06:50
Outlining the learning objectives	Segment 1	00:01:25 - 00:01:32
Using appropriate changes in tone of voice	Segment 15	00:26:47 - 00:26:52
	Segment 19	00:33:58 - 00:34:06

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	Segment 23	00:41:51 - 00:41:57
	Segment 25	00:48:57 - 00:49:03
	Segment 6	00:09:15 - 00:09:22
	Segment 7	00:11:25 - 00:11:34
	Segment 9	00:15:35 - 00:15:41
Facial expressions	Segment 13	00:23:42 - 00:23:47
	Segment 17	00:31:25 - 00:31:32
	Segment 20	00:35:44 - 00:35:49
	Segment 42	01:17:17 - 01:17:23
Encouraging collaborative learning activities	N/A	N/A
	Segment 14	00:26:26 - 00:26:32
	Segment 22	00:39:12 - 00:39:18
Eye contact	Segment 26	00:50:47 - 00:50:52
	Segment 36	01:09:28 - 01:09:34
	Segment 39	01:14:39 - 01:14:45
	Segment 44	01:23:18 - 01:23:24

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	Segment 10	00:19:19 - 00:19:26
	Segment 27	00:53:19 - 00:53:25
	Segment 29	00:57:42 - 00:57:48
Appropriate body language	Segment 32	01:04:33 - 01:04:39
	Segment 35	01:08:08 - 01:08:15
	Segment 37	01:10:10 - 01:10:15
	Segment 41	01:16:23 - 01:16:28
	Segment 43	01:22:11 - 01:22:16
Encouraging meaningful interaction	N/A	N/A
Screensharing & Enabling Chat, Camera, and Microphone	Segment 3	00:02:38 - 00:02:42
Varying the presentation media	N/A	N/A

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## APPENDIX D. Scripting for the proposed AI model

```
# Importing necessary packages
import cv2 # for capturing videos
import math # for mathematical operations
import matplotlib.pyplot as plt # for plotting the images
%matplotlib inline
import pandas as pd
import numpy as np # for mathematical operations
from sklearn.model_selection import train_test_split
from glob import glob
from tqdm import tqdm
import os
import pandas as pd

import keras
from keras.models import Sequential
from keras.applications.vgg16 import VGG16
from keras.layers import Dense, InputLayer, Dropout, Flatten
from keras.layers import Conv2D, MaxPooling2D, GlobalMaxPooling2D
import keras.utils as image
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from tqdm import tqdm
from sklearn.model_selection import train_test_split
from sklearn.model_selection import StratifiedShuffleSplit

import moviepy.editor as mp
from skimage.transform import resize # for resizing images
from keras.preprocessing import image # for preprocessing the images
from moviepy.video.io.ffmpeg_tools import ffmpeg_extract_subclip

from sklearn.metrics import multilabel_confusion_matrix
from sklearn.metrics import classification_report
from keras.models import load_model
from sklearn.metrics import roc_auc_score, average_precision_score,
roc_curve, precision_recall_curve
import matplotlib.pyplot as plt
```

```

# Videos Preprocessing

## Input: Consolidated 25 Videos data in excel with video chunk, start time,
end time, and label.

## Output: Split each video based on the start and end time. The ouput get
saved in VideosAVI folder.

video_labels=pd.read_excel('videochunks_labelling.xlsx',sheet_name='complete_labels_25_videos')

def split_video(input_video, start_times, end_times, output_folder):
    for i, (start, end) in enumerate(zip(start_times, end_times)):
        try:
            output_path = output_folder +
            "//EDE3103_Session_3_Scaffolding_for_placement_interr_20200429_102301_38_chunk_{}.avi".format(i)
            ffmpeg_extract_subclip(str(input_video), start, end,
            targetname=output_path)
        except:
            print("error", start, end, output_folder +
            "//EDE3103_Session_3_Scaffolding_for_placement_interr_20200429_102301_38_chunk_{}.avi".format(i))

start_times = [i[0] for i in video_labels[['start_time',
'end_time']].iloc[810:].values]
end_times = [i[1] for i in video_labels[['start_time',
'end_time']].iloc[810:].values]
output_folder = "VideosAVI"
input_video =
"VA_Project_25_Videos//EDE3103_Session_3_Scaffolding_for_placement_interr_20200429_102301_38.mp4"
split_video(input_video, start_times, end_times, output_folder)

# Each Video Chunk further split into Image Frames
## Input: A text file with the video chunk and its label.
## Output: Image frames for each video chunk saved in train folder. Generate
a csv file with two columns: image frame and label.

f = open("testtrain/videos_25.txt", "r")

# open the .txt file which have names of training videos

```

```

f = open("testtrain/videos_25.txt", "r")
temp = f.read()
videos = temp.split('\n')

# creating a dataframe having video names
train = pd.DataFrame()
train['video_name'] = videos
train = train[:-1]

# creating tags for training videos
train_video_tag = []
train_video_name=[]
for i in range(train.shape[0]):
    train_video_tag.append(train['video_name'][i].split(',')[0])

train['tag'] = train_video_tag

# storing the frames from training videos
for i in tqdm(range(train.shape[0])):
    count = 0
    videoFile = train['video_name'][i]
    cap = cv2.VideoCapture('VideosAVI/'+videoFile.split(',')[0]+'avi') #
capturing the video from the given path
    print('VideosAVI/'+videoFile.split(',')[0]+'avi')
    frameRate = cap.get(5) #frame rate
    x=1
    while(cap.isOpened()):
        frameId = cap.get(1) #current frame number
        ret, frame = cap.read()
        if (ret != True):
            break
        if (frameId % math.floor(frameRate) == 0):
            # storing the frames in a new folder named train_1
            filename = 'train/' + videoFile.split(',')[1]+'$' +videoFile.split(',')[0]
            + "_frame%d.jpg" % count;count+=1
            cv2.imwrite(filename, frame)
        cap.release()

# getting the names of all the images
images = glob("train/*.jpg")
train_image = []
train_class = []

```

```

for i in tqdm(range(len(images))):
    # creating the image name
    train_image.append((images[i].split('$'))[1])
    # creating the class of image
    train_class.append((images[i].split('$'))[0][6:])

# storing the images and their class in a dataframe
train_data = pd.DataFrame()
train_data['image'] = train_image
train_data['class'] = train_class

# converting the dataframe into csv file
train_data.to_csv('train_new.csv',header=True, index=False)

```

```

train=train[train['class']!= '_DEFAULT']

```

### Now the train\_new.csv (with images and indicator labels from 25 videos) is now processed to have theme level and characteristic level labels.

```

def charac_label(value):
    if value in [1,2,3,4,5]:
        return 1
    elif value in [17, 18]:
        return 2
    elif value in [34]:
        return 7
    elif value in [36]:
        return 8
    elif value in [39,43,45]:
        return 10
    elif value in [7, 8, 12]:
        return 11

```

```

def theme_label(value):
    if value in [1,2,3,4,5,17,18,34,36]:
        return 1
    elif value in [39,43,45]:
        return 2
    elif value in [7, 8, 12]:
        return 3

```

```

# Use apply to create a new column

```

```

train['charac_label'] = train['indicator_level'].apply(charac_label)
# Use apply to create a new column
train['theme_label'] = train['indicator_level'].apply(theme_label)

# creating an empty list
train_image = []

# for loop to read and store frames
for i in tqdm(range(train.shape[0])):
    # loading the image and keeping the target size as (224,224,3)
    img = image.load_img('train/'+str(train['class'][i])+'$'+train['image'][i],
target_size=(224,224,3))
    # converting it to array
    img = image.img_to_array(img)
    # normalizing the pixel value
    img = img/255
    # appending the image to the train_image list
    train_image.append(img)

# converting the list to numpy array
X = np.array(train_image)

# shape of the array
X.shape

# separating the target
y = train['class']

# creating the training and validation set
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=42,
test_size=0.25, stratify=y)

# creating dummies of target variable for train and validation set
y_train = pd.get_dummies(y_train)
y_test = pd.get_dummies(y_test)

# creating the base model of pre-trained VGG16 model
base_model = VGG16(weights='imagenet', include_top=False)

# extracting features for training frames

```

```

X_train = base_model.predict(X_train)
X_train.shape

# extracting features for validation frames
X_test = base_model.predict(X_test)
X_test.shape

# reshaping the training as well as validation frames in single dimension
X_train = X_train.reshape(2469, 7*7*512)
X_test = X_test.reshape(823, 7*7*512)

# normalizing the pixel values
max = X_train.max()
X_train = X_train/max
X_test = X_test/max

#defining the model architecture
model = Sequential()
model.add(Dense(1024, activation='relu', input_shape=(25088,)))
model.add(Dropout(0.5))
model.add(Dense(512, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(256, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(128, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(15, activation='softmax'))

# defining a function to save the weights of best model
from keras.callbacks import ModelCheckpoint, EarlyStopping
mcp_save = ModelCheckpoint('C:\\Users\\U1119894\\weight.hdf5',
save_best_only=True, monitor='val_loss', mode='min')
es = EarlyStopping(monitor='val_accuracy', patience=5)
callbacks_list = [mcp_save, es]

# compiling the model
model.compile(loss='categorical_crossentropy', optimizer='Adam', metrics=['acc
uracy'])

```

```

# training the model
model.fit(X_train, y_train, epochs=100, validation_data=(X_test, y_test),
callbacks=callbacks_list, batch_size=128)

y_pred=model.predict(X_test)

predicted_classes_=[]
for sample in y_pred:
    predicted_classes_.append([1 if i==np.max(sample) else 0 for i in sample] )
predicted_classes_ = np.array(predicted_classes_)

multilabel_confusion_matrix(y_test, predicted_classes_)

print(classification_report(y_test, predicted_classes_,target_names=['1',
'12',
'17',
'18',
'2',
'3',
'34',
'36',
'39',
'4',
'43',
'45',
'5',
'7',
'8']))

# Charateristic Level Analysis

X2 = X1
y2 = train['charac_label']

y2 = pd.get_dummies(y2)

# Theme Level
X3 = X1
y3 = train['theme_label']

```

```
y3 = pd.get_dummies(y3)
```

```
# Proposed Model Training for Indicator Level
```

```
#defining the model architecture
```

```
model = Sequential()  
model.add(Dense(1024, activation='relu', input_shape=(25088,)))  
model.add(Dropout(0.5))  
model.add(Dense(512, activation='relu'))  
model.add(Dropout(0.5))  
model.add(Dense(256, activation='relu'))  
model.add(Dropout(0.5))  
model.add(Dense(128, activation='relu'))  
model.add(Dropout(0.5))  
model.add(Dense(15, activation='softmax'))
```

```
# defining a function to save the weights of best model
```

```
from keras.callbacks import ModelCheckpoint, EarlyStopping  
mcp_save = ModelCheckpoint('C:\\Users\\U1119894\\weight.hdf5',  
save_best_only=True, monitor='val_loss', mode='min')  
es = EarlyStopping(monitor='val_accuracy', patience=5)  
callbacks_list = [mcp_save, es]
```

```
# compiling the model
```

```
model.compile(loss='categorical_crossentropy', optimizer='Adam', metrics=['acc  
uracy'])  
# training the model  
model.fit(X1, y1, epochs=100, validation_data=(X1, y1),  
callbacks=callbacks_list, batch_size=128)
```

```
# Proposed Model Training for Characteristics Level
```

```
#defining the model architecture
```

```
model = Sequential()  
model.add(Dense(1024, activation='relu', input_shape=(25088,)))  
model.add(Dropout(0.5))  
model.add(Dense(512, activation='relu'))  
model.add(Dropout(0.5))  
model.add(Dense(256, activation='relu'))  
model.add(Dropout(0.5))  
model.add(Dense(128, activation='relu'))
```

```

model.add(Dropout(0.5))
model.add(Dense(6, activation='softmax'))
# defining a function to save the weights of best model
from keras.callbacks import ModelCheckpoint, EarlyStopping
mcp_save =
ModelCheckpoint('C:\\Users\\U1119894\\weight_charac_level.hdf5',
save_best_only=True, monitor='val_loss', mode='min')
es = EarlyStopping(monitor='val_accuracy', patience=5)
callbacks_list = [mcp_save, es]
# compiling the model
model.compile(loss='categorical_crossentropy', optimizer='Adam', metrics=['acc
uracy'])
# training the model
model.fit(X1, y2, epochs=100, validation_data=(X1, y2),
callbacks=callbacks_list, batch_size=128)

```

# Proposed Model Training for Theme Level

```

#defining the model architecture
model = Sequential()
model.add(Dense(1024, activation='relu', input_shape=(25088,)))
model.add(Dropout(0.5))
model.add(Dense(512, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(256, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(128, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(3, activation='softmax'))
# defining a function to save the weights of best model
from keras.callbacks import ModelCheckpoint, EarlyStopping
mcp_save =
ModelCheckpoint('C:\\Users\\U1119894\\weight_theme_level.hdf5',
save_best_only=True, monitor='val_loss', mode='min')
es = EarlyStopping(monitor='val_accuracy', patience=5)
callbacks_list = [mcp_save, es]
# compiling the model
model.compile(loss='categorical_crossentropy', optimizer='Adam', metrics=['acc
uracy'])
# training the model
model.fit(X1, y3, epochs=100, validation_data=(X1, y3),
callbacks=callbacks_list, batch_size=128)

```

```

# Evaluation of the model with new videos

eval_video_labels=pd.read_excel(r'Evaluation
Videos//Evaluation_videochunks_labelling.xlsx',sheet_name='mp4')

def split_video(input_video, start_times, end_times, output_folder):
    for i, (start, end) in enumerate(zip(start_times, end_times)):
        try:
            output_path = output_folder + "//BIO3109_lecture_1_rec_-
_20200224_171342_38_chunk_{}.avi".format(i)
            ffmpeg_extract_subclip(str(input_video), start, end,
targetname=output_path)
        except:
            print("error", start, end, output_folder + "//BIO3109_lecture_1_rec_-
_20200224_171342_38_chunk_{}.avi".format(i))

start_times = [i[0] for i in eval_video_labels[['start_time',
'end_time']].iloc[:12].values]
end_times = [i[1] for i in eval_video_labels[['start_time',
'end_time']].iloc[:12].values]
output_folder = "Evaluation Videos//Eval_VideosAVI"
input_video = "Evaluation
Videos//VA_Evaluation_Videos//BIO3109_lecture_1_rec_-
_20200224_171342_38.mp4"

split_video(input_video, start_times, end_times, output_folder)

eval_video_avi_list=pd.read_excel(r'Evaluation
Videos//Evaluation_videochunks_labelling.xlsx',sheet_name='avi')
eval_video_avi_list['combined'] = eval_video_avi_list['video'] + "," +
eval_video_avi_list['label'].astype(str)

# creating a dataframe having video names
train = pd.DataFrame()
train['video_name'] = eval_video_avi_list['combined']
train = train[:-1]

# creating tags for training videos
train_video_tag = []
train_video_name=[]
for i in range(train.shape[0]):

```

```

train_video_tag.append(train['video_name'][i].split(',')[0])

train['tag'] = train_video_tag

# storing the frames from training videos
for i in tqdm(range(train.shape[0])):
    count = 0
    videoFile = train['video_name'][i]
    cap = cv2.VideoCapture('Evaluation
Videos//Eval_VideosAVI//'+videoFile.split(',')[0]) # capturing the video from
the given path
    frameRate = cap.get(5) #frame rate
    x=1
    if not cap.isOpened():
        print(f"Failed to open video: {videoFile}")
        continue
    while(cap.isOpened()):
        frameId = cap.get(1) #current frame number
        ret, frame = cap.read()
        if (ret != True):
            break
        if (frameId % math.floor(frameRate) == 0):
            # storing the frames in a new folder named train_1
            filename ='Evaluation Videos//train//' + videoFile.split(',')[1]+'$'
+videoFile.split(',')[0] + "_frame%d.jpg" % count;count+=1
            cv2.imwrite(filename, frame)
        cap.release()

# getting the names of all the images
images = glob("Evaluation Videos//train//*.jpg")
train_image = []
train_class = []
for i in tqdm(range(len(images))):
    print(images[i])
    # creating the image name
    train_image.append((images[i].split('$'))[1])
    # creating the class of image
    train_class.append((images[i].split('$')[0]).split('\')[1])

# storing the images and their class in a dataframe
train_data = pd.DataFrame()
train_data['image'] = train_image
train_data['class'] = train_class

```

```

# converting the dataframe into csv file
train_data.to_csv('Evaluation Videos//eval_train_new.csv',header=True,
index=False)

eval_train = pd.read_csv('Evaluation Videos//eval_train_new.csv')
eval_train.head()

def charac_label(value):
    if value in [1,2,3,4,5]:
        return 1
    elif value in [17, 18]:
        return 2
    elif value in [34]:
        return 7
    elif value in [36]:
        return 8
    elif value in [39,43,45]:
        return 10
    elif value in [7, 8, 12]:
        return 11

def theme_label(value):
    if value in [1,2,3,4,5,17,18,34,36]:
        return 1
    elif value in [39,43,45]:
        return 2
    elif value in [7, 8, 12]:
        return 3

# Use apply to create a new column
eval_train['charac_label'] = eval_train['class'].apply(charac_label)
# Use apply to create a new column
eval_train['theme_label'] = eval_train['class'].apply(theme_label)

# creating an empty list
eval_train_image = []

# for loop to read and store frames

```

```

for i in tqdm(range(eval_train.shape[0])):
    # loading the image and keeping the target size as (224,224,3)
    img = image.load_img('Evaluation
Videos//train//'+str(eval_train['class'][i])+'$'+eval_train['image'][i],
target_size=(224,224,3))
    # converting it to array
    img = image.img_to_array(img)
    # normalizing the pixel value
    img = img/255
    # appending the image to the train_image list
    eval_train_image.append(img)

# converting the list to numpy array

# Indicator Level
X1_Eval = np.array(eval_train_image)
y1_Eval = eval_train['class']

# creating the base model of pre-trained VGG16 model
base_model = VGG16(weights='imagenet', include_top=False)

# extracting features for training frames
X1_Eval = base_model.predict(X1_Eval)
X1_Eval.shape

X1_Eval = X1_Eval.reshape(391, 7*7*512)

# Indicator Level
y1_Eval=pd.get_dummies(y1_Eval, dtype=float)
y1_Eval= y1_Eval.astype(int)

# Characteristics Level
y2_Eval = eval_train['charac_label']
y2_Eval=pd.get_dummies(y2_Eval, dtype=float)

# themes Level
y3_Eval = eval_train['theme_label']
y3_Eval=pd.get_dummies(y3_Eval, dtype=float)

loaded_model_indicator = load_model('weight.hdf5')
y_pred_ind=loaded_model_indicator.predict(X1_Eval)

```

```

predicted_classes_=[]
for sample in y_pred_ind:
    predicted_classes_.append([1 if i>0.18 else 0 for i in sample] )
predicted_classes_ = np.array(predicted_classes_)
len(predicted_classes_)

predicted_classes_=pd.DataFrame(predicted_classes_)
predicted_classes_.loc[:, (predicted_classes_!=0).any(axis=0)]
predicted_classes_.loc[:,
(predicted_classes_!=0).any(axis=0)].to_csv('indicator_pred_result.csv',index=
None)

def evaluate_classification(y_true, y_prob):
    # Compute AUC-ROC
    roc_auc = roc_auc_score(y_true, y_prob)
    print(f"AUC-ROC: {roc_auc:.2f}")

    # Compute AUC-PR
    pr_auc = average_precision_score(y_true, y_prob)
    print(f"AUC-PR: {pr_auc:.2f}")

    # Plot ROC curve
    fpr, tpr, _ = roc_curve(y_true, y_prob)
    plt.figure(figsize=(10, 5))
    plt.subplot(1, 2, 1)
    plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (area =
{roc_auc:.2f})')
    plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver Operating Characteristic (ROC) Curve')
    plt.legend(loc="lower right")

    # Plot Precision-Recall curve
    precision, recall, _ = precision_recall_curve(y_true, y_prob)
    plt.subplot(1, 2, 2)
    plt.plot(recall, precision, color='blue', lw=2, label=f'PR curve (area =
{pr_auc:.2f})')
    plt.xlabel('Recall')
    plt.ylabel('Precision')
    plt.title('Precision-Recall (PR) Curve')
    plt.legend(loc="upper right")

plt.tight_layout()

```

```

plt.show()

evaluate_classification(y1_Eval.values, predicted_classes_.loc[:,
(predicted_classes_!=0).any(axis=0)].values)

# Characteristics Evaluation
from keras.models import load_model

loaded_model_characteritics = load_model('weight_charac_level.hdf5')
y_pred_char=loaded_model_characteritics.predict(X1_Eval)
predicted_classes_=[]
for sample in y_pred_char:
    predicted_classes_.append([1 if i>0.1 else 0 for i in sample] )
predicted_classes_ = np.array(predicted_classes_)
len(predicted_classes_)
pd.DataFrame(y_pred_char)
predicted_classes_=pd.DataFrame(predicted_classes_)

evaluate_classification(y2_Eval.values, predicted_classes_.loc[:,
(predicted_classes_!=0).any(axis=0)].values)

```

## **APPENDIX E. AI Definitions**

### **AUC (Area Under the Curve)**

The area under the ROC curve (AUC) represents the probability that the model if given a randomly chosen positive and negative example, will rank the positive higher than the negative.

### **Cohen's Kappa**

Cohen's kappa coefficient is a statistic used to measure inter-rater reliability for qualitative items.

### **CNN (Convolutional Neural Network)**

A convolutional neural network (CNN) is a network architecture for deep learning that learns directly from data.

### **Deep Learning**

Deep learning is a type of machine learning that uses artificial neural networks to learn from data.

### **GPT (Generative Pre-trained Transformer)**

A generative pre-trained transformer is a type of large language model and a prominent framework for generative artificial intelligence

### **LLM (Large Language Models)**

A large language model (LLM) is an artificial intelligence (AI) program trained on vast data sets and can recognise and generate text, among other tasks.

### **RNN (Recurrent Neural Network)**

A recurrent neural network (RNN) is a deep learning model trained to process and convert a sequential data input into a specific sequential data output.