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Doctoral Dissertation

ARTIFICIAL INTELLIGENCE IN SMART LEARNING ENVIRONMENTS: AN OVERVIEW AND CASE STUDIES

Eleni A. Dimitriadou

Limassol, March 2024

CYPRUS UNIVERSITY OF TECHNOLOGY

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DEPARTMENT OF MULTIMEDIA AND GRAPHIC ARTS

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Approval Form

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Limassol, March 2024

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«*.. And if you find her poor, Ithaka won't have fooled you.*
Wise as you will have become, so full of experience,
you will have understood by then what these Ithakas mean.»

Constantine P. Cavafy (1863 – 1933)

This doctoral dissertation is not just the fruit of my personal effort, but it is also the result of the constant support of some very important people. Thus, I would like to thank these people from the bottom of my heart and say how fortunate I feel to have had them by my side to help me during this process. I would like to thank my supervisor Dr. Andreas Lanitis from the Department of Multimedia and Graphic Arts at Cyprus University of Technology who supervised me throughout my work. With his guidance, his useful advice and his emotional support I was able to conclude this dissertation. I would like to thank him, in particular, for his support at difficult times as well as for his immediate response when I needed his help.

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ABSTRACT

This thesis provides a review of research work on smart classroom technologies, with a focus on emerging and Artificial Intelligence (AI)-related technologies. Smart classroom technologies related to the effective class management that enhance the convenience of classroom environments, the use of teaching aids during the educational process and the use of performance assessment technologies are presented. Apart from discussing the range of technological achievements in each of the aforementioned areas, the role of AI in smart learning environments is thoroughly discussed. Furthermore, the development of two automated artificial intelligence systems that aim to address modern education issues and enhance the professional skills of educators are presented.

The first system aims to maximise the interaction between educators and students during tele-education, by monitoring the actions of the students in online courses while protecting as much as possible students' privacy. In addition, as an attempt to assist educators to improve their teaching style, a second system that assesses the body language of educators was developed. Furthermore, the operation, role and impact of these two proposed systems was assessed with comprehensive quantitative and qualitative evaluations. Conclusions derived from this thesis indicate the acceptance of stakeholders for AI-based systems that can facilitate the educational process through the provision of tools that enhance the educator-student interaction, and tools that help educators improve their teaching style.

Keywords: *Artificial Intelligence, Emerging Technologies, Smart Classroom, Student Action Recognition, Teaching Style Assessment.*

LIST OF PUBLICATIONS

A large body of work presented in this thesis has already been published in journals and conferences.

- Anastasiadou, Z., Dimitriadou, E., & Lanitis, A. (2024). Design and Evaluation of a Memory-Recalling Virtual Reality Application for Elderly Users. *Multimodal Technologies and Interaction*, *8*(3), 24.

- Dimitriadou, E., & Lanitis, A. (2023). Student Action Recognition for Improving Teacher Feedback During Tele-Education. *IEEE Transactions on Learning Technologies*, vol. 17, pp. 569-584, 2024, doi: 10.1109/TLT.2023.3301094.

- Dimitriadou, E., & Lanitis, A. (2023). A critical evaluation, challenges, and future perspectives of using artificial intelligence and emerging technologies in smart classrooms. *Smart Learning Environments*, *10*(1), 1-26.

- Dimitriadou, E., & Lanitis, A. (2023). A Systematic Approach for Automated Lecture Style Evaluation Using Biometric Features. *20th International Conference on Computer Analysis of Images and Patterns.* Springer

- Dimitriadou, E., & Lanitis, A. (2023). Evaluating the potential of using automated action recognition for monitoring student activity in tele-education. In *INTED2023 Proceedings* (pp. 3605-3609). IATED.

- Dimitriadou, E., & Lanitis, A. (2022, June). The role of artificial intelligence in smart classes: A survey. In *2022 IEEE 21st Mediterranean Electrotechnical Conference (MELECON)* (pp. 642-647). IEEE.

- Kontos, M., Dimitriadou, E., Ioannou, L., Lanitis, A. (2022). An Integrated Approach for Visualizing Student Activity During Distance Education. In 14th Cyprus Workshop on Signal Processing and Informatics (CWSPI)

- Dimitriadou, E., & Lanitis, A. (2022). Using Student Action Recognition to Enhance the Efficiency of Tele-education. In *VISIGRAPP (5: VISAPP)* (pp. 543-549).

- Dimitriadou, E., & Lanitis, A. (2021). Student action recognition as a means of supporting remote learning. In *ICERI2021 Proceedings* (pp. 8175-8180). IATED.

Furthermore, during my Ph.D. studies the following articles have been submitted, and they are currently under review.

- Dimitriadou, E., & Lanitis, A. (2024). An integrated framework for developing and evaluating a lecture style assessment methodology. *Multimedia Tools and Applications* (under review). Available at arXiv : *https://doi.org/10.48550/arXiv.2312.00201*

- Dimitriadou, E., & Lanitis, A. (2024). Evaluating the impact of an automated teaching style assessment system. *Education and Information Technologies* (under review).

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LIST OF ABBREVIATIONS

AI:	Artificial Intelligence
AIED:	Artificial Intelligence in Education
AR:	Augmented Reality
CAVE:	Cave Automatic Virtual Environment
ChatGPT:	Chat Generative Pre-trained Transformer
CNN:	Convolutional Neural Networks
DT:	Digital Twin
ELE:	Explanatory Learning Environments
HMDs:	Head-mounted displays
IoT:	Internet of Things
ITS:	Intelligent Tutoring Systems
LA:	Learning Analytics
LMS:	Learning Management Systems
ML:	Machine Learning
MCC:	Matthews Correlation Coefficient
MAE:	Mean Absolute Error
MR:	Mixed Reality
NLP:	Natural Language Processing
RMS:	Root Mean Square
TSA:	Teaching Style Assessment
VR:	Virtual Reality

Chapter 1

Introduction

Artificial Intelligence (AI) has emerged as a transformative force, demonstrating remarkable potential in revolutionizing education. Within the realm of learning, AI stands as a powerful tool reshaping the dynamics of teaching and learning. Through its unparalleled capacity to analyze vast data sets, personalize learning experiences, and expedite decision-making processes, AI holds the promise of crafting a more adaptive and efficient educational landscape (Alam, 2021). AI integration in education, marks a shift towards a student-centric approach, empowering educators to address individual needs and preferences in unprecedented ways, ushering in an era where tailored learning experiences become the norm. This amalgamation of technology and education isn't just about enhancing traditional methods; it's about creating a finely tuned ecosystem where learning experiences are uniquely crafted for each learner, representing a significant stride towards a more inclusive, personalized, and effective educational paradigm.

The objective of this thesis is to delve into the vast possibilities that arise from the application of automated AI systems in education. By conducting an in-depth investigation, this study aims to explore how AI can be leveraged to enhance the teaching-learning process, foster student engagement, and optimize educational outcomes. The study analyzes the impact of AI applications in education and propose innovative ways to integrate AI systems effectively into various educational contexts. In this thesis, the following topics were addressed: (1) the use of AI and emerging technologies in the context of smart classrooms; (2) the development and evaluation of an AI-based system for recognizing students' actions during online courses; and (3) the development and evaluation of an AI-based educator performance assessment tools that provide instant feedback to educators. We mainly focus on these aspects because it is an important step towards understanding the role of artificial intelligence in education and the acceptance of automated systems by stakeholders. In the following sections, we elaborate on each of the topics considered in this thesis.

1.1 Artificial Intelligence and Emerging Technologies in Smart Classrooms

The concept of "Smart Classroom" was first proposed by Rescigno (1988) in relation to the classroom use of several technologies that flourished during the eighties, such as personal computers, video programs presentation, the use of closed-circuit television, and the use of networking facilities. Through the years the meaning of a "Smart Classroom" evolved to reflect technological advances. Recently, Micrea et al. (2021) state that a smart classroom is based on devices of automated communication and mobile learning, mobile technologies, video projectors, sensors, cameras, facial recognition algorithms and other modules controlling different physical environment parameters. Based on the latest technological developments, in this dissertation we define a smart classroom as an integrated learning space that combines Artificial Intelligence (AI) and emerging technologies to offer an intelligent learning space either in-class or remotely. Emerging technologies are defined as the most impactful and recent technologies of our era (Have et al., 2021) while "Artificial Intelligence" (AI) is defined as the ability of computer systems to do human tasks (like learning and thinking) that frequently can only be attained with the use of human intelligence (Sadiku et al., 2022).

This dissertation provides a review of research work on smart classroom technologies, with a focus on emerging and AI-related technologies. A wide range of smart-class technologies that belong to the three main pillars of "Class Management", "Teaching Aids", and "Performance Assessment" are presented, while attention is focused on existing and future applications of AI in smart classes, enabling the readers to gain an insight related to the opportunities and challenges involved in applying AI in smart classes. Previous surveys related to smart classes include the work of Saini and Goel (2019), who focus on technologies related to smart content preparation and distribution, smart student engagement, smart assessment, and smart physical environment. While this survey has some similarities to our approach, in our case we focus our attention on the use of AI in conjunction with emerging technologies in a smart class environment. In a more recent survey Li and Wong (2021) present application domains, research issues, research participants, learning devices or tools, learning environments and learning features, which were found in 90 studies related to smart classrooms. Unlike the current work, the work of Li and Wong (2021) is directed towards educators, to help them understand their role in smart learning practice. Spector et al. (2014) point out the significance of technological advancements into the introduction of innovative learning approaches, and hence divide smart learning environment foundations into three main cores, philosophical, phycological and technological. These fields contribute into the creation of an effective, adaptive and innovative learning environment with the aim to develop the mindset of students. In addition, Tabuenca et al. (2021) state that a smart learning environment includes both the students and the educator as it gives them the opportunity to exploit technological tools in order to execute their tasks.

The purpose of the dissertation is to provide complete research on the emerging technologies and the use of AI in smart classes. The material presented in this thesis can be useful for researchers in educational technology and educators, but most importantly it is useful for researchers related to emerging technologies and AI, as information about the existing systems and prospects for future developments are outlined.

Having conducted thorough research in the existing literature including the most recent articles, it was found that the use of artificial intelligence in combination with emerging technologies in the context of the smart classroom has not been thoroughly presented and analyzed. Most researchers focus on a particular technology and theory and conduct their research on it, while in our study the full spectrum of technologies and methods used in education is presented. Moreover, these technologies are analyzed in detail and also insights of the use of AI are given regarding the way researchers could proceed utilizing these tools to deal with the challenges that arise from AI in education and find new perspectives.

Based on the literature, a significant number of limitations of AI were identified. In correlation to the limitations of existing AI-based educational systems, two topics that need further investigation were identified. The topic of enhancing interaction between educators and students in on-line class delivery, and the topic of automated educator performance evaluation. These topics were further investigated in this thesis by considering relevant case studies.

1.2 AI-based system for recognizing students' actions during tele-education

The term "Teleconferencing" refers to the use of telecommunications technology to conduct meetings or conferences between individuals or groups located at different locations (Katsika, M., 2019). It allows students and educators to communicate in real-time through audio, video, or text-based channels, facilitating collaboration and remote interactions. In relation to the problems of teleconferencing, and more specifically in relation to student concentration and academic performance, many studies have been published in this field (especially since the outbreak of COVID-19) (Rees-Jones et al., 2021). This shows how the pandemic had a very strong negative impact on student learning. As a result, active learning techniques turned out to be absolutely crucial for bringing online teaching back up to speed. The lack of such techniques was linked to poor results, and the impact was not restricted to certain age groups.

According to Cellini et al. (2021) students do worse in online coursework than face-to-face classrooms. This is particularly true for less academically prepared students and bachelor's degree seekers. Course completion rates declined during the transition to teleconferencing forced by the pandemic, and students with poorer academic skills were more negatively impacted by teleconferencing environments. Walters et al. (2021) looked into the unique problems faced by secondary school students caused by COVID-19. This study pointed out that the transition to teleconferencing diminished students ' focus and dedication, which led to a decline in academic achievement and self-esteem. It is interesting to note that the negative effects of teleconferencing were more severe among students with learning disabilities (Walters et al., 2022).

A major issue related to teleconferencing is the level of concentration of students during the course delivery process (Moubayed et al., 2020). This is especially true for primary school students, who find it more difficult to concentrate and attend a class delivered online (Putri et al., 2020). To make the situation worse, in many countries the use of cameras during the delivery of online courses to primary school students is forbidden as a means of preserving student privacy, and since the educator has no optical contact with the students, it is very common that student's lose concentration during the course delivery process.

To deal with this problem, a machine vision-based approach for monitoring student's actions during the class delivery process and report to the instructor the status and level of concentration of the students was developed. An important aspect of this approach is that images of students captured during the process are processed locally and only information about the actions of the students is transmitted to the instructor so that privacy issues are not violated. When the proposed system is used in real classes, it is assumed that both parents and students should give their prior consent, ensuring that no ethical considerations related to privacy protection arise.

Several researchers addressed the problem of automated student attendance registration. Li et al. (2019) describes the use of four cameras, to record the students' actions from various viewpoints. Unlike the work of Li et al. (2019), in our work we use images captured from a single laptop camera rather than employing multiple fixed cameras. Recently, Rashmi et al. (2021), proposed a system, that recognizes multiple actions of students given an image frame captured by a CCTV camera. While this study is related to our work, in our study we recognize the actions of a student in a single image frame during the online courses using a camera pointing at each student. The work of Bian et al. (2019), is closely related to our work since they consider the problem of facial expression recognition during the delivery of on-line courses. In our work, instead of focusing on the analysis of facial expressions, we consider the recognition of actions that relate to the physical presence (Raddon, 2006), active participation (Pratton and Hales, 1986), and distraction (Baron, 1986) as indicated in the relevant literature.

Although the recognition of student's actions has been addressed in the literature before, to the best of our knowledge, the proposed formation of the application within the domain of teleconferencing has not been considered before. The study is distinguished by its originality and innovation compared to previous approaches. The primary differences include:

- The proposed method provides educators with information solely concerning students' actions during online lessons, ensuring a targeted and precise approach to instructional feedback while protecting students’ privacy as much as possible.
- The proposed method introduces an automated, real-time feedback system for individual students while concurrently benefiting the entire class. This dual functionality promotes an efficient and dynamic teaching-learning process.
- This method provides 3D view of the classroom where every student is represented by an animated avatar that demonstrates their activity.
- Notably, the proposed method demands minimal computational resources and lacks the need for specialized equipment. It relies solely on the educator's and students’ personal computers, ensuring accessibility and ease of implementation across diverse educational settings. This streamlined approach prioritizes practicality without compromising the effectiveness of the feedback system.

1.3 AI-based educator performance assessment

Another issue examined in this thesis is the performance assessment of educator. The term "educator" encompasses educators across all levels of education, from kindergarten to postgraduate, including K-20. Performance assessment of educator is pivotal in maintaining high quality teaching style during lectures. Feedback related to teaching style can empower self-reflection and improvement allowing educators to become more efficient in lecture delivery. However, in most cases the provision of feedback related to teaching style quality is based either on peer observation or student evaluations that do not provide frequent, objective, and continuous feedback, hence automated lecture style quality estimation can prove highly important for this task.

Few systems that use automated approaches to assess lecture quality and/or educator’s body language are reported in the literature (Barmaki and Hughes 2018; Zhu et al., 2022). Barmaki and Hughes (2018) describe an automated educator body language evaluation system designed to detect and provide feedback on non-verbal "closed" gestures prevalent in virtual teaching sessions. In relation to our proposed system, Barmaki and Hughes (2018), require specialized equipment (Kinect sensor) to evaluate educators' body language. Unlike the above studies, Zhao and Tang (2019) use a neural network with student evaluations and teaching team assessments as input data, in order to evaluate teaching quality.

Furthermore, there are several applications available for evaluating speaking or lecture performance, albeit indirectly. The "VirtualSpeech" app assists in practicing public speaking with features like voice analysis [1]. "SmallTalk2Me" is an AI-powered simulator for enhancing spoken English which might aid in evaluating educator's language proficiency [2], while the "Voice Analyst" app offers real-time and remote voice analysis for evaluating vocal aspects of educator's performance[3]. However, those applications do not offer automated educator body language assessment. The non-existence of a teaching style evaluation application that combines indicators derived from both verbal and non-verbal body language highlights a research gap that can be fulfilled by our work.

In this thesis, an innovative method for assessing the educators' body language during teaching was developed. The innovation comes from the use of multitude biometric features (such as facial expressions, body activity, speech, hand movement, and facial pose), and their processing in real time. As the proposed methodology requires only a standard personal computer, it provides an affordable and convenient way for educators to get immediate feedback regarding their teaching style.

In comparison to previous research work and available applications, this study has an innovative nature that makes it unique among all similar existing solutions. When compared to existing research work reported in the literature, the main differences of the proposed approach are:

[1] https://virtualspeech.com

[2] https://smalltalk2.me

[3] https://speechtools.co

- The system provides a generic operation allowing the application to lectures of different thematic areas, and languages.
- A wide range of quality indicators utilize to provide a total lecture style quality based on both verbal and non-verbal features.
- The proposed application operates in real time without the need for dedicated equipment (i.e. movement sensors, dedicated cameras or dedicated lighting). The only hardware requirements for running the application is a general-purpose PC, and the existence of a web-camera and a microphone.
- Feedback provided to educators presents in a way that allows self-reflection and improvement.
- Apart from the usability and feature extraction accuracy of the system, the impact of using the application in improving educator's teaching style was defined, documenting in that way the added value of the system.
- For the first time a comprehensive performance evaluation framework that includes comparison with performance of humans for the task of automated lecture style quality estimation is presented.

When compared to existing applications available, the main differences are:

- Unlike existing apps that focus primarily on speech and vocal analysis, the proposed application would consider lecture style quality indicators derived from both verbal and non-verbal features.
- In contrast to existing tools, the proposed application have the ability to operate in real-time to assess educators in real time.
- Our system presents a customized solution for educators, rather than being a generic public speaking improvement tool.
- Through its targeted design, the proposed system delivers automated, holistic feedback to help educators improve their overall lecture delivery performance.

Given the above this study have a significant innovative nature that make it stand out from any existing experimental or commercial solutions currently available.

1.4 Purpose of the Study

The aim of this work is to investigate the role of AI in education along with advantages and disadvantages of its implementation, which will shine a light on obstacles that need to be overcome for AI to reach its maximum potential in smart educational environments. The ultimate aim is to help stakeholders in all levels of education – students to learn faster, more efficiently, and educator to better understand their students. As part of the work, pilot AI-based educational applications were developed, and following an evaluation process the impact and acceptance of those applications was assessed. In summary the main objectives of this dissertation are:

- To investigate the current situation with the use of AI in classrooms.
- To identify gaps/needs for improvements.
- To develop novel AI-based approaches for case studies and to evaluate their impact on the educational process. Case studies include the recognizing students' actions during online courses and educator performance assessment tools.
- To assess the acceptance of the proposed technologies by stakeholders.

A block diagram of the overall structure the work carried out is shown in Figure 1.1.

The work carried out can is divided into five main phases as exemplified in the following below:

Phase I: Identifying and understanding the needs of students and educators.

The first phase is the foundational step, which incorporates an in-depth literature evaluate. This phase isn't always restrained to theoretical analysis. In order to determine the needs of students and educators, the latest technological developments were analyzed, using questionnaires, interviews with educators, students and parents.

Phase II: Design of Educational Applications

Building upon the educational framework established in the previous phase, Phase II is centered around the design of educational applications based on the stakeholder needs. These applications are uniquely tailored to meet the needs identified earlier.

Phase III: Development of AI Applications and Data Collection

This section is devoted to the actual development of AI systems, regarding elaborate strategies along with coding, checking out, and refining AI algorithms. In this phase, pilot AI-based applications for the problems considered were developed and relevant data was collected for training the AI based algorithms. This phase involves training of suitable Machine Learning models and implementation of pilot applications.

Phase IV: Assessment of AI Applications

Phase IV, focuses on the analysis of the impact and benefits of the AI applications developed for the case studies considered. In the last phase, the impact of AI-based applications was assessed so that conclusions related to the suitability and efficiency of the proposed applications are derived. The evaluation stage includes both quantitative evaluation, and user evaluation.

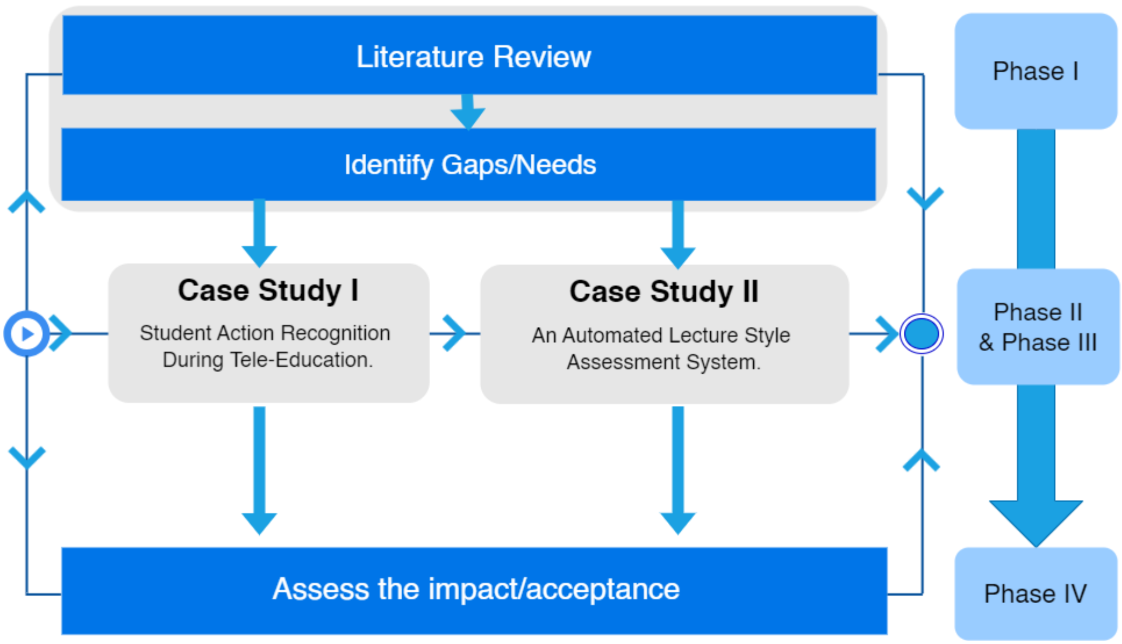

Figure 1.1: Thesis Structure.

1.5 Contribution, Innovation and Impact of the proposed work

The proposed study is innovative as it:

a. Provides a comprehensive review of research work on smart classroom technologies under one umbrella, with a focus on emerging and AI-related technologies that targets a multidisciplinary research audience that includes Researchers/Developers related to Emerging Technologies, AI-related Researchers (Machine learning, computer decision, signal processing), researchers in educational technology and Educators.

b. Uses advanced AI techniques to monitor student activity during tele-education, contributing in that way to enhanced interaction between an educator and a remote class. This feature is particularly innovative as it addresses the growing need for effective teleconferencing solutions, which has become increasingly relevant in the wake of recent global educational shifts.

c. Introduces AI algorithms capable of analyzing and interpreting educator body language, a relatively unexplored area in educational technology. This innovation lies in the system's ability to provide real-time feedback to educators, enhancing their non-verbal communication skills, crucial in both physical and virtual environments and classrooms.

Apart from being innovative, this study aims to have a practical impact on the teaching profession through the evaluation of educators' body language and also through the use of applications that inform the educator about the level of students' concentration in online courses. These prototype tools provide increased opportunities for educators to refine their teaching methods, adapt to various learning environments, and foster more effective student-educator interactions. By facilitating a deeper understanding of non-verbal cues and student engagement, these AI-driven tools can significantly enhance the quality of education delivered. This study, with its focus on innovation and practical application, not only contributes to the field of educational technology but also has the potential to transform the dynamics of teaching and learning in the digital age.

1.6 Research Questions

The research questions considered are related to the acceptance and impact of the systems developed as part of the two case studies considered:

- *Case Study I: The use AI based teleconferencing methods that protect privacy and support educators.*
- *Case Study II: The development of smart educator performance assessment methods.*

The primary aim of this study was to develop systems and assess their performance to achieve the research objectives effectively. In particular, this thesis involves the development of two innovative/contemporary systems. Furthermore, this study describes an innovative, rigorous and systematic methodology for assessing the performance of the systems developed. As part of this methodology, test data were collected as no suitable datasets were available. In the case of the first case study, the classification accuracy of the proposed system was evaluated while in the second case study, in addition to the performance evaluation of the system, the human performance was compared with the performance of the proposed system. Furthermore, the following RQ's are examined which are related to the acceptance and impact of the systems developed as part of the two case studies considered.

In relation to Case Study I the following Research Questions were formulated:

RQ1: How learners, educators and parents *perceive* the feasibility of using privacy-protecting methods for monitoring student actions during tele-education ?

RQ2: How is the acceptance of using privacy-protecting methods for monitoring student actions during tele-education *perceived* by the learners, educators and parents?

RQ3: How learners, educators and parents *perceive* the impact of using privacy-protecting methods for monitoring student actions during tele-education?

In relation to Case Study II the following Research Questions were formulated:

RQ4: Can this application potentially contribute to the improvement of the educators' teaching style?

RQ5: Does the application provide sufficient feedback regarding the teaching style of educators?

RQ6: Is the use of this application feasible in actual classroom conditions?

1.7 Structure of thesis

The current thesis is structured as followed:

- **Chapter 2:** *Literature Review*. This chapter examines the uses of AI and emerging technologies in the context of the smart class. Apart from the detailed analysis of these technologies, this chapter gives insights into the use of AI and on how researchers could proceed utilizing these tools in order to deal with the challenges that arise from AI in education and find new perspectives.
- **Chapter 3:** *Student Action Recognition During Tele-Education*. This chapter presents an integrated system that could contribute to resolves the problem of the active participation of students in online classes. This application focuses on the improvement of the interaction between educators and students. Moreover, this chapter examines the feedback and the approval of this application by students, parents and educators.
- **Chapter 4:** *An Automated Lecture Style Assessment System.* This chapter presents all stages of the development of an integrated system in which educators could be assisted to improve the style and the quality of their lecture delivery. Furthermore, this chapter contains the performance evaluation of the proposed teaching style assessment tool described in Chapter 4, including also a comparison of the performance of the system against the performance of human observers in the same task. Furthermore, this chapter includes an assessment of the impact of the application by stakeholders.
- **Chapter 5:** *Conclusions and Future Works*. In this chapter a summary of the main findings regarding the inquiries of the research as well as the limitations of this study, future plans and conclusions are presented.

Chapter 2

Literature Review

The term "Smart Classroom" has evolved over time and nowadays reflects the technological advancements incorporated in educational spaces. The rapid advances in technology, and the need to create more efficient and creative classes that support both in-class and remote activities, have led to the integration of Artificial Intelligence and smart technologies in smart classes. In this chapter we discuss the concept of Artificial Intelligence and Emerging Technologies in Education and present a literature review related to smart classroom technology, with an emphasis on emerging technologies such as AI-related technologies. As part of this survey key technologies related to smart classes used for effective class management that enhance the convenience of classroom environments, the use of different types of smart teaching aids during the educational process and the use of automated performance assessment technologies are presented. Apart from discussing a variety of technological accomplishments in each of the aforementioned areas, the role of AI is discussed, allowing the readers to comprehend the importance of AI in key technologies related to smart classes. Furthermore, through a SWOT analysis, the Strengths, Weaknesses, Opportunities, and Threats of adopting AI in smart classes are presented, while the future perspectives and challenges in utilizing AI-based techniques in smart classes are discussed. This survey targets educators and AI professionals so that the former get informed about the potential, and limitations of AI in education, while the latter can get inspiration from the challenges and peculiarities of educational AI-based systems.

Shorter versions of the literature review presented in this chapter are also available in Dimitriadou et al. (2022;2023).

2.1 Introduction

The term “S.M.A.R.T” Classroom stands for Showing, Manageable, Accessible, Real-time Interactive, and Testing (Huang et al., 2019), and refers to a setting where the physical space is infused with carefully constructed digital tools and resources to encourage student connection on various social levels, enhance face-to-face interaction in real-time, and record the collective knowledge of the entire class (Lui & Slotta, 2014). The concept of “Smart Classroom” was first proposed by Rescigno (1988) in relation to the classroom use of several technologies that flourished during the eighties, such as personal computers, video presentations, closed-circuit television, and networking. Through the years the meaning of a “Smart Classroom” evolved to reflect technological advances. For example in the recent years, Micrea et al. (2021) state that a smart classroom is based on devices of automated communication and mobile learning, mobile technologies, video projectors, sensors, cameras, facial recognition algorithms and other modules controlling different physical environment parameters, while Pishiva et al. (2008) state that “Smart classrooms integrate voice-recognition, computer-vision, and other technologies, collectively referred to as intelligent agents, to provide an online education experience similar to a traditional classroom experience”. The role of educators in the smart classroom is to enhance students' performance, creative and thinking skills (Palanisamy et al., 2020) while also using new teaching methodologies such as social learning, mobile learning, ubiquitous learning (Chen et al., 2016). Although a smart class combines technology with other elements, such as teaching strategies and classroom models, in this dissertation we focus our attention on the technological dimension of a smart class. A clear trend in the evolution of the smart classroom concept is attributed to the introduction of Artificial Intelligence (AI) in combination with emerging technologies in the form of mobile, interactive, and remote computing in physical and/or virtual environments.

Based on the latest technological developments, in this study we define a smart classroom as an integrated learning space that combines artificial intelligence and emerging technologies to offer an intelligent learning space either in-class or remotely (see Figure 2.1). Emerging technologies are defined as the most impactful and recent technologies of our era (Have et al., 2021). Furthermore, we focus our attention on emerging technologies exploited in educational environments such as the Internet of Things (IoT), virtual/augmented/mixed reality technologies, robotics, metaverse, e-learning platforms, high-tech display screens, smart student performance evaluation tools, and on recent pedagogies that include the concepts of flipped/virtual classroom.

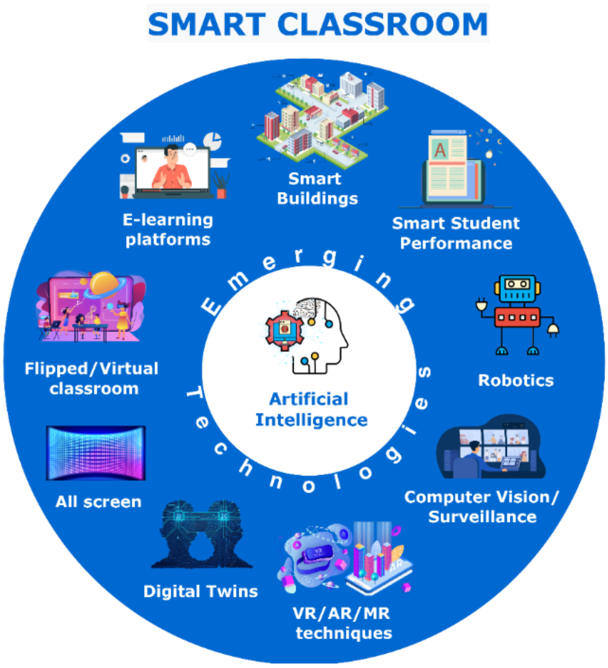

Figure 2.1 : The main technologies encountered in a smart classroom.

The term "*Artificial Intelligence*" (AI) was first mentioned by John McCarthyin in 1956 and refers to the ability of computer systems to do human tasks (like learning and thinking) that frequently can only be attained through human intelligence (Sadiku et al., 2021). From the 1970s, the specific field of Artificial Intelligence in Education (AIED) has begun to influence the application of technology to instruction and learning, in an attempt to improve the learning process, and promote student achievements (Southgate et al. 2019). The aim of AIED is to establish AI-powered systems such as virtual pedagogical agents, AI robots and intelligent systems which allow flexible, engaging and personalised learning as well as to automate daily tasks of teaching (e.g. feedback and assessment) (AlFarsi et al., 2021). The last few years, the topic of AI has been empowered by the groundbreaking technology of deep learning (Sejnowski, 2020) that allowed the successful application of AI to several complex machine learning tasks. For the introduction of AI in education two major associations, the AAAI (https://aaai.org/) and CSTA (https://csteachers.org/), have presented their vision of introducing AI in education in the form of "The 5 great ideas in AI" (Touretzky et al., 2020). The five ideas expressed include the: Perception of the world with the use of sensors, knowledge representation and reasoning, learning in the form of machine intelligence, human-machine interaction, and social impact.

In order to provide readers with an understanding of the main issues related to the introduction and use of AI empowered tools in education, the following topics are covered:

- Review of the latest technologies and discussion of future directions that could support the creation of a next-generation smart classroom.

- Presentation of the new opportunities that a next-generation smart classroom may provide, along with a discussion regarding the most significant advantages, disadvantages and limitations of existing smart class technologies.

- Understanding the use of AI in connection to the technologies used in a smart classroom, allowing the readers to get acquainted with the use of AI in most aspects of a smart educational process.

This literature review provides a comprehensive review of research work on smart classroom technologies under one umbrella, with a focus on emerging and AI-related technologies that targets a multidisciplinary research audience that includes Researchers/Developers related to Emerging Technologies, AI-related Researchers (Machine learning, computer decision, signal processing), researchers in educational technology and Educators. Table 2.1 provides information of how professionals from the target audience, from different specializations, and backgrounds can benefit from this survey.

Table 2.1 : Target Audience.

Target Audience Category	Benefits From This Survey
Researchers/Developers related to Emerging Technologies	· Learn about existing and novel applications of emerging technologies in education. · Get inspiration related to challenges and future trends of emerging technologies in contemporary learning environments.
Researchers/Developers AI-Related Researchers (Machine learning, computer decision, signal processing)	· Learn about existing use of AI education applications. · Learn about future possibilities of applying AI in combination with emerging technologies for the acceleration of innovation in education.
Researchers in educational technology	· Identify the research gaps related to educational technology. · Suggest future directions for further research in the area of educational technology.
Educators	· Get informed about the latest trends in educational technology in smart classes. · Understand better the use of innovative technologies, consider them as a powerful tool and thus, be able to apply contemporary approaches in their teaching practices.

In the remainder of the chapter, we present a literature review for studies related to smart classes and AI in education (Section 2.2), and present smart classroom technologies related to classroom management, teaching aids, and performance assessment (Section 2.3). In Section 2.4, we describe the advantages, and disadvantages of smart classroom technologies. In Section 2.5, we elaborate on the role of AI in smart classes, followed by a discussion and possible future research directions related to smart classrooms.

2.2 Related Studies

In this section, related articles that focus on smart classes, and AI in education are discussed.

2.2.1 Smart Classes

Previous studies regarding smart classrooms have contributed to a better understanding regarding the impact of technology on teaching and learning and the factors related to the acceptance and implementation of information technology by educators and students. However, in most cases existing smart class technology studies focus on a single perspective and do not provide a holistic review of the wide range of technologies adopted in smart classrooms. For example, Leon et al. (2017) explored only the design and development of an interaction system in order to be implemented in a smart classroom. The proposed system uses different interaction strategies based on touch, gesture and gesture on interactive surfaces. Gallagher and Sixsmith (2014) tried to specifically understand how IT undergraduates may be engaged in non-IT content by adopting an eLearning information system in the classroom. Raman et al. (2014) investigated the particular factors that are related to technology acceptance on smart board among educators; smart boards were also the focus of a research conducted by Martin, Shaw and Daughenbaugh (2014), who explored their use in elementary school classrooms. Zhang et al. (2019) reviewed existing surveys regarding the integration of assessment, pedagogy, and technology in a smart classroom.

Although the above research studies are important for understanding the main concepts related to smart classrooms, they do not provide a holistic view of all technologies involved in smart classrooms. Hence, it is essential to discuss such studies under one umbrella, which is the aim of this chapter. In a more recent survey Li and Wong (2021), analysed application domains, research issues, research participants, learning devices or tools, learning environments and learning features, which were found in 90 studies related to smart classrooms. The study of Li and Wong (2021) is directed towards educators, to help them understand their role in smart learning practice and the use of smart learning technologies and allow them to cope with learner needs. As a result, in the survey, Li and Wong present only the patterns and trends of smart learning practice, in terms of aspects such as device or tool, learning environment and purpose. In contrast, the present survey aims to clarify how the effectiveness of smart classroom may be maximized by using smart learning technologies which combine online and face-to-face teaching, allowing readers to find better smart classroom solutions.

In a comprehensive survey regarding smart classrooms, Saini and Goel (2019) focus on technologies related to smart content preparation and distribution, smart student engagement, smart assessment, and smart physical environment. For each pillar Saini and Goel (2019) provide a review of different technologies and techniques used in a smart classroom and provide recommendations for future research directions. While this survey has some similarities to our approach towards the presentation of concepts related to smart classes, in our case we focus our attention on the use of emerging technologies in conjunction with artificial intelligence in smart classes. Furthermore, when compared to the article by Saini and Goel (2019), a wider range of smart technologies are presented in this chapter.

2.2.2 Artificial Intelligence in Education

Around the 1960's, Artificial Intelligence (AI) was a relatively new and emerging field, and its applications in education were limited. However, there were some notable examples of early AI applications in the education field during that time. One of the earliest AI applications in education was the "Logic Theorist" program developed by Allen Newell and Herbert A. Simon at the RAND Corporation in 1955. The program was designed to prove mathematical theorems by generating logical inferences, and it was used to demonstrate the power of AI to automate intellectual tasks. Another early AI application in education was the "STUDENT" program developed by Daniel Bobrow at MIT in the 1960's. The program used natural language processing to help students solve algebra problems. In addition to these early examples, researchers in the 1960s also explored the potential of AI for developing intelligent tutoring systems, computer-based instructional systems, and other educational technologies. While the technology was still in its early stages, these early applications laid the groundwork for the development of more sophisticated AI applications in the education field in subsequent decades (Doroudi, 2022; Finn, 1960; Papert, 1980).

Nowadays, lots of efforts are being made to incorporate AI into teaching and learning (Kim and Kim, 2022). The topic of AI and education has also gained interest in the scientific community. The number of papers is rising since 2008 (Jordan and Mitchell, 2015) and according to Bozkurt et al. (2021), by 2018 and 2019, there is a sharp increase in the number of publications on AI in education. AI can be used in education in several ways. Chatbots that interact with students (Deveci Topal et al., 2021), education software for specific fields (e.g. Mathia for mathematics), Intelligent Tutoring Systems (ITS), Dialogue Based Tutoring Systems (e.g. Chatbots that interact with students (Deveci Topal et al., 2021), Explanatory Learning Environments (ELE) and Learning Management Systems (LMS). Also, AI applications have been used to capture and analyze students' behaviors, emotions, gestures, and expressions during the education procedure. The adaptive nature of such a system is that it frequently utilizes real-time emotion/behavior signals linked to student involvement to adjust the teaching strategy and attempts to mimic human educators (Behera et al., 2020). In this developing field of study, there are several papers that cope with these issues. Some examples are the (positive or negative) climate in a classroom with automated observation (Ramakrishnan et al., 2019) or the collection of non-verbal cues of participants of online classrooms (Shingjergji et al., 2021).

In a literature review Chen, Chen and Lin (2020) state that AI has been extensively used in education in different forms. More precisely AI was used in the form of computer programs; eventually, AI transitioned to the use of humanoid robots and web-based chatbots, which assisted teaching. Moreover, platforms are being used that facilitate educators administrative work and communication with students. Chen, Chen and Lin (2020) conclude that AI may improve learners' experience and increase quality of learning. Despite the fact that they present a wide range of literature, our research focuses more on the different technologies used in class and the principles that guide them. Another literature review was conducted by Roll and Wylie (2016), who found a focus of research on the use of AI in building "faster classrooms" and achieving similar learning gains in a reduced amount of time. This paper focuses only on the technologies used to shorten the duration of learning.

Hwang et al. (2020), in a theoretical study, highlight the use of AI in education. They, postulate that AI may serve as an intelligent tutor, a smart tutee, an efficient learning tool and a wise policy-making advisor. Hence the authors suggest that AI may be used for personalized assistance and guidance for both educators and students. When compared to Hwang et al. (2020), the focus of this literature review elaborates at a greater extend in the concept of AI as a tutor and a performance assisting system, and also disadvantages and challenges of AI in education are presented. Chen et al. (2022), in their literature review, indicate the usefulness of AI in education, which may be used in the form of intelligent tutoring systems for special education, natural language processing, educational robots, performance prediction, discourse analysis, teaching evaluation, learner emotion detection and personalized learning. Despite the fact that Chen et al. (2022) presents a wide variety of literature they focus only on showing statistical results and not into elaborating more into these issues.

Ocaña-Fernández, et al. (2019) state that AI may provide students with personalized learning, which is important for their improvement. Hence, according to the authors, what is left for universities is to design programs to better train educators to develop their technological environment according to their needs. On the other hand, Chen et al. (2020) in their literature review, highlight that even though traditional AI technologies, for example language processing, have been extensively used in education, more advanced technologies are not that frequent. For this reason, the authors suggest that more research is essential, aiming to better clarify the potential of using AI in school settings and its relationship with students' learning outcomes. Similarly, Renz and Hilbig (2020) believe that further research into the potential of Learning Analytics (LA) and artificial intelligence is needed, in order to develop dynamic education routes in schools. Through our study we also specify the need of AI and its importance to education and management of the learning process.

Ikedinachi et al. (2019), in a theoretical paper, question the utilization of AI in education, based on the notion that AI benefits are unfound, while long-term issues arise regarding the relevance of educators and teaching in the modern AI form of education. Based on the Marxian Alienation theory (Cox 1998), authors criticize the efforts to present AI as the panacea for all education problems and call scholars to better search the problems related to the application of AI in education. To deal with these issues in our study we present both the benefits of using AI in education but also delve into the threats and dangers of such technologies and their impact both in students and educators as well. In contrast, Holmes, Bialik and Fadel (2019) are advocates of AI and believe that the only problem in education is what educators teach, and how they teach it. Hence, by introducing AI in education educators may teach better what they teach. Likewise, McArthur et al., (2005) answer to opponents of AI by claiming that AI and knowledge-based systems will not program students to behave in a rigid procedure neither will they assume that there is only one right answer. In contrast intelligent systems will not pretend they know everything and will not replace the educator.

2.3 Smart Classroom Technologies

In this section the key technologies related to smart classes are presented while emphasis is given to the role of AI in the technologies described. The main topics presented are separated in three main categories that refer to technologies related to effective class management that enhance the convenience of classroom environments, the use of teaching aids during the educational process and the use of performance assessment technologies. An indicative taxonomy of the technologies presented is shown in Table 2.2.

Table 2.2 : Taxonomy of Smart Classroom Technologies presented.

Classroom Management	**Teaching Aids**	**Performance Assessment**
Smart Environment Attendance Management Surveillance/Security	Robotics Natural Language Models/Generative AI Models Virtual/Augmented/Mixed Reality E-learning Platforms All Screen Flipped/Virtual/Remote Classroom Digital Twins	Student performance assessment/prediction Educator performance Assessment

2.3.1 Classroom Management

The term classroom management refers to the way or approach that educator uses to control / manage his / her classroom. Within this scope the management aims to maintain a comfortable and safe teaching environment that contributes to the efficient class delivery. For example, a smart classroom management system may allow educator to decide when to speak louder when students lose interest or the level of concentration decreases (Rytivaara, 2012) or control the student access to a classroom. In relation to class management technologies, in this survey we focus on the issues of Smart Environment, Attendance Management, and Surveillance/Security.

2.3.1.1 Smart Environment

A smart class can be considered as a dedicate type of a smart environment. According to Diedrich et al. (2017) smart environments are characterized as ubiquitous and interactive smart systems integrated in the physical environment. Augusto et al. (2013) presents another definition for the smart environment by defining it as an autonomous environment that utilizes any aspects of artificial intelligence, like robots, and generating complete and accurate functionalities that improve human life.

The term "smart" involves the application of artificial intelligence, whereas "environment" denotes the physical space (any space in our environment, such as buildings or residences). Along these lines smart buildings are described as whole structures that use existing technology resources and AI to produce a secure, functioning and friendly setting that utilizes resources wisely and economically (Dryjanski et al., 2020). Such buildings are often supplied with interrelated computing equipment including detectors, algorithms, and electronic interfaces to track smart building processes and acquire, evaluate, and generate data to enhance the building's performance as well as the protection and convenience of its residents (Taha & Elabd, 2021). Smart buildings provide numerous advantages for both users and the ecosystem, since the utilization of smart technologies allows power consumption to be reduced, repair expenses to be decreased, real-time activities to be enabled, problems to be predicted beforehand, devices to be controlled in real time, and environmental effects to be improved (Yang et al., 2021). All these variables combine to create pleasant, secure, and environmentally friendly places.

Sensor technology, the Internet of Things (IoT), external telecommunications and smartphone software technology are commonly used to power advanced technologies in smart classrooms (Wu et al., 2020). IoT technologies can offer unparalleled opportunities to students improving their lives as well as their progress. IoT employs sensors, networks, big data, and artificial intelligence technology to deliver perfect services systems (Abdel-Basset et al. 2008). Bayani & Quesada (2017), proposed an efficient intelligent cable calling system in the classroom (SCRCS – Smart Classroom

Roll Caller System) using the IoT architecture to collect or record student attendance after each period accurately and on time. The RFID tags (Radio Frequency Identification) are associated with student ID cards. SCRCS can be installed in any classroom and collectively read student IDs. It shows not only the total participation in the LED display at the beginning of any class but also the identity of all ID cards in multiple SCRCS slots (Bayani & Quesada, 2017).

Smart buildings utilize a range of sensors that are typically linked to a larger system, allowing them to collect sensitive details that are used to understand real-world circumstances and react accordingly by taking smart actions (Wolter et al., 2017). The capacity of AI technologies to forecast and identify patterns is a crucial feature; as a result, they can be flexible and cope with complicated human habits and meet their unique demands by combining data offered by IoT devices (Norman, 2007). Another important aspect is the ability to severely reduce costs via automation and optimization of procedures by using for example information about the architecture of the building, water and energy supply (Butner et al., 2019).

AI is crucial in the creation and implementation of computer applications able to control specific urban activities and operations. AI could be used to simulate and automate the generation of zoning laws, building ordinances and floodplains, combined with augmented and virtual reality (AR and VR). Real-time city-wide data on energy, water consumption and availability, traffic flows, people flow and weather could create an "urban dashboard" to optimize urban sustainability. Efficiency increases are thought to be environmentally and socially valuable for smart environments. For all these reasons, the use of AI in smart environments is essential to achieve high efficiency and automation (Inclezan et al., 2017).

2.3.1.2 Computer Vision/Surveillance

Computer Vision techniques in smart classroom are often used to help educators by analysing videos and images of students as means of acquiring important information regarding students, assisting in that way the process of class supervision during the teaching-learning process. Along these lines automated image processing and the use of cameras contributed to the computers' understanding and interpretation of visual information from video sequences and static images (Radlak et al., 2015, Bebis et al.,

2003) in order to extract important information that allow educators to get real-time feedback for each student or for the whole class (Rashmi & Ashwin, 2020). In the following sub-sectors, work related to the tasks of Attendance Registration and Action (Behaviours) Recognition applied either in class or in teleconferencing sessions, is presented.

2.3.1.3 Attendance recognition

Typically, class attendance is registered by educators based on the time-consuming process of writing down who is present or not in a classroom. Facial recognition can be utilized to implement innovative attendance systems in smart classrooms that automatically record the presence of students in classes (Kawaguchi, 2005). An automated attendance system could provide certain advantages, such as reducing the administration workload of its employees (Lukas, 2016), and minimizing the teaching time lost for registering attendances. The presence of students in class is critical in evaluating their academic achievement if students.

Several researchers addressed the problem of using AI in the form of Computer Vision algorithms for automated student attendance registration. Chowdhury et al. (2020), proposed an automatic student attendance system based on face recognition using Convolutional Neural Networks (CNN's). The proposed system can detect and recognize multiple students from real-time video stream obtained by a static camera located in a classroom, and records everyday attendance automatically. Instead of using a static camera, Mery et al. (2019) describe an automated student attendance system based on deep learning used in crowded classrooms (70 students), in which the session images are captured by a smartphone camera. Ten face recognition algorithms were evaluated, and the proposed system could detect the students faces in the picture(s) and records class attendance. Chintalapati and Raghunadh (2013), suggested an automated attendance management system based on face detection and recognition algorithms to detect the students who are entering the classroom. Instead of using a static or a mobile camera, Gupta et al. (2008), presented a Computer Vision based Unobtrusive Classroom Attendance Management System, that uses a rotating camera to capture images of the students, and a Max Margin Face Detection Technique was used for detecting students' faces. This technique is trained with the use of Inception-V3 Convolutional Neural Network (CNN) that identifies students.

2.3.1.4 Action (Behaviour) Recognition

Human action recognition is a vision-based technique that can identify a complete action performed by a human in a video sequence (Kong et al., 2018). Within this context, actions can be defined as a continuing sequence of motions that lead to a specific movement, like walking, reading a book or having a conversation. Action recognition is considered a classification problem, meaning that the action must be identified as a specific type of motion or activity and labelled accordingly. Researchers use different types of taxonomy for action recognition based for example on the recognition of the movement, the activity and the action or how an action starts, traced, how the pose is estimated and finally recognised (Poppe 2010). Action recognition is not limited only on body movements but also extends to facial expressions.

The ability to recognize human behavior can be extremely important inside a smart classroom (Wang, 2021). Student action recognition is a technique often used for analyzing student behaviour. These systems can recognize any difference in the behavior of students and their emotions, whether they feel uncomfortable or not, if they experience anxiety and report these results to educators in order to provide extra assistance to these students and avoid unwanted events inside the class. In addition, action recognition systems can analyse students' behaviour during the course and estimate their engagement (Thomas and Jayagopi, 2017). These systems can identify whether students are active or not through eye, face movements and head position and provide feedback to educators accordingly. Automated action recognition also helps students with special needs by monitoring them and warning educators for potential episodes, for example in case they have an epilepsy episode (Lau et al., 2014).

Recently, automated methods for the behaviour analysis of the students and their engagement estimation are widely utilized in a classroom. Anh et al. (2019), presented a system using computer vision techniques to monitor the behaviour of students in the classroom. Initially, various computer vision techniques such as face embedding, gaze estimation, face detection and facial landmark detection were used for data processing. Similarly, Thomas and Jayagopi (2017), used a machine learning algorithm to analyze the students' engagement in a classroom. Particularly, this study attempted to analyze students' head position, direction of eye gaze and facial expressions. Furthermore, Yang and Chen (2011), presented an automatic smart class system which was focused on eye and face detection to determine if the students were active or not.

Previous studies related to recognizing students ‘action in smart classroom include the work of Li et al. (2019) who proposed a new spontaneous actions database. The smart classroom, in this study, included round-tables for students and four cameras, which were fixed on the wall (front and back of classroom), to record the students’ actions from various viewpoints. Furthermore, they studied 15 different types of student’s actions, To evaluate the proposed model, four algorithms were tested: IDT (Improved Dense Trajectory) used with Support Vector Machines (SVM) and KNN and CNN implemented with VGG-16 and Inception V3. Recently, Dimitriadou and Lanitis (2022) proposed an action recognition system that recognizes seven actions performed by students attending online courses, which are recognized using CNN architectures. Experimental results indicated that the proposed action recognition system provides promising classification results, when dealing with new instances of previously enrolled students or when dealing with previously unseen students.

Ashwin and Guddeti (2019), demonstrated a Hybrid Convolutional Neural Network to analyze students’ body postures, gestures and facial expressions to investigate engagement. Three states of student’s engagement were examined: boredom, engaged and neutral. Rashmi and Ashwin (2021), proposed an automatic system, that monitors students’ activities in real time in a laboratory of computers in a smart campus. The aim of this study is to localize and recognize multiple actions of the students in an image frame captured by a CCTV camera. The dataset of student’s actions included the actions of sleeping, eating, using phone, discussion and being engaged. The YOLOv3 framework was used for object detection and students’ action recognition.

Bian et al. (2019), developed a database for an Online Learning Spontaneous Facial Expression (OL-SFED) regarding automatic inference of academic emotions. This OL-SFED database included five academic emotions of confusion, neutral emotion, distraction, fatigue and enjoyment. OL-SFED included videos and facial images captured from a web-camera during online courses. Facial expression algorithms for the prediction of the emotions consisted of a VGG16 algorithm and different CNN architectures together with data augmentation techniques. According to the results, CNN using data augmentation techniques achieved the best performance with an emotion recognition accuracy of 91.6%.

Similar technologies can be used for recognizing student actions in school yards. For example, suspicious actions, such as student fights, drug delivery, bullying incidents could be detected automatically allowing the prevention of mental and physical health injuries of students. Ye (2018) suggested a strategy to identify occurrences of abuse in the environment of school utilizing motion and audio sensors to evaluate activities and verbal expression. Gutierrez et al. (2014) describe a simulator named SimBully to illustrate the impact of public belief and attitudes on abuse occurrences by classmates. Ali et al. (2020) conducted a research at SUST (Shaanxi University of Science and Technology) by using YOLOv3 to recognize student behaviours such as calling, napping, or reading a book indoors or outdoors with the goal to discover any undesirable behaviours. More specifically, they predicted their movements by monitoring students' postures along with their attitude and engagement with objects based on static images, rather than using videos. In another survey Fjrtoft (2009) investigated how often kids engage in physical exercises by recording their heartbeat and tracking their position using GPS.

2.3.2 Teaching Aids

In a modern smart-classroom, the teaching process is assisted by a plethora of technological means, to maximize the engagement and interaction of students. Towards this end different types of technology in the form of robotics, virtual/augmented reality, e-learning platforms, visualization techniques, and flipped classroom, technologies are being used. In this section we provide an overview of these technologies.

2.3.2.1 Robotics

Robotics can play an important role as a key component in smart learning environments. Robots used in education can be ‘Real’ devices (Shiomi et al., 2015; Weibel et al., 2020), or they can be software agents mainly in the form of chatbots (Pereira and Juanan, 2016; Kollia et al., 2016).

2.3.2.1.1 ‘ Real ’ robots

A real robot is a device that can perform actions usually undertaken by humans. Since the introduction of the first robot back in 1980 (Johal et al., 2018) several educational animal-like or human-like robots have been presented to suit different levels of education. Educational robots constitute a subgroup of educational technology, as they are employed to make learning easier, enhance the educational performance of students (Mubin et al., 2013) and assist the students in their active participation in the process of problem solving. Educational robots are usually programmed to demonstrate the content of a subject topic interactively, and to allow students to ask questions that a robot answer. The main driving force in introducing robots in the learning process is for creating systems that offer more social interaction fitting our biological predispositions to enhance and support learning (Timms et al., 2016).

Students accept and form relationships with robots far more effortlessly because of their interaction, which has been shown to improve psychosocial and physical development (Feil-Seifer, 2009), as well as their capacity to interact, which improves the process of learning, makes it more exciting and help learners acquire more knowledge (Han, 2005). Social robots, specifically, have been successful in assisting kids with autism in comprehending concepts such as boundaries between individuals and emotional intimacy and in improving independent learning skills (Woo, 2021). Robots can become familiar with the personal needs of each student and respond accordingly (Jones et al., 2018). Another important feature of robots is their ability to record students’ expressions and mood changes. Robots not only assist students during their courses, but they are also in advance evaluating their behavior and any emotional disturbances that may suggest despair or stress (Werner-Seidler, 2017).

Examples of educational robots used over the years are summarized in Table 2.3. One of the first robots introduced in classrooms was the Logo turtle created by Papert (Johal et. al., 2018). Logo is a programming language developed by Papert and his colleagues with the intention to introduce students in programming and make math easier to understand. The robot resembled a turtle due to its round shape and had wheels necessary for its movement, while a pen was also attached at its centre in order to create drawings based on programmed moves (see Figure 2.2).

Figure 2.2 : S. Papert and his creation Logo turtle.

(Source : https://news.elearninginside.com/seymour-papert-logo-turtles-and-the-origin-of-educational-robots/).

Table 2.3 : Examples of educational robots used over the years.

Year	Robot name	Appearance	Main Abilities	Reference
1980	Logo Turtle	Animal like (turtle)	Walk, draw	Johal et al., 2018
2000	Asimo	Humanoid Robot	Walk, talk, see	Okita et al., 2009
2001	Robovie	Humanoid robot	See, hear, speak	Ishiguro et al., 2001
2004	Nao	Humanoid robot	Walk, dance, speak, see	Loos, 2015 and Kennedy et al. 2015
2006	PaPeRo	Semi-Humanoid	Speak, see, walk	Osada et al., 2006
2006	Maggie	Semi-Humanoid	Speak, see, dance	Salichs, Miguel A., et al., 2006
2007	Tiro	Humanoid	Walk, talk, see, dance	Han et al., 2009
2009	Saya	Semi-Humanoid	Speak, see	Hashimoto et al., 2011
2020	AV1	Human like	Speak, see	Weibel, Mette, et al., 2020
2020	ZenoBot	Human like	Speak, see	Pham, Tuan V., et al., 2020
Various years	Pet Robots	Animal like	Speak, dance, see	Causo, Albert, et al., 2016

Asimo is a humanoid robot created by Honda and it has been deployed by schools for learning purposes (Okita et al., 2009). It is equipped with cameras and microphones that allow it to perform face and voice recognition, while it has the ability to move items. In education it has been used as an assistant for children in both learning and communication (see Figure 2.3).

Figure 2.3 : Asimo robot

(Source : https://global.honda/innovation/robotics/ASIMO/history.html)

Robovie is a tele-operated robot that resembles a human and is able to answer students' science questions (Ishiguro et al., 2001). Since the robot was tele-operated, it could initiate discussions about class topics and thereby prompt the children to ask questions about science. The study indicated that indeed some children had increased curiosity to interact with Robovie, asking it questions about science, albeit not the entire class. Robovie's distinguishing feature is its communication system, while its sensing systems enable the development of human-like actions. Robovie R3 is the latest version used and has many additional features than the original one including chatting, playing games and hugging (You, 2006) (see Figure 2.4).

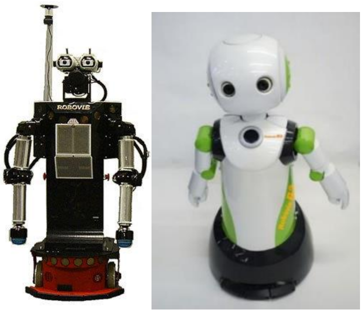

Figure 2.4 : Robovie (left) and Robovie R3 (right).

(Source : https://www.researchgate.net/figure/Humanoid-robots-Robovie-and-ASIMO_fig3_3450622).

Nao is a human like robot introduced by Aldebaran Robotics and has almost all the characteristics of a human body except the size (see Figure 2.5). One of its first uses was to assist students with writing alphabet letters and this was achieved by changing the roles and motivate students to teach the robot how to write those letters (Loos, 2015). In a study by Kennedy et al. (2015) students utilized a touch screen in order to understand prime numbers and the robot could identify their moves from the feedback it received from the screen. A large number of Nao robots have been deployed by schools and colleges around the world for educational purposes. They are used now mostly to help students with programming and they have also been used to assist students with autism.

Figure 2.5 : Humanoid robot Nao.
(Source : https://en.wikipedia.org/wiki/Nao_(robot).)

PaPeRo is a semi-humanoid robot, equipped with cameras, microphones and sensors. (Osada, 2006). It can walk around, interact and communicate with others and connect to the Wi-Fi in order to seek information to reply to questions (see Figure 2.6).

Figure 2.6 : PaPeRo.

(Source : https://www.roboticstoday.com/robots/papero-r500.)

Maggie is a robotic platform created by RoboticsLab as a social robot (Salichs, 2006). It is mostly utilized for communication purposes, as it can also speak in Spanish, and it has the ability to dance with people (see Figure 2.7).

Figure 2.7 : Maggie (Source: https://robots.ros.org/maggie/.)

Tiro is a semi-humanoid robot used for educational purposes as a teaching assistant. In particular, it presented and discussed the educational content allowing the educator to assist each student individually. Educators can access Tiro remotely and students could utilize it to learn music and English (Han, 2009 and Han et al., 2009). Some extra features are its ability to monitor student's enrollment, pay attention on time management and assist students as an instructor as well as motivating students (see Figure 2.8).

Figure 2.8 : Tiro (Source: https://www.roboticstoday.com/robots/tiro)

Saya is a tele-operated semi-humanoid robot that has been used as a teacher first in school in Tokyo (Hashimoto, 2011). It can move its head and eyes to display emotions and communicate with students and help them as an assistant. Some of the motions it can express are happiness, anger, fear and sadness (see Figure 2.9).

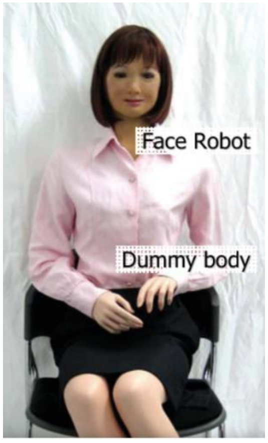

Figure 2.9 : Saya

(Source: https://www.semanticscholar.org/paper/Educational-system-with-the-android-robot-SAYA-and-Hashimoto-Kobayashi/b21e4bc21c0ca3e3a55c1ae6735ebe3c9faaa1e4/figure/0.)

AV1 is a telepresence robot with built-in camera, microphone and speaker that can be placed inside or outside the classroom and be controlled from home. In this way, students can participate in the activities that take place anywhere in the school and interact with other students, as if he/she was physically present (Weibel et al., 2020) (see Figure 2.10).

Figure 2.10 : AV1

(Source: https://onlinelibrary.wiley.com/doi/full/10.1002/nop2.471)

Another category of real robots are pet robots like Pleo, eMuu, Probo, Aibo, The Huggable, Dragonbot, Leonardo, iCat (Causo, 2016). These robots are mostly utilized as social robots, can interact with children and express emotions (see Figure 2.11).

Figure 2.11 : Pet robots

(Source: https://link.springer.com/chapter/10.1007/978-3-319-22368-1_8).

While educational robotics can be extremely useful within a class environment, their use can also extend to teaching activities for students who cannot be physically present be in class supporting in that way remote teaching activities. For example, children that are obliged to stay home or being treated at hospitals may face serious consequences regarding their social development. Thus, missing out long periods of school and social interactions with their peers, due to factors that are beyond the control of children, may result to social isolation and feeling lonely (Helms et al., 2016). To combat the above negative situation, robots may ensure that no classes and time with friends are missed, by enabling children to have a continuous connection with their educator and peers (Soares, Kay & Craven, 2017).

Initially, robots were constructed to perform repetitive tasks, without any AI. However, the importance of having intelligent machines that may perform advanced tasks eventually led to the use of a series of sensors that provide information about the environment along with the integration of AI for processing and making decisions based on the information received by the sensors (Brady, Gerhardt & Davidson, 2012, West, 2018). Typical sensors used in robotics include microphones, Time-of-flight (ToF) optic sensors and motion detectors (Ben-Ari, 2018) that can be used in conjunction with AI algorithms for sensing an environment (Poppinga et al., 2019). All of the data received by sensors is usually used to train neural network models and educate robots to execute all of their duties, from comprehending a user to effectively reacting (Thomaz, 2005). AI-based functionality incorporated in robots include speech recognition, motion control, computer vision, natural language processing, smart agent technology, movement control, and control for grasping objects.

2.3.2.1.2 Chatbots

The notion chatbot is a combination of two words: "chat" demonstrating conversation and "bot" standing for robot (Chocarro et al., 2020). Chatbots are simulating conversation with human users via the use of instant messaging services and students being facilitated as chatbots can answer questions regarding the educational material. Chatbots, demonstrate high potential as a learning teaching tool for remote students and can offer: (a) personal assistance, (b) educational content support (Colace, De Santo, Lombardi, Pascale, Pietrosanto, & Lemma, 2018) and (c) used as tutors accompanying the process of learning (Chocarro et al., 2020). Nowadays, modern messaging applications such as Facebook, SMS, Messenger, WeChat and Telegram include chatbots.

Chatbots are gaining popularity in a wide range of industries, especially education and intelligent classes. Several surveys indicated that these machines could potentially change the way pupil study, as well as how they gain knowledge (Winkler et al., 2018). Chatbots can effectively stimulate communication, engagement, provide a wide variety of resources and information via active learning and handy displays, and they may even be utilized as personal decision-making devices for educators. Chatbots are becoming increasingly popular owing to their interactive instructional approach as well as their ability to be present all the time and everywhere (Zhou et al., 2020). Most studies demonstrated that using bots in classes may offer pupil a more pleasant educational procedure through close engagement (Kim et al., 2019), enhance communication and learning abilities (Hill et al., 2015), plus boost pupil intellectual development (Wu et al., 2020).

Examples of educational chatbots used over the years are summarized in Table 2.4, while screenshots of interfaces with chatbots are shown in Figure 2.12.

Table 2.4 : Examples of educational chatbots used over the years.

Year	Chatbot name	Main Abilities	Reference or web page
2011	StuddyBuddy	Reply to questions, deliver courses	Tian, Xiaoyi, et al. 2021
2013	IBM Watson	Reply to questions, distribute material	Morrissey et al., 2013
2014	Mongoose Harmony	Reply to questions, enroll, book appointments	https://www.mongooseresearch.com/harmony
2016	Dawebot	Create quiz, reply to questions	Pereira and Juanan, 2016
2016	Botsify	Reply to questions, enroll	Lee, Jang Ho, et al., 2020
2017	Nerdy Bot	Reply to questions	Singh et al., 2019
2019	Amazon QnABot	Reply to questions	Pakanati et al., 2020
2020	Google Assistant	Reply to questions, play videos and games	Karri et al., 2020

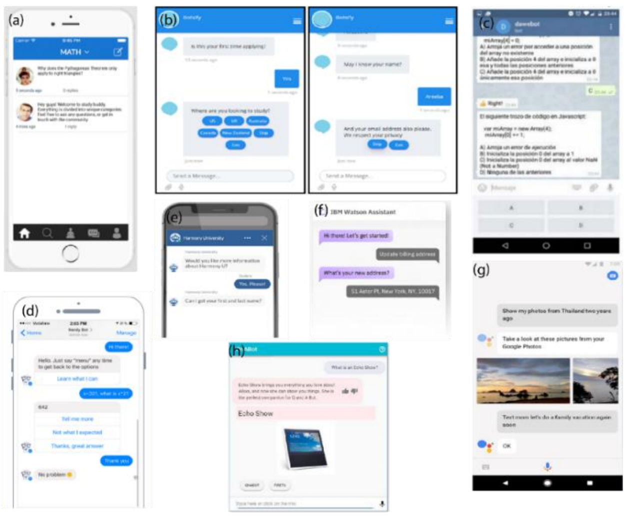

Figure 2.12 : Screenshots showing different chatbots: (a) StuddyBuddy, (b) Botsify, (c) Dawebot, (d) Nerdy Bot, (e) Mongoose Harmony, (f) IBM Watson, (g) Google Assistant, (h) Amazon QnABot.

StuddyBuddy is a software application that helps students under 12 years old with their courses, like English, History and Math. It is a teaching assistant that uses simple methods like 3 Dimensional representations, real exercises and cutting-edge technology, ensuring that every idea and information is understood. It can assist both students and educators and its interface is pretty easy to access.

IBM Watson is a chatbot produced by IBM with the ability to reply to answers (Kollia et. al., 2016). This chatbot has been deployed by many universities around the world for educational purposes due to its interactivity. It offers the ability to respond to student questions, collect and distribute files when requested and respond to queries related to the course.

Mongoose Harmony can be considered a smart chatbot created exclusively for academic purposes to support the rising demands of interaction and accessibility. It utilizes artificial intelligence to create a more personalized approach and can offer not only answers to queries but also initiate registration, schedule appointments and contact you with the appropriate person immediately.

Dawebot (Pereira and Juanan, 2016) is a chatbot used to create tests for the preparation of students for exams, provide extra material and inform educators for their performance. The quizzes usually have the form of multiple-choice questions, and the interface is pretty easy to use.

Botsify is a multipurpose chatbot that was also used in educational applications. Botsify is easy to use and helps students engage faster with their academic institution. It makes enrollment procedure automatic; it provides a more personalized learning environment where students can learn in a fun way and receive answers to their problems, allowing students to have access to the material any time.

Nerdy Bot is a chatbot developed by Nerdify and it is mostly used to execute university assignments in various disciplines, like math and history. This bot utilizes machine learning techniques and natural language processing to retrieve the information it needs in order to reply to questions. It is a study assistant that is available through Facebook Messenger making the process much easier.

Amazon QnABot is a bot developed by Amazon that combines both Alexa and Lex in order to provide an interactive interface where students can make inquires and search through content efficiently. This bot promotes the concept that students must be able to easily access the necessary information that might be extremely beneficial during the educational process. QnABot gives the ability to add extra functions and also students can express their opinion through a forum.

Google Assistant is a powerful tool that offers many benefits in education. The *Google Assistant* can answer questions and provide useful information during a course, while it can be utilized in the school libraries as well. Some other features are the ability to assist students with their homework, whether this has to do with math or history, and even help them with language tasks.

A number of researchers investigated the effectiveness of chatbots in education:

Clarizia (2018) designed and installed a chatbot in the University of Salerno's e-learning systems to assess how effectively chatbots reply to inquiries. During the term, students were required to utilize the chatbot, and only those who completed their tests were able to review it. According to the statistics, 71.13% of the students said the chatbot offered right suggestions, while 12.83% said the ideas were incorrect. Wu (2020) did a similar study in which the suggested chatbot succeeded to reply virtually like a human while also reducing students' negative sentiments.

Pereira and Juanan (2016) built Dawebot, a bot that supplied learners with tests to help them prepare for examinations. After the test, it also provided students with other sources of information and notified educators for their performance in every section of the curricula. Twenty students participated in this research and almost nine out of ten thought this type of learning is an excellent method for studying, while seven out of ten said they helped them participate and understand what they have been taught.

A significant survey has been conducted to determine the impact of chatbots in the teaching of English (Kim 2019). The study included 70 students split into two teams: those who utilized a bot for assistance and those who had a human instructor. Experiments revealed that almost all students, regardless the team they were managed to strengthen language abilities and in advance pupils who utilized chatbots outperformed their peers (by two more credits).

The primary function of chatbots is to engage with people via written language or speech. The operation of chatbots is a mix of artificial intelligence and Natural Language Processing (NLP). Natural Language Processing is a branch of artificial intelligence concerned with computers' capacity to grasp written and auditory speech in the same way that humans do (Chowdhury et al., 2003). NLP is consisted of three primary elements strongly correlated with AI, speech recognition, speech generation, which is based on AI approaches, like deep neural networks like GANs(Generative Adversarial Networks), in order to enhance the quality of the generated speech (Hsu, Po-chun, et al., 2019) and reasoning, that helps bots make predictions and draw conclusions with the aim to respond appropriately in every interaction with a human. Initially, chatbots used keyword matching techniques, which involved recognizing fundamental key phrases, determining a minimal context, picking applicable transformations, and lastly producing responses that did not include the key words (Weizenbaum, 1966). Voice interactive interfaces arose primarily as a result of breakthroughs in computer and speech recognition technology (Guttormsen et al., 2011) The Amazon Echo is an instance of a voice-interaction-based technology (Teja, 2020). It uses DNN (Deep Neural Network) to process any given dataset (e.g., in the form of arrays) and translate any language for example and Recurrent Neural Networks (RNN) as a controller.

2.3.2.2 Natural Language Models/Generative AI Models

From education to journalism and the arts, there is every reason to believe that AI technologies, and specifically, AI generative models, are changing the ways we relate to content. An AI generative model, trained on data and powered by algorithms, is an example of something that can automatically create content from text to images, code, even music, and other forms of media. In the context of education, these models serve as a tool that boosts the experience of teaching and learning. The most known example is ChatGPT among other generative AI models that are elaborated exactly to make the educational process more efficient. As observed by Brizuela and Merchan (2023), ChatGPT and such technologies have the potential to transform learning environments into personalized ones.

Chat Generative Pre-trained Transformer (ChatGPT) was released by OpenAI and has the potential to be an effective tool in education. ChatGPT has the ability to generate human-like texts, it's fast, and the text cannot be detected as plagiarism (Adheshola et al., 2023). ChatGPT has become a rather hot topic in education. Its role has been widely discussed while mixed reviews have been received regarding its potential and contribution. A recent study analyzing Twitter data shortly after ChatGPT has been released, found many positive views among users about its impact on education, highlighting potential opportunities as well as challenges (Korkmaz et al., 2023). However, there are concerns about the students' efficient assessment based on traditional methods on writing and theory. One of the studies on the subject (Singh et al., 2022), investigated the teaching application of ChatGPT, revealing its potential as a transformative tool in science education. A similar study by Dan et al. (2023) contribute to the understanding of the emerging applications and impact that ChatGPT brings in education. Despite these insights, the overall impact of ChatGPT in education still remains an evolving area of research, requiring continued research and critical debate.

In addition to ChatGPT, other AI models have furthered the knowledge of advanced education in some distinct abilities (Ijaz 2023). A couple of them are:

(a) *Jasper*: Jasper is primarily an intelligent assistant for content marketing, but it has been altered to assist students in terms of writing assignments, generating ideas for projects, and learning languages.

(b) *GPT-3 by OpenAI*: The predecessor to ChatGPT, GPT-3, has been used in the development of tutoring systems, learning modules, and even the simulation of conversations with figures.

(c) *EduBirdie*: EduBirdie is a company that uses AI to help students in their writing through giving tools that check for grammar, syntax etc.

(d) *Socratic*: Socratic is an AI tool introduced by Google. It was designed especially for assistance with students' homework or study questions. It uses intelligence in analyzing questions and even aiding in their stepwise explanation as well as providing assistance in solving problems.

These examples demonstrate the potential that generative AI models hold in transforming the realm of education. The advantages of employing AI models using customizable settings are that they can personalize the learning experience in the sense of changing content in order to suit the students' individual needs so that they can achieve their optimum potential. This way of learning would fit the varied learning styles and would lead to better involvement and understanding among the students.

Furthermore, the usage of AI models will probably aid educators to reduce their workload regarding simple tasks such as content creation, assessment marking, and feedback. These tasks can become automated by using AI. Thus, educators can have time to focus on the core parts of teaching and mentoring their students, for they are saved from doing those types of tasks. Baidoo Anu and Ansah (2023) point out how these technologies could empower learning through the generation of educational material. Lim et al. (2023) argue the way AI would shape the future of education, pointing out how it could create an inclusive educational landscape despite challenges related to integration. Generative AI models shape the future, where it enables inclusion, places experiences that are captivating, and where learning becomes personalized for each and every student. These AI models, in changing education, can provide resources that will foster growth and creativity in education.

2.3.2.3 Virtual/Augmented/Mixed Reality

Smart classrooms often incorporate virtual, augmented, and mixed reality as a means of introducing immersive learning experiences. Virtual Reality (VR) concerns the 3D simulation of an imaginary or real environment, that the user can visualize, explore and interact with it (Górski et al., 2017). The key elements of VR are summarized as the '3Is' - Immersion, Interaction, and Imagination (Cheng, 2014; Li et al., 2009) reflecting the fact that successful VR applications allow the uses to get immersed and interact in artificial environments in a way that simulates the imagination of the user. Recent developments in the VR technology have resulted in affordable software and hardware tools allowing the use of VR applications in several fields, including educational applications.

Carmigiani and Furh, (2011) defined Augmented Reality (AR) "as a real-time direct or indirect view of a physical real-world environment that has been enhanced/augmented by adding virtual computer-generated information to it". In other words, AR offers an interactive experience to users, by adding virtual information to the physical environment of the students and enabling them to use their whole body as a means of interacting with both virtual and real content (Billinghurst et al., 2015).

Mixed Reality (MR) was firstly mentioned by Paul Miligram (1994) and refers to a blending of real-world and virtual/digital world objects which are visualized together on only one display in a coherent space (Kasapakis et al., 2018). Virtual objects are more predominant in MR from physical objects instead of AR that contains more physical objects. Thus, compared to AR, which is situated in the real world, and VR, which takes place in a virtual world, MR is a hybrid form of both reality and virtual reality that combines both worlds into one user experience (Lee, 2012). MR references to as Hybrid Reality (including both AR and Augmented Virtuality) which results to the creation of mixed environments and visualizations of co-existing and interacting virtual and real objects in real-time (see Figure 2.13).

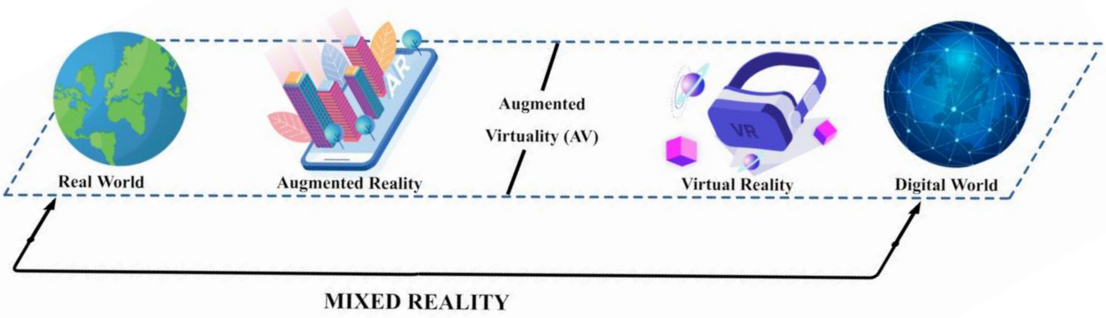

Figure 2.13 : The differences between virtual, augmented and mixed reality.

2.3.2.3.1 Virtual Reality in Education

VR can provide laboratories for students to carry out experiments in similar conditions as real laboratories where students can use their gaze, voice or gesture to interact with objects in the virtual world (Elkoubati and Mrabet, 2018). According to Sobota et al. 2017, the two techniques that are widely used to offer immersive and semi-immersive experience regarding virtual reality in smart classroom environment are: (a) CAVE (Cave automatic virtual environment) and HMDs (Head-mounted displays) and (b) Interactive school desk. CAVE constitutes a room sized pace including several projection walls where the user is able to move freely in the space and experience their body in immediate interaction with virtual scene and HMDs are suitable devices that offer virtual environment to one user every time. Furthermore, there are different VR accessories which can combine with HMDs and CAVEs, such as gloves, suits or controllers which can offer more exciting experience.

The application of VR in education changed some of the previous teaching ideas, but also some of the already existing teaching models (Chen and Tsai 2012; Gu, 2017). Several studies concluded that VR technologies are more likely to influence the motivation and academic performance of students in a positive way (Ibáñez et al., 2014; Martín-Gutiérrez et al., 2017). Furthermore, Hampel and Dancsházy (2014) argues that the creation of an environment of virtual learning is quite helpful for students, since students are able to acquire knowledge by themselves. Additionally, there is evidence that VR technologies enhance students' collaborative and communicative skills along with their cognitive and psychomotor skills (Martín-Gutiérrez et al., 2017; Zhou et al., 2008; Kaufmann and Schmalstieg 2002) whereas VR technologies can be used for the training of the educators as well (Stavroulia et al., 2016).

An important application of VR in a smart class are the Pedagogical Agents (PAs). PAs are virtual characters integrated in learning technologies. They are created to communicate with the learners in educator-like ways. They are also created to involve social and emotional reactions in realistic 3D characters. They are distinguished from the common conversational agents such as Apple's Siri, by their instructional function. Their greater asset is that they can be teachable. PAs can also be enbodied in robots in a classroom environment and develop in order to sense, interpret and stimulate the student's emotions (Papoutsi & Rangousi, 2020).

Virtual Reality can be considered a pioneer in education as it has developed an innovative method of learning. In Table 2.5 below we cite few representative works conducted in classrooms incorporating VR.

Table 2.5 : Examples of VR applications used over the years.

Year	Author	Topic	Equipment Used
2001	Mintz et al., 2001	Physics/Astronomy	Computer
2002	Knudsen & Naeve, 2002	Mathematics	Head Mounted Displays (HMD)
2008	Adams et al., 2008	Computer Science	Computer, HMD
2010	Sampaio, Alcínia Z., et al., 2010	Civil Engineering	Computer
2015	Valdez et al., 2015	Electrical Engineering	Computer, 3D Max Studio, Vray
2016	Parmar et al., 2016	STEM	Oculus Rift HMD
2018	Wong et al., 2018	Autism students	Projection Screens, Camera
2018	Blyth et al., 2018	Geography	Computer
2019	Alfalah et al., 2019	Medicine	Projector, Computer, 3D Glasses

Virtual reality has revolutionized the way astronomy and space technology are taught. Mintz et al. (2001) developed a novel immersive virtual environment that used a dynamic 3D representation of the universe. The student has the opportunity to explore a virtual replica of the external surroundings. They can expand their view and alter their standpoint, while the generated virtual environment functions normally. A major benefit of this teaching resource is the capacity to move in space and provide students with a one-of-a-kind experience.

According to Knudsen & Naeve (2002) CyberMath is a virtual environment that was developed with the aim to create an interactive exploration of mathematics. In particular, this virtual environment supports CAVE and Head Mounted Displays (HMD) and there are many different sections with exhibitions in the program, each one including a collection of mathematical structures with similar topic, while in every wall you can project material that refers to a certain topic and virtual participants can move anywhere and read the topics.

Adams et al. (2008) developed a realistic, 6 DOF VR application that provides an engaging world for students in the field of computer science. In particular, with their method they aim to attract the attention of students as many of them are accustomed to video gaming. This application was first utilized in a Computer Graphics course, where students could build a 3D apartment and also navigate to their classmates' rooms and interact with them. This made the procedure more fun and engaging for students who even showed their creations to their friends and families.

Sampaio, Alcínia Z., et al. (2010) point out the significance of VR systems in courses like Civil Engineering and Architecture introduced in universities in Portugal. VR technology could be leveraged to create educationally relevant instructional content in the field of building operations and aid in the understanding of construction-related issues. The 3D models used can assist students into monitoring possible anomalies and find different solutions.

Valdez et al. (2015) demonstrated a virtual reality application to assist electrical engineering learning. In, particular, they created virtual labs allowing students to attend them remotely utilizing VR. Through the experiments provided via labs students could undertake fundamental electronic research in this field using online circuits and equipment. The software developed had accurate 3D model representations of instruments along with essential electronic parts in order to conduct the experiments. These online environments can offer many benefits to both students and educators by offering a safe place to experiment, avoid buying expensive tools and provide an interactive and engaging way of learning.

VEnvI (Virtual Environment Interactions) is a virtual programming application developed by Parmar et al. (2016) that blends dancing, mathematical reasoning, and physical engagement. The method was designed especially for girls (high school) in order to enhance their understanding in STEM subjects. This system is fully realistic and includes a first-person character in the form of an avatar. Girls in this experiment were required to apply computer programming and coding skills to create dance movements for their characters. The students were able to view the avatar they were designing, experience dance in first person, propose modifications and fix faults using the Oculus Rift HMD.

Wong et al. (2018) describe a VR application that can improve the emotional and social adjustment abilities in students with autism. The program includes six distinct emerging topics: emotion regulation and meditation, modelling of diverse social circumstances, stability and encouragement. The software is built and designed with cognitive therapy tools and methods.

Google Expeditions is an application designed by Google (Blyth et al., 2018) that creates an engaging and interactive way that can be used to teach geography in class. For example, it enables educators to conduct a virtual tour including all the students. Employing Google Street View technology, the program replicates an interactive environment of the actual world by utilizing 360-degree footage filmed in various sites including an aquatic investigation of islands in the Atlantic Ocean or a visit in the Great Wall in China.

Alfalah et al. (2019) provide an application that supports the representation of heart anatomy through an immersive experience. This 3D program enables specific interactivity, including unlimited inspection and represents dismantle to display genuine anatomical relationships of various components of the heart. To obtain a realistic picture of the model's numerous structures, several hues of flesh colors have been applied with moderate exaggeration. Furthermore, the heart's location is fixed to the right anatomic direction. The system’s goal is to aid in comprehending the complexities of heart anatomy and to elucidate the anatomical relationships between its various sections.

The idea of Metaverse has risen the last few years and is expected to be part of our reality the next few decades. Metaverse is a parallel digital universe which allows multiple users to emerge into environments that combine both the physical and digital world (Mystakides et al., 2022). Metaverse employs technologies like virtual reality, augmented reality and blockchain to achieve the immersion, as these technologies can achieve multisensory interactions. It provides genuine, physical user interaction and complex interrelationships with virtual objects.

2.3.2.3.2 Augmented Reality in Education

Compared to VR, AR may provide additional information to learners, because not only it combines the real and virtual world, but also it offers an augmented experience of real-time interaction with real objects, which are enhanced through multiple sensory modalities that are used to create an enriched perception of reality and the alignment of real and virtual objects (Wu et al., 2013). According to Chen et al. (2011), AR may maximize learning, because the placement of virtual 3-D objects in real environments may enable students to learn in 3-D perspectives and visualize something that is not real yet. Moreover, as Bower et al. (2014) postulate, the combination of real and virtual data may facilitate users to have access to enriched multimedia contents that make sense, because, on the one hand, they are contextually relevant and accessible, and on the other, they are not synthetic like in VR, albeit their virtual overlay.

The use of AR in education has been associated with particular learning benefits (Radu 2014). Chen et al. (2017) carried out a review about AR applications in education between 2011 and 2016, considering various benefits, characteristics, AR effectiveness and factors in educational environments. The primary result of their research suggested that scientific research concerning AR applications has risen significantly from 2013 and ahead.

The interaction between students and staff in AR activities can be facilitated through specific tools/software and mobile devices. There are different types of augmented display devices in a smart class environment such as tablets, smartphones, smartboards and different software which enables the creation of augmented scenarios such as Aurasma[4], Layar[5], Augment[6] and Aumentaty[7] (Chamba-Eras and Aguilar 2017). Oculus Quest, Microsoft HoloLens and Windows Mixed Reality are AR headsets/glasses utilized as augmented display devices. According to Torres et al. (2011), AR in smart classrooms can be used the following forms: Enlarged book, Virtual models of specific complicated structures, Educational games for the classroom, Virtual models which produce sounds, Magic eyeglasses, Magic mirrors, Magic doors and windows, Navigation support and Cooperative space. According to Chamba-Eras and Aguilar (2017), AR is recommended to compensate various deficiencies that might occur in a smart classroom environment such as: difficulties in doing complicated and dangerous experiments, carrying out actual experiments due to equipment costs, unavailability of appropriate facilities.

AR in education has been used for many applications including Augmented books, which may enhance the learning experience through virtual graphics that complement print content and interactivity (Allagui, 2019). For example, the Magic Book presents virtual content that is overlaid on the real book pages, while users may immerse into a fully

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[4] https://www.aurasma.com

[5] https://www.layar.com/

[6] http://www.augment.com/es/

[7] http://www.aumentaty.com/

virtual environment by pushing a button on the display. Additionally, collaborative viewing is supported, since more than one person are able to view the same content, rendering reading a multiscale immersive experience (Billinghurst, Kato & Poupyrev, 2001). As a result of the multiple sensory modalities, an enriched perception of reality may be created and the real and virtual objects may be aligned, resulting in better learning compared to traditional books (Wu et al., 2013).

Billinghurst and Dünser (2012) described the CityViewAR application that may be used with mobile phones to walk through the city of Christchurch and see virtually reconstructed buildings in the form they had before having been demolished, instead of the actual ruins. This is possible, because the application uses GPS and sensors to locate the user's viewpoint and thereby position the virtual picture on the actual one. Moreover, the application offers students the option to learn about the history of the building they see through the application, by touching the latter on the screen of the mobile phone. According to Billinghurst and Dünser (2012), the comparison between traditional learning through printed pictures and using the above application indicated more engaged students and improved learning outcomes.

The importance of Augmented Reality technology in education has led to its implementation in various topics as shown in Table 2.6.

AR technology has been applied in the field of Mathematics in a few different studies. Kaufmann et al. (2002) designed a system that incorporated AR technology for the courses of mathematics and geometry for high school and university students. They combined Construct3D and some features of "Studierstube", which is an AR system. Students could wear Head Mounted Displays (HMDs) and hold some other items that they used in order to perform some tasks, like inscribing a sphere in a cone. They managed to improve the perception of students regarding 3D geometry and students seemed to be confident about what they have created. In a more recent paper Cai, Su, et al. (2019) created a number of mathematical courses, related to statistics and probabilities, utilizing AR technology again, with the intention to assess the influence of AR through the analysis and evaluation of ideas and learning techniques among high school students based on their level of understanding. Therefore, they split students into two teams according to their understanding in mathematics. According to the findings, AR applications can assist students that have a better understanding of mathematics to stay more focused and acknowledge advanced concepts. In advance, it can assist such students in implementing more sophisticated methods when studying mathematics.

Table 2.6 : Examples of AR applications used over the years.

Year	Author	Topic	Equipment Used
2002	Kaufmann et al., 2002	Mathematics	Head Mounted Displays (HMDs), projector, computer
2007	Dünser et al., 2007	AR books for language education	Camera, Computers, AR markers
2012	Yoon, Susan A., et al. 2012	STEM and museums	Camera, projector, computer
2014	Ibáñez, María Blanca, et al., 2014	Physics	Tablet
2015	Lu et al., 2015	Marine Education	Webcam, AR markers, computer, projector
2017	Alakärppä, Ismo, et al., 2017	Environment	Android tablets, AR markers
2019	Cai, Su, et al., 2019	Mathematics	Tablet
2020	Kerr et al., 2020	Landscape Architecture	Google Assistant
2020	Dimitriadou, et al., 2020	Mathematics	Tablet/mobile, AR markers
2021	Reeves, Laura E., et al., 2021	Biochemistry	Tablet, AR markers.
2022	Kim et al., 2022	Computer Science and Engineering	Camera, AR markers.

Researchers have also tried to introduce AR in the early stages of education. Dünser et. al. (2007) proposed the use of AR books in elementary schools with the intention to improve their learning understanding. For the purposes of this study, they utilized a camera attached on the back of a computer in order to detect the AR markers attached on real pages. All the content is viewed on the screen of the computer allowing students to navigate through buttons shown on it. The experiment involved students in the age 6-7 and the findings showed that they could interact easily after the first attempt and read a book on their own. Moreover, Alakärppä, Ismo, et al. (2017) developed a game-based application in combination with AR for educational purposes. They used items from the nature, like leaves, as AR markers that are scanned via the camera of a tablet to provide a quiz with the intention to improve the way students learn. They assessed their application through the results retrieved from primary school students and found that the combination of outdoor activities and education can be fruitful, with natural items being an engaging method and an element in the process of learning. In a research conducted by Yoon, Susan A., et al. (2012) the authors investigated four different scenarios for understanding STEM knowledge in a science museum that used augmented reality and comprehension frameworks that have been shown to be effective in traditional classes. The experiment took place in a science museum in USA, with primary school students that visited it during a school trip and took advantage of AR technologies. According to the findings, the use of such frameworks showed that pupils displayed stronger cognitive advances.

AR technology has been also successfully implemented in physics and chemistry. Ibáñez, María Blanca, et al. (2014) designed an augmented reality system to explain the fundamentals of physics and more specifically the electromagnetic theory. Through this app learners can investigate all about the role of magnets, the filed they create and forces. To identify the equipment used for the experiments, such as magnets and batteries, a tablet's camera can be utilized. As a consequence, students may use the tablet to view overlay details including electromagnetic forces. According to the findings of this study, augmented reality increased school performance and offered rapid responses. In their study Reeves, Laura E., et al. (2021) attempted to incorporate AR technology into a biochemistry course with the aim to assist educators to conduct their lectures on protein structure and function. Typically, such a course would only involve 2D images unable to reveal the complex structure of a protein. Students could use a tablet to view the 3D structures with the contribution of Zapworks AR platform. Not only such a technology made it possible to view the 3D structures but also encouraged cooperation between students.

Marine Education is a really important issue for many countries, like Taiwan. In a study by Lu et al. (2015) the authors created a learning program for primary school students that incorporated augmented reality in order to make teaching enjoyable and engaging. In order to assess this program, they introduced it to 51 schools around the country. Students enjoyed the learning process, learned the desired information, while the innovative learning approach assisted weak students in strengthening their academic achievement. The technology used integrates materials from nature with virtual ones. More specifically, Webcam to recognize AR marker, a computer to upload them and a projector to show the material to students.

Kerr et al. (2020) describe in this paper the creation of an augmented reality model, called Master of Time, to teach academic students the fundamental concepts of landscape architecture at Queensland University of Technology. The idea is viewed as a means of generating revolutionary learning methods and developing innovative approaches regarding design and architecture. The applications' instructional purpose is to educate students about the fundamental underpinnings of landscape architectural design in the City Botanic Gardens. The intention of this app is to see the garden through the perspective of design professionals and to study the basic concept of what is important in a design.

Kim et al. (2022) created an AR application in conjunction with AI and tested it on undergraduate students that didn't have any special knowledge regarding computer science and engineering. This teaching software generated a visual solution that depicts the method of instantly addressing issues via basic operations, allowing students to comprehend the concepts of Machine Learning (ML). The use of this application revealed a positive perspective and motivational belief to adopt AR technology in AI education.

2.3.2.3.3 Mixed Reality in Education

MR may extend the opportunities for enhanced learning of real contents (Guo, 2015). According to Maas and Hughes (2020), MR may enable students to understand spatial structure and function, to make associations during language learning, to retain new learning in long-term memory, to be more engaged with the learning process and to feel motivated. MR worlds achieve high levels of immersion through Head Mounted Displays (HDMs), such as Microsoft HoloLens, HTC Vive, Oculus Rift and Magic Leap One, or AjnaLens.

MR applications in real and smart classroom environment have many benefits from the perspective of the students in learning and the procedure of obtaining knowledge or skills. According to Dascalu et al. (2014), some benefits by MR to educational uses are: (a) students remain focused on the task at-hand, (b) it is fostered the affective side of learning, (c) computer-based learning gets more human-oriented, and (d) students' interest and motivation towards learning is enhanced. Furthermore, MR offers immersive and engaging experiences via creative problem solving.

Nevertheless, there is a lack of research concerning the development of MR applications for a smart classroom. To address the gap, Gardner and Elliott (2014), deployed MiRTLE (Mixed Reality Teaching & Learning Environment) within smart environments. MiRTLE is a method designed to create online and mixed classes in the platform Shanghai NEC eLearning system in which both the students and the educators are presented by avatars in virtual classrooms.

Different educational tools were developed to enhance the efficiency of teaching-process and can be used in smart classroom environment such as Virtual Toolkit, SMALLable, TIWE Linguistico and Robostage. Virtual Toolkit presented by Mateu et al. (2015) intended to allow the educational activities development via a MR environment. One instance of this toolkit is a Virtual Touch Book, which enables students to read a book in a traditional way, even though activities are performed in the virtual world. SMALLable (Tolentino et al. 2019) is a framework for mixed reality systems which enables students and educators to collaborate in designing various scenarios. TIWE Linguistico (Fiore et al. 2014) constitutes a competition which enables students who attend high school in Italy to learn English with the use of a mixed reality environment involving Android mobile devices and virtual worlds. RoboStage (Chang et al., 2010) is a MR learning environment employed by high school students as a means of learning English as a second language.

2.3.2.3.4 The role of AI for VR, AR and MR

The combination of artificial intelligence and virtual/augmented/mixed reality can be considered a match in the digital environment. The integration of AI in VR/AR applications has the potential to improve its effectiveness, enabling programmers to develop more engaging and fascinating applications (Kaviyaraj et al., 2021).

The key areas where AI is used in conjunction with AI include the generation of 3D assets, Interaction, Reasoning, Visualization, and especially for the case of AR and MR computer vision capabilities to support the process of object/marker detection.

Procedural Content Generation is an AI approach for creating novel personalities and accurate 3D model settings with no previous information (Liu et al., 2020). Furthermore, AI may be utilized to generate avatars, digital humanoid characters or complementing users that interact and take decisions immediately according to the gamers' choices, resulting in more engaging experiences (Mohamed et al., 2019). Computer vision techniques like pose estimation, object detection, scene labeling, and semantic segmentation are used to control AR content, project an object in the scene, trigger a spot or occlude objects from the scene, accordingly (Sahu et al., 2021). Other techniques involve voice and word identification, which help the player by identifying auditory speech or words in a visual content.

Example of AI-assisted VR/AR/MR application include the work of Zhang et al. (2016) who explored the characteristics of VR technology as well as its functions in physical education. Their initiative was to encourage students to participate and engage more in this course. Monitoring sensors, motion recording systems and hand movement input devices are the principal data collecting equipment. The program for the VR application featured a base to collect data, a programming framework and an interface with expanded limits. All the above utilize AI to keep track of students and analyze the data provided.

Weitze et al. (2020) examined how the development of game-based learning may help students achieve certain online learning competencies. Students utilized this approach to build instructional VR games employing CoSpaces Edu, an interactive 3D program. In this framework AI can be deployed by incorporating autonomous agents and by allowing the system to create and adapt the narrative as well as the environment.

2.3.2.4 E-Learning Platforms

E-learning platforms are systems that use on-line content to support synchronous or asynchronous learning in platforms such as Moodle and Blackboard (Beetham & Sharpe, 2013). Synchronous learning is educator-led and occurs in real time; to this end, students log on at a predetermined time and communicate directly with the educator and their peers. In asynchronous learning, the process is student-led and occurs at a time, which is most convenient for the student; thus, students join the platform at a time and place of their choice and interact with the learning material (Potode & Manjare, 2015). Hybrid learning combines synchronous and asynchronous learning offering flexibility and combining the best features of the two modes. The synchronous and asynchronous online education do not compete with each other. Conversely, each one integrates the other when functioning together. The synchronous one, offers directness of educator-student contact to the educational process. The asynchronous one, gives the student the possibility of concentrating on the lesson and acquiring deeper understanding.

E-learning in the smart classroom aims to develop students' learning ability, as it concentrates on linking the digital generation, enhancing individualized opportunities of learning, sparking learning innovation, promoting educators' digital pedagogy and acquiring the best ICT investment by schools (Al-Sharhan et al., 2016). According to Xu et al. (2002) "The Smart Classroom demonstrates an intelligent classroom for educators involved in tele-education, in which educators could have the same experiences as in a real classroom." The concept of Smart classroom has developed from the general concept of the system of distance education which used Internet as a means of transforming a conventional classroom into a space of intelligence, having various software and hardware components (Xie et al., 2001).

In a smart e-learning environment, technology includes, but it was not limited to computer applications, intranet, satellite communication, interactive TV, broadcast, video, CBT applications and learning management systems (Al-Sharhan et al., 2016). Some activities carried out during e-learning utilizing these technologies are: (a) learning and discussing learning content synchronously and in real-time with local students, (b) Completing assignments in real-time in the classroom, (c) Asking a question to the educator in real-time and (d) Giving a presentation to the local students being in a remote area (Uskov et al., 2015). Furthermore, the use of intelligent virtual tutors has important role in an e-learning environment as it aims to promote online education by evaluating student weaknesses and strengths and identifying why students make certain mistakes.

E-Learning platforms developed over the past two decades have brought many benefits in education as they provide a space to upload material, assign tasks and communicate with students. In addition, many online course sites have been created in order to offer a wide range of online courses in almost every scientific topic including video, audio and text lectures and providing users with certificates after the completion of a course. In the following tables we present the most significant e-learning platforms (see Table 2.7) as well as online course sites (see Table 2.8) :

Table 2.7 : E-learning platforms developed over the years.

Name	**Date**	**Synchronous /Asynchronous**	**Main Features**	**Reference**
Blackboard Learn	1997	Synchronous	Assignments, tests, communication, grades, announcements	Dobre, Iuliana, 2015
Desire2Learn(D2L) Brightspace	1999	Asynchronous	Documents, communication, feedback, record videos, assignments, data storage, authentication	Moseley et al., 2015
MOODLE	2002	Synchronous and Asynchronous	Course material, assignments, grades, quiz, workshops, communication	Kc, Deepak, 2017
Sakai	2005	Synchronous and Asynchronous	Assignments, grades, feedback, collaboration, calendar, polls, tests	Abuhlfaia et al., 2018
Canvas LMS	2011	Asynchronous	Documents, assignments, grades, quiz, communication, analytics, interactive tools	Burrack et al., 2021
TalentLMS	2012	Synchronous and Asynchronous	Grades, authentication, communication, gamification, calendar, reports, virtual classes	Agarwa et al., 2019
Google Classroom	2014	Asynchronous	Documents, email, calendar	Zulkifli et. al., 2021

Table 2.8 : Online Course sites developed over the years.

Online Course Sites				
ALISON	2007	Asynchronous	Certificates, diploma, courses, tests, webinars	https://alison.com/
Udemy	2010	Asynchronous	Video/audio/text lectures, quiz, certificate, notes, assignments	Cetina et al., 2018
Udacity	2012	Asynchronous	Videos, certificates, text material,	Anyatasia et al., 2020
Coursera	2012	Synchronous	Grades, quiz, assignment, feedback, certificates, videos, tests, readings	Bates, Tony 2019
edX	2012	Asynchronous	Assessment, courses, discussion, certificates, online laboratories	Parry et al., 2012

Technological advances are becoming part of schools more than ever. E-learning systems are developed including teaching materials, tests and services with the goal to increase learning quality by simplifying the use of tools and facilities and enabling distant sharing and cooperation. Safsouf et al. (2020) concentrate on students' satisfaction with e-learning platforms and present a scientific framework that incorporates various aspects to further explain students' experience with e-learning platforms. The findings revealed that examination variety, curriculum versatility, personal connection, performance expectancy and user satisfaction all have a beneficial impact on student satisfaction.

Pham et al. (2021) demonstrate how the worldwide outbreak of Covid-19 has impacted and revealed a new perspective for educational institutions regarding the benefits of e-learning platforms. They describe the background and progress of e-learning in higher education before the pandemic in Vietnam, address how it has affected higher education, as well as how institutions are adapting to this new situation. They also highlight various potential approaches for the use of e-learning platforms in education. Similarly, according to Agarwal, Avani, et al. (2021) e-learning platform is by far the most promising initiative as it effectively provides students with knowledge. In their survey they assess the efficacy and acceptance of e-learning technologies across students by examining the use of e-learning platforms like Zoom, Google Classroom and Microsoft Teams in schools. According to the results of the evaluations, students claim that they want some characteristics of e-learning technologies to be used in their everyday classroom instruction.

Previous studies have focused on teleconferencing within the framework of a smart classroom. Xie W et al. (2001) developed a smart classroom for Tele-education. Educators were able to write on a wall-sized media board using just their hands, or speeches and gestures to carry out the discussion in the class including the remote students. Yuanchun et al. (2003) multimedia communication systems enabled students and educators being in various locations to take part synchronously while being in class. Educators used various natural modalities at the time of interacting with students remotely so as to have the exact result as being in a classroom with physically present students. However, Pishva et al. (2008) offers an overview regarding the technologies which are used in smart classrooms concerning distance education by making a classification of smart classrooms into four different categories and analyzing the kind of technologies being used in their process of implementation. During the same year, Suo, Y. et al. (2008) developed a real-time interactive virtual classroom with tele-education that can be used via the students' mobile devices, known as Open Smart Classroom.

There are several advantages that e-learning platforms have introduced to smart classes. It has been demonstrated that kids who spend a lot of time on such platforms are more engaged and obtain greater grades because they modify their perception of their schoolwork (Benta et al., 2015). Students seem to be more activated by the way these platforms work and managed to do the assignments they had and create a sense of responsibility to their submissions, as well as to complete some difficult activities (Benta et al., 2014). Students also claimed that this type of environment intrigued them to participate in extra lectures and seminars. In addition, instructors consider it a handy application that helps them to utilize it for administration issues and to upload data. Educators may submit course content, exercises, and lectures that are accessible to students whenever they want, allowing them to learn at their own rate. They may also keep track of each student's development independently and utilize resources for evaluation. Duplicating assignments can also be prevented by employing the plagiarism tools usually provided in e-learning platforms.

Quite often AI is introduced in E-learning platforms in order to maximize the learning experience of students through the use of adaptive educational systems. The latter can adapt to individual needs and offer support that is tailored to each student, aiming to help students meet their individual goals in the best possible way that fits their personalities and characteristics (Khalid et al., 2017). To this end, adaptive educational systems use the learner profile to diagnose individual characteristics and abilities, the taught model to present the learning material and the instructional model to formulate the content in a dynamic and adaptive way. The efficiency of adaptive educational systems proves the capability of AI to assist learning in multiple ways (Durlach, 2012). Apart from supporting adaptive learning, AI is also utilized in other aspects of the learning process. For example, natural language processing algorithms (Chowdhary, 2020) are often used to identify plagiarism and avoid transcribing in assignments submitted by students (Chong et al., 2010). Furthermore, advanced data search capabilities allow the extraction and indexing of massive amounts of data in colleges and major academic institutions (Hersh, 2021). In some cases, data related to notes taking and discussions between peers is analysed to indicate any misunderstandings or even student interests, and it is then delivered back to instructors as a summary for every participant (Diwanji, 2018).

The influence of the coronavirus pandemic on the traditional educational system has been a major issue for the world during the last two years. We are on the threshold of smart education, thanks to the availability of remote classrooms. Remote classrooms are distant learning technologies that enable students who are not actually present in class to participate in their studies (Hiltz et al., 2005). Accessibility is one of the advantages of distant lectures, since some students lack adequate access to school resources, whether due to their remote setting or because they are cognitively disabled. Remote learning programs enable students to study and advance in an atmosphere that is both safe and favourable to their success, while also providing flexibility (2020, Francisco). Students may choose when, where, and how they study by determining the time, location and medium for their education. Another advantage is that weak students may study at their own pace because they are not required to keep up with their peers, and they can also revisit a course as many times as they want. Educators may still monitor pupils and change their courses to meet the requirements of each individual using technology (Jackson, 2019).

Remote synchronous learning has particularly become a crucial method of distance education enabling the delivery of the educator's instructions via technology. There are many online applications to provide a unique eLearning experience such as Zoom Cloud Meeting, Microsoft Teams, Skype, Google Classroom etc. During remote synchronous learning the voice of the educator is transmitted through speakers, so when the educator's voice is relatively low, the speaker volume can be increased, but in a smart remote synchronous classroom there are several speakers with the volume having automated level control, and consequently, there is no need of allocating an extra student representative or support staff to adjust the speaker's volume when the educator's voice is perceived as low (Jayahari et al., 2017). Synchronous learning technology in a smart environment can involve, one-way audio (radio broadcasting), one-way audio-video along with two-way written communication (discussion groups, chat rooms, email etc.), and two-way audio-video (video conference systems) (Cai et al., 2017).

However, in remote asynchronous learning, student-educator interactions include file-sharing component through a platform (Cruz et al., 2021). Some widely online applications that can be used in remote asynchronous learning are Quizizz Application for self-assessment, record videos on Zoom, YouTube, or slides with audio and Learning Management systems such as Moodle. Remote asynchronous learning is used in different cases like, for example: (a) students in various times zone and (b) students having slow internet or various technical difficulties (Wasdahal et al., 2020). For the next generation smart remote asynchronous learning, taking advantages of 5G services will enable the sharing of a wide area of resources as well as distribution of the content in areas without having access on the internet (Cruz et al., 2021).

To explore the effectiveness of remote learning, Fitter et al. (2020) conducted a study, in which three different ways of learning were compared: in person, via teleconferencing tools and via a telepresence robot, which is a system that is capable of two-way audio and video conferencing and navigating a distant environment. The authors found that using a telepresence robot prompted students to feel more present in the remote classroom, to be more self-aware and to express their opinion more easily. On the other hand, although the educators that participated in the above research mentioned that they preferred in-person learning, they chose the telepresence robot over teleconferencing tools for the remote classroom. Adding more tools to the above research, Cajun, Xi and Zhenzhou (2021) suggest using big data and cloud computing to capture and process the data that should be presented in real time in the remote classroom. Hence, it may be concluded that AI constitutes the foundation of the modern smart classroom, which may maximize learning and render it both a shared and personal responsibility

AI has a major place in remote classroom through Intelligent Tutoring Systems (ITS), which are complex, integrated software systems that use the methods of AI to solve the problems and fulfil the needs of teaching and learning. Those systems allow recognizing the student level of knowledge and suggest learning strategies, to increase or correct the students' knowledge. They are created to support and improve the teaching and learning process in a personalized way, while respecting the individuality of the learner (Soares & Jorge, 2013).

AI technologies can give individualized advice, assistance or assessment by adapting educational material to individual students' learning behaviors or level of knowledge (Hwang et al., 2020). AI systems save educators time by responding to students' basic, repeated inquiries in remote classroom environment, allowing educators to devote time to more difficult exercises or communicate and engage with them. By decoding user activity statistics, AI analytics give educators the ability to gain a better understanding of their students' behavior, growth and prospective.

AI technologies provide excellent assistance for remote classrooms by customizing knowledge acquisition, optimizing mundane activities for educators and generating adaptable evaluations (Seo et al., 2021). Student and educator engagement (including conversation, assistance and attendance) has a significant influence on student experience and achievement in remote classes. Therefore, understanding how educators and students experience the influence of AI systems on their interactions is critical for detecting any inadequacies, problems or constraints that are limiting AI applications from reaching their desired prospective and endangering the security of these relationships. AI tools have been praised for enhancing the amount and quality of interaction, offering equitable, individualized assistance for vast contexts and boosting the sense of connection.

2.3.2.5 All Screen

All Screen refers to the ability to project multimedia including audio, photographs, and movies on many screens such as TVs and smartphones. Communication across machines is often accomplished using screen mirroring and a second screen. Screen mirroring allows you to access and view the same image or video in two or more screens, whereas second screen forces you to view distinct content on each (Brudy et al., 2019). Mirroring can be performed immediately using either a wired or wireless connection. Screen mirroring is valuable since it might improve the connectivity among a cellphone and a different device, such as smart TVs (Ouyang & Zhou, 2018). Thus, touch gesture input, with virtual buttons on the screen, is a frequent technique for interacting with screens (Ouyang, Zhou & Xiang, 2021). Unfortunately, technical issues can occur due to the fact that some devices can't connect with other devices restricting the use of all screen (McGill, Williamson & Brewster, 2014).

There are several advantages that all screens may provide to a smart class. To begin with, only wireless screen mirroring makes the connection between instructors' and students' devices straightforward and reliable (Ellern, 2018). The projector performs better in low-light conditions because the pictures are lighter and crisper, which may cause students to feel tired and create difficulties in copying the notes. Of course, the sound produced from the projector can be annoying and distract students. The above disadvantages can be mitigated if tutors use smart classroom technology to view educational information through all screens. In this way the material projected is clearer and fosters engaging tasks. Courses can start and proceed without any disturbances from cable problems and since there is no physical connection between the device and the display, the educators are no longer chained to their seats (Sahlström et al., 2019). They may move around and teach the course from any place they desire. They can connect with pupils who would otherwise sit at the back of the room or avoid engaging at all.

2.3.2.6 Flipped Classroom

Flipped Classroom is considered as one of the most recent pedagogies which focus on active learning including the use of technology as an intermediary in teaching and learning (Rahman et al., 2014). The term 'flipped classroom' was firstly mentioned by Lage et al. (2000) as "Inverting the classroom means that events that have traditionally taken place inside the classroom, now take place outside the classroom and vice versa". In other words, flipped classroom, is an educational technique of blended learning which involves elements of both an online course and a traditional classroom. In previous years, the shifting process from a traditional classroom into a flipped classroom could be a challenge due to the lack of internet accessibility, effective models, and facilities. However, today the concept of "flipping the classroom" became popular due to the technology advancements. The term 'Flip' has four elements: F- Flexible environment, L-Learning culture, I-Intentional content and P-Professional educator, which are important to be achieved by the instructor in a traditional and in a smart classroom (Ozdamli et al., 2016).

Flipped classroom focuses more on the learner and therefore is characterized as a valuable complement to an intelligent classroom (Ozdamli, 2016). In a flipped classroom students must prepare for school beforehand and gain any adequate assistance from the educator during the course, giving them the ability to be accountable and find a way that fits them during studying (Lai, 2016). Another feature of this technique is that it encourages students to seek for information and participate more in what they learn. As this model allows for diverse classroom organization, the instructor can support every learner independently and interact more making discussions about things that interest them. It also improves pupils' collaboration skills and other talents that they gain from one another since they can interact longer than they would usually do (Enfield, 2013). Many students might face difficulties during courses and in this case the flipped classroom gives them the ability to study their subjects in advance and have extra assistance in school either from the professors or their classmates. Furthermore, students of all abilities may benefit from this technique because the information can be enhanced based on their choices and personal growth (see Table 2.9).

Table 2.9 : Educator's role, students' role and pedagogical benefits in a flipped classroom.

Pedagogical Benefits	Educators' role	Student's role
Promotes critical thinking and creativity (Vargas et al. 2018).	Acting as a guide so as to facilitate learning (Johnson & Renner,2012).	Watching videos of lectures prior the lesson and then preparing for the lesson (Milman, 2012).
Enhances autonomy by increasing both their motivation and interest regarding learning.	Making learning individual for every student (Schmidt & Ralph, 2014).	Being able to learn at his own speed of learning (Ozdamali 2012).
Encourages collaborative teamwork.	Being able to share lecture videos as a means of class activity (Bishop &Verleger, 2013).	Interacting with his friends and educator. Taking part in team working (Formica, Easley, & Spraker, 2010).
Increases academic performance (Pozo Sanchez et al.2019).	Creating interactive discussions (Millard, 2012).	Giving and receiving feedback (Tucker, 2012).

Lo, Hew and Chen (2017) believe that AI has great potential in the flipped classroom approach, because it may enable the personalization and adaptation of the learning process to the students' needs. In addition, according to Shan and Liu (2021), flipped classroom may transform educators and students to learning instructors and autonomous learners, respectively. Shan and Liu (2021) suggest a model of Hybrid Teaching of Artificial Intelligence and Flipped Classroom, which combines big data, cloud and online applications to implement comprehensive and individualized learning. Within this framework, adaptive learning technology may automatically adapt to the different learning profiles of students, the progress of students may be recorded through continuous collection of data, lessons and resources may be shared through intelligent teaching platforms, resulting to increased students' interest, engagement and learning. Tangkittipon et al. (2020) suggest an alternative approach, which includes the implementation of a chatbot that should be integrated to the flipped classroom, because of the related increased students' motivation. The authors believe that the above automated answering program may assist students by providing answers even to complex problems, encouraging in this way students to participate in the flipped classroom. Based on the above it seems that the flipped classroom that is based on AI may increase students' learning potential.

The preparation of pupils at home is a critical component of flipped classes. It has been discovered that both students and educators use artificial intelligence, such as chatbots or teaching assistants, for preparation reasons. Students appear to prefer AI-based digital instructors for assignments because they are more personalized and adaptable (Diwanji, 2018). Students can utilize chatbots and bots specially to practice different languages at home (Fryer et al., 2017). Moreover, bots help professors manage the course by addressing any query students might have or inspiring them to finish homework (McNeal, 2017). In advance, chatbots use artificial intelligence approaches and store any statistics regarding each student, encourage them to strive harder in a nice manner, and alert instructors about the performance they have (Pereire and Juanan, 2016). Students that might face particular conditions can be assisted by employing chatbots that utilize vocals something made possible due to AI (Jean-Charles, 2018). Data science, meaning the science that deals with data and the features that can be extracted from them, is further utilized to help educators respond immediately by taking quick decisions.

2.3.2.7 Virtual Classroom

According to Fernando Batista et al. (2020), virtual classrooms open up new learning opportunities, because they enable educators and learners to interact in a way that enhances and enriches their experience of a differentiated learning process. Thus, research has shown that the virtual classroom is beneficial for students because it is related with the development of important abilities, which constitute prerequisites for effective learning (Greenwald et al., 2017). Kuznetcova, Lin and Glassman (2021) postulated that the diminished educator presence, which has been considered by some researchers as a shortcoming of the virtual classroom (Xu & Jaggars, 2013), may benefit students, because of prompting them to develop a democratic and student-led classroom.

Kuznetcova, Lin and Glassman (2021), who conducted a quasi-experimental study, conclude that students in virtual classrooms with educators supporting students' autonomy may achieve self-regulated, independent and active learning, while their satisfaction from the learning experience may increase. Likewise, Martin, Parker and Oyarzun (2013) underline the increased satisfaction of students in virtual classrooms, where interactive and communicational tools are used. Martín-Gutiérrez et al. (2017) add to the above study that the virtual classroom has many advantages because it may enhance a real-life experience and enable students to explore new domains. In this way, as the above authors argue, the virtual classroom may improve the students' academic performance, as well as their social and collaborative skills. Hence, it seems that the virtual classroom may be a source of both increased students' learning and satisfaction.

In previous years, the virtual classroom considered as a head-mounted display (HMD) virtual system. The virtual classroom involved a standard rectangular environment of a classroom consisting of three rows of desks, a blackboard on the front wall, a desk for the educator at the front, a virtual educator between the blackboard and the desk, a large window overlooking a playground with buildings on the left of the wall, people, vehicles, and on every end of the wall, there is a pair of doorways opposite the window through which activity occurs (Rizzo et al., 2000). However, a next generation smart virtual classroom, include highly specialized educational technologies such as AI, VR, AR and any computational smart devices with IoT, which are connected to create an effective intelligent environment of virtual classroom providing delivery of knowledge anywhere and at any time via remote access.

Ren and Xu et al. (2002) state that smart classes could be considered as virtual classes where the blackboard is replaced by a screen, students are viewed via the platform used for the online course and there are other features similar to a physical classroom. Virtual classrooms are widely popular as e-conferencing or web-conferencing systems which enable communications in real-time with multiple users being able to interact simultaneously with each other through the internet to conduct seminars and meetings, guide discussions, make demonstrations and presentations, and carry out other functions (Martin et al., 2014).

The smart virtual classroom should offer all the possibilities offered by a traditional classroom and can offer more possibilities such as application sharing, educational games, augmented reality techniques, virtual laboratories, interactive intelligent tutoring systems etc. Furthermore, smart virtual classrooms give the opportunity to instructors and students to synchronously communicate through features like text chat, video, audio, application sharing and interactive whiteboard instead of a traditional classroom, in which instructors communicate with their students using office hours, phone, electronic tools of communication and email. In other words, the smart virtual classroom offers an alternative and interactive way of learning, as a result teleconferencing is more interesting while at the same time increasing students' motivation.

Developing an online presence in the smart virtual classroom is crucial for the success of the students. If a student who is having an online lesson feels that their educator is not present and they are not provided with timely feedback, it is less likely for them to take on an active role during the course. However, an intelligent virtual tutor in smart virtual classroom can offer their help to remote students as a means of enhancing their understanding regarding the content to encourage the interaction between remote students and the tutor. Furthermore, remote students can depict themselves in the form of avatars which enable 'the students to have a visible persona' in a virtual world, giving them the opportunity to take part in imaginary and surreal experiences which exceed the world in which they now live' (Deuchar & Nodder, 2003). AI could also help recognize student's actions during the course by synchronizing the movements of the avatar in the virtual class with the actual moves of students in the physical place.

AI technology can yet be incorporated in virtual classes and provide assistance to educators as this type of environment is more challenging as it requires immediate responses and the control of an entire class that is not physically present. Differ is a bot program that immediately generates and proposes student groups and begins group conversations by posting on the forum. It assists students to complete activities beforehand by giving advice and ideas through messages that provide guidance for task completion (Differ, 2017). These procedures rely on natural language processing and use machine learning in order to be able to adjust in different situations. Through the utilization of artificial intelligence technology, the communication between students throughout lectures, including the data captured for their examinations and quizzes, may be highly instructive (Tissenbaum et al., 2016). These online platforms can provide educators with displays of data, giving information about the actual status of the class including individual student accomplishments (Vatrapu et al., 2011).

2.3.2.8 Digital Twins

Michael Grieves (Grieves, 2015) defines Digital Twin - DT as a digital information system that corresponds to a physical object, operates as an independent system and is associated with that physical system. In an ideal scenario, the digital representation would use all of the required data about the system's components that might be gained by a comprehensive investigation in the actual world (Grieves, 2015). Glaessgen and Stargel (2012) provide a more thorough and broadly supported definition: «*A digital twin is a complete manifold scale and multiple physical functions probabilistic simulation of the function a composite product that uses the best available natural models, sensor technology, etc., to reflect the operation of the physical product throughout its life*.»

A connection between the DT and education is presented by Madni et al. (2019). The study describes an effective educational strategy that employs digital twin technology to transform typical teaching into "learning-to-practice" experiences in an engineering lab. The purpose of this process was to examine whether students can have the same learning experiences, in a lab simulated platform utilizing digital twins, with the experiences they would have in a real environment. Vikhman et al. (2021) investigate the prospects of digital twin technology in education as well as the difficulties to implement it in real time. In order to achieve digital innovation and transformation in education, the authors state that a wide variety of network technologies must be implemented. The authors bring up the question of the impact this technology will have in the society, despite the fact that it has not been broadly employed in schools.

The article by Furini et al. (2022) analyzes a problem of the modern education, where educational systems have not evolved in parallel with the average student. With the help of DTs, the authors believe that a personalized learning model can be created. Students' DTs will be able to understand students' gaps or weaknesses and focus on areas that need improvement, proposing the necessary solutions, depending on the student's character. However, this article does not address the ways of connecting students to their digital twin, nor how is it possible to make that connection. It refers only on how the student can benefit from his digital duo, a work that may be offered by a qualified counselor. Personalized learning has become a subject of study in recent years, and it does not require the help of technology alone (Major & Francis, 2020). Nevertheless, this article mentions many of the problems that this technology could solve (such as modern distance education, the creation of a virtual classroom, etc.) and the requirements of technology that modern educational institutions must incorporate. Future research could focus on the classroom experience with digital twin, which may involve both teamwork and individual work. Laboratory experience can provide deeper information about the system development process and evolving system behavior. In this way, students can continue to acquire important knowledge throughout the life cycle of the system.

David, Lobov, and Lanz (2018) examined the integration of digital twin technology in education within the framework of Kolb's (1984) experiential learning theory. In this model designed in the context of Kolb's experiential learning cycle, in the first stage the learner is passive, and the educator provides the steps that must be followed throughout the interface. In the second stage, the educator acts as a guide, learners become active and work in a virtual environment created with digital twin technology. After the second stage, we have the stage of applying the knowledge and skills acquired by the learners. Immediately after this process, in which the educator starts the evaluation process, the measurement and evaluation phase follows. Based on digital twin technology, learners have the chance to practice more and experience more situations. In addition, David, Lobov, and Lanz (2018) indicate that with this model, the changes in the physical world can be directly reflected on the learning objectives.

Massive open online courses offer learning experiences to wider the abilities of their audience. A great deal of data can be collected regarding the interests, needs and experiences of learners attending these courses offered through online course providers. This data collected about learners can be processed through AI-assisted digital twin technology to create personalized adaptive instructional designs and be used in the feedback process. In addition, with individualized digital twin technology, virtual learning friends can be created to mediate between the interests and experiences of individuals and their learning goals, and thus, the learning experience can be enriched.

2.3.3 Performance Assessment

Performance assessment and feedback is a highly important educational task because it may present the students' progress and accomplishments, resulting in the discovery of new learning trends (Zughoul et al., 2018). On the other hand, performance assessment of educators is also highly important as a means of safeguarding the quality of the teaching activities. Although traditionally performance assessment/prediction has been a quite complex and time-question process, it has been extremely facilitated through automated assessment in a smart classroom environment (Balfour, 2013), as exemplified in the following sections.

2.3.3.1 Smart Student performance assessment/prediction

Student performance assessment aims on the one hand to inform the educator about the degree to which students have learnt the content of the lesson and how well they are expected to perform in the future, and on the other, to grade students and provide feedback to them about their performance during the learning process (Saini & Goel, 2019). Traditionally, performance assessment was carried out in written or oral exams. However, the aforementioned method has many disadvantages, since it is a time-consuming and tiring process for both the educator and the student, while it results to piles of wasted paper and writing material (Parmar & Kumbharana, 2016). Moreover, when the class consists of a large number of students, practical difficulties arise in setting and conducting the evaluation process, which continue throughout the process of correction, evaluation and returning assignments and tests to students (Saini & Goel, 2019).

In contrast, in a smart classroom dedicated tools can facilitate the performance assessment/prediction through the automation of the assessment. The easiest tool to assess students in a smart classroom is the employment of multiple-choice questions, which allow automated evaluation and feedback, with the aid of an online web server that compares students' answers with the configured correct answer (Balfour, 2013). An important application of AI in student assessment is plagiarism checking, with Turnitin as a frequently used tool (Ahmed, 2015). Bhatia and Kaur (2021) add an innovative performance assessment/prediction tool based on quantum game theoretic (QGT) decision making. This tool incorporates IoT to gather information and data about students, which are evaluated over a computing platform, aiming to analyze performance and determine the academic enhancement of students.

Previous studies addressed the problem of introducing smart machine learning for automatic prediction of students’ performance. Plenty of machine learning techniques, such as artificial neural networks, decision trees, matrix factorization, probabilistic graphical models and collaborative filters have been used to establish prediction algorithms. However, it is unclear which one, among the different machine models achieves the best performance since different authors have demonstrated conflicting outcomes concerning the model’s accuracy of prediction (Ofori et al., 2020). Amra and Maghari (2017) promoted a system giving predictions regarding the future performance of secondary students based on several attributes. They compared two distinct machine learning algorithms: K-Nearest Neighbors (KNN) and the Naïve Bayes classifier. The results being presented indicated that the model of Naïve Bayes outperformed the KNN model. Waheed et al. (2020), propose a system to predict the students’ academic performance in a virtual learning environment. Their system used artificial neural networks to classify students in two classes: failure and success. Authors made a comparison of the results using baseline methods: logistic regression, support vector machines and Artificial Neural Networks (ANN). The ANN method had the best performance out of the tested models. Warschauer and Grimes (2008), propose the automatic assessment of writing essay assignments with the use of artificial intelligence. Students and educators had positive approach (i.e., student motivation rising, proposing autonomous student activity, constituting a saver of time for educators).

During the COVID-19 pandemic, AI-based proctoring tools experienced a surge in popularity as institutions sought innovative ways to conduct remote exams (Labayen et al., 2021). These tools, such as Proctorio, ProctorU, and Examity, utilize machine learning algorithms to analyze patterns and behaviors of test-takers during online exams (Dadashzadeh et al., 2021). By monitoring activities such as eye movements, keystrokes, and background noise, these systems aim to detect potential cheating behaviors and ensure the integrity of the assessment process. While controversial due to privacy concerns and accuracy issues, AI-based proctoring tools represent a sophisticated approach to remote exam invigilation, leveraging advancements in machine learning and data analysis to adapt to the evolving landscape of education (Tweissi et al., 2022).

Usually AI-based proctoring tools utilize the following techniques for detecting potential cheating behaviors and ensuring the integrity of the assessment process: (a) Eye tracking: Monitoring the test-taker's eye movements to detect any unusual patterns or signs of cheating, such as looking off-screen frequently. (b) Keystroke analysis: Analyzing typing speed, typing rhythm, and keystroke patterns to identify irregularities or suspicious behavior, such as copying and pasting answers. (c) Background noise analysis: Monitoring background noise levels to detect any unusual sounds or disturbances that may indicate the presence of unauthorized aids or communication. (d) Facial recognition: Utilizing facial recognition technology to verify the identity of the test-taker and ensure that they are the authorized person taking the exam and (e) Browser monitoring: Keeping track of browser activity to detect any attempts to access unauthorized websites or resources during the exam.

AI-based proctoring tools typically transmit data such as keystroke patterns, eye movements, and background noise levels rather than transmitting actual images or videos of the test-taker. Regarding accuracy issues, while AI-based proctoring tools represent a sophisticated approach to remote exam invigilation, there can still be challenges in ensuring perfect accuracy. Factors such as variations in individual behavior, technical glitches, and environmental factors may impact the reliability of these tools. Continuous improvement and refinement of algorithms, along with rigorous testing and validation processes, are essential to enhance the accuracy of AI-based proctoring systems.

Proctoring systems focus on monitoring and analyzing test-taker behavior during exams, transmitting data related to activities like eye movements and keystrokes to ensure exam integrity. In contrast, our proposed system that recognize student actions in online classes (see Section 3) transmits information specifically related to behavioral participation and behavioral disaffection in online classes, such as raising hands or writing emphasizing participation rather than assessment integrity.

2.3.3.2 *Educator performance assessment*

The educator performance assessment can be defined as a framework utilized in a classroom to assess and evaluate the performance of educators incorporating technological tools for this purpose (Jensen, Emily, et al., 2020). Not only students should be evaluated in order to improve their knowledge and skills but educators as well. Traditional assessment methods are usually based on the observation of educators from experts during course time something that can be expensive, not accurate and usually the feedback provided is infrequent and is related to the performance and not on how educators can enhance their techniques (Archer, Jeff, et al., 2016). To overcome this crucial impediment in educator development, new technologies are used to produce high quality and meaningful automatic feedback for the educators.

Bhatia et al. (2021) use IoT systems in classes to collect information regarding students and educators in order to identify their progress. Student data collected relates to different student activities performed in the school environment (e.g. academic performance, attendance, teamwork) while educators' data relates to the evaluation of their performance (e.g. quality of content, student satisfaction, number of assignments). Utilizing the Bayesian modelling approach, the collected information is assessed through a fog-cloud computing device with the aim to determine a quantitative description of success likelihood. Furthermore, this progress measure is computed over time from both students' and educators' performance. Lastly, their progress is analysed by employing the two-player quantum gametic decision-making. The results of this method are viewed through the experiments conducted using four datasets and prove the efficiency of the method.

Srivastava et al. (2020) use also IoT systems that collect data during class hours and process them by utilizing Machine Learning models and cloud computing. Moreover, IoT systems supported by artificial intelligence models such as fog-computing has stimulated new studies in the field (Chang et al., 2017). Fog computing is a cloud-additional environment that can deliver information instantly (Chiang et al., 2016). The combination of IoT, Fog and Cloud computing improves the capabilities of many systems used in academic institutions. Furthermore, IoT-fog-cloud computing offers an important application for providing an intelligent educational experience and assessing students and educator instantly.

Jensen, et al. (2020) devised a method for educators to effortlessly audiotape the conversations and lectures in a classroom. They also utilized voice recognition and machine learning algorithms to provide generalized estimations, in the form of scores extracted from computers, of essential aspects of educator speech. Specifically, the authors assessed the audio quality from educators' recording with a rating of A, B, C or F. "A" denoted outstanding recording quality, "B" denoted satisfactory quality with minor volume or background noise issues, "C" denoted recordings with flawed segments, and an "F" denoted audio files that were either lost or contained irreparable technical errors. In a comparison with human interpreters, they observed that automatic methods were relatively precise and that voice recognition mistakes had little effect on performance. Therefore, they state that actual instructor conversation can be captured and evaluated for automated feedback. The automated algorithms can also be integrated into/ a dynamic visualization system that will offer educators the necessary feedback for their level of speech. The comparison refers to the evaluation of actual speaker performance as these algorithms utilize voice recognition and machine learning to provide generalized estimations and scores extracted from computers, specifically assessing important aspects of educator speech. This indicates that the focus is on evaluating the content and delivery of the instructor's speech rather than just the technical quality of the audio recording. Furthermore, the feedback offered to educators is tailored to their "level of speech," which suggests that it pertains to assessing how effectively the educators communicate and engage with their students during lectures and conversations in the classroom. In general, these algorithms aim to provide valuable feedback on how well the educators deliver their lectures and interact with their students, helping them improve their communication skills and instructional effectiveness. The approach adopted by Jensen, et al. (2020) considers only audio features, and as a result, it does not cater to visual features related to a educator 's in-class activity.

Jensen et al. (2021) also address the issue of designing a framework for automatic educator feedback that necessitates several considerations about audio data harvesting processes, automatic assessment and the way feedback is displayed. The authors employ machine learning techniques, including Random Forest classifiers, alongside transfer learning from the Bidirectional Encoder Representations from Transformers (BERT) algorithm for natural language processing (NLP). BERT, a pre-trained language model based on transformer architecture, is utilized to achieve bidirectional contextual understanding of language, enabling it to capture intricate contextual relationships within sentences. This deep learning model incorporates word embeddings, positional embeddings, and segment embeddings to represent sub word tokens, their positions, and sentence-level distinctions, respectively. The input to both the Random Forest Classifier (RF) and the Bidirectional Encoder Representations from Transformers (BERT) models consists of transcribed utterances. The Random Forest Classifier, features are derived using a bag of n-grams approach, which computes counts of words and phrases (unigrams, bigrams, and trigrams) from the automatically transcribed utterances. During pre-training, BERT learns contextual representations by solving masked language modelling (MLM) tasks and next sentence prediction (NSP) tasks. The results demonstrate that BERT offers superior and more accurate input across various degrees, rendering it the most practical technique for delivering automated feedback on educator discourse, surpassing the performance of other machine learning techniques, such as Random Forest classifiers.

2.4 Impact of smart classroom

In this section, the impact of smart classroom on the learning process is analyzed while disadvantages of using smart class technologies are also discussed.

2.4.1 Smart classroom advantages

The installation of specialized equipment in smart classrooms enables educators to improve students' learning through the use of AI and emerging technologies. This offers a plethora of benefits such as:

- ***Comfortable and safe educational environment***

Smart class environments establish a creative and comfortable atmosphere, in which students acquire knowledge using their own alternative solutions and strengths (Hébert, Thomas P., et al., 2014). The integration of AI systems that process data collected by IoT and other sensors, can help monitor the circumstances of the classroom, offering a safe and eco-friendly environment as well. In addition, such systems can also monitor students and inform educators in the case of a student misconduct or potential accidents. All these tools and systems can be a valuable asset in a smart class and more generally contribute to the establishment of a better and safer learning environment.

- ***Interactive environment***

The interaction with the learning material can help boost student's learning, information may be retained more easily, and self-efficiency may increase (León et al., 2017). Interactive environments are also crucial for students with special needs. The enhanced interactively offered in smart classes help students have an active role in the class delivery process rather than having a passive role that causes loss of concentration and interest. Moreover, the access to interactive devices, such as smart robots, can boost the student's engagement, enrich the learning process with relevancy and excitement and thereby result to improved and sustainable knowledge (Belpaeme, Tony, et al., 2018).

- ***Individualized Teaching Support***

Lin et al. (2019) suggest that an adjustable smart system can assist students, improve the learning process and foster a considerable quantity of intellectual learners. Smart classrooms and emerging technologies may overcome the problems related to the provision of timely and individualized support to students, through the use of smart applications that respond to students and provide automated feedback immediately, make comparisons regarding current and previous student performance and motivate students to become more responsible for their own learning (Parmar & Kumbharana, 2016).

- ***Better Visualization***

Since a smart classroom is equipped with contemporary visualization technologies, which include interactive whiteboards, projectors, virtual/augmented reality headsets, cameras and sensors, students have the ability to better visualize the content they are taught, enhancing in that way the learning experience. In a smart classroom students may be immersed in online virtual environments using headsets; as a result, distractions are removed, and the students' attention is captured. Furthermore, perspective changing in virtual reality visualizations allows students to become actors rather than just observers, transforming the learning process into a highly experiential experience (Krüger et al., 2019).

- ***Immersive Multisensory Experiences***

Virtual spaces in a smart classroom resemble real places allowing students to have an immersive experience and create real memories. Moreover, seeing, 'touching' and hearing involves more senses in the learning process and links the learning subjects in multiple ways. Therefore, enriched presentation of the learning material and better visualization, that resembles reality and involves more senses, enhances students' experience and learning becomes sustainable (Lui & Slotta, 2014). Moreover, the students' motivation is triggered, situated scaffolding is provided and learning is connected with the students' everyday life (Bower et al., 2014) through an experiential learning process.

- ***Combination of synchronous/ asynchronous education***

Smart classes support the provision of synchronous and asynchronous education through. In this way, learning may become a dual process, which involves both educator-led and student-centered activities in real time or at a time of student's choice (Beetham & Sharpe, 2013). Moreover, the above combination allows to enrich learning with the provision of extra material, improve and retain knowledge through the students' longer interaction with the learning subject, the educators and their peers. At the same time, the style of the traditional classroom that is offered on scheduled dates and time is retained, resulting to keeping students aware and alert. As a result, learning may be maximized (Khalid et al., 2017).

- ***Effective student attendance and supervision systems***

Smart classrooms provide real-time video analysis to educators that want to recognize the behavioral participation and behavioral disaffection of their students (Michalsky, Tova, 2021). The employment of smart tools and applications, such as cameras, plagiarism checking, and recording, combined with the continuous gathering of data, allows educators to control student attendance and supervise them both in class and during online assessments (Saini & Goel, 2019). Students' monitoring with specialized equipment provides better feedback to educators with regards to the students' performance in the lesson and hence, contributing to better school results.

2.4.2 Smart classroom disadvantages

Although, the deployment of smart-class technologies has several advantages, there are several issues that prevent utilization of these technologies, due to several limitations such as:

- ***Equipment cost***

The overall cost of equipment required for a comprehensive smart class deployment is quite high, preventing in that way the widespread use of smart-class technologies. Bearing in mind that the cost does not refer only to the equipment purchase and initial installation, but also to the continuous upgrade and maintenance required, the use of smart class technology involves significant running expenses. Also, because all components of a smart class are somehow disconnected from each other, it is not seamless to integrate all technologies under a common framework, and as a result the task of setting up the equipment can be a lengthy and time-consuming procedure.

- ***Prerequisite technological knowledge***

Many educators are not familiar with technology, while some of them only focus on the use of usual software such as Word, PowerPoint, etc. Thus, the educators may face difficulties, or they may need technical support for the full utilization of the emerging and artificial intelligence tools. These educators need appropriate education to support the successful implementation of a smart classroom with new technologies.

- ***Security and privacy***

Technologically advanced smart class technologies incorporating AI capabilities, are threatened by security and privacy issues because they store and process data that may contain personal and sensitive information that may be exposed to potential invaders (Manca et al., 2016). Furthermore, sensors used in classes (i.e. camera sensors or microphones) often used as part of smart-class technological tools, are associated with privacy issues.

- ***Bias in AI***

A challenge concerning the use of advanced technological systems is bias in AI. More specifically, there is a concern regarding how fair can AI systems be to every single student despite the personal attributes of a student (i.e., race and gender (Li et al., 2021)). Groups that face discrimination in the community of technology, like female students, might face more severe inequalities if programmers who create these AI systems don't consider how to mitigate such biases. Developers' prejudices can eventually result to faults in the systems as well as exacerbated biases in the actual world, hence creating a problem in the adoption of AI in smart classes.

- ***Disconnected students***

The use of technology for teaching and learning may be related to disconnectedness, which is usually expressed as feelings of separation from learning, the curriculum, the peers and the educators and the learning devices. Disconnection of students may jeopardize the learning outcomes of students because it results to disengagement, decreased student ownership and absence of student agency. For this reason, educators in smart classrooms should find ways to remove the barriers to meaningful student involvement and encourage their engagement with the school and the learning process (Wankel & Blessinger, 2013).

2.5 AI in smart classes: A SWOT Analysis

The use of AI in smart classes can have an important impact. However, based on the analysis presented in the previous subsections, the advantages of using AI and emerging technologies may also involve risks that may jeopardise the learning efficiency and experience. In this section a SWOT analysis of using AI in smart classes is presented (see Table 2.10) as a means of summarizing the potential of using AI in smart classes, along with possible drawbacks.

Table 2.10 : A SWOT Analysis of AI in smart classes.

Strengths	**Weaknesses**
• Continuous environment monitoring through sensors that results in an optimized learning environment. • Enhanced Interactivity, including immersive experiences. • Adaptability to individual needs of students. • On sight/remote/mixed class delivery.	• No integrated smart class technology offered. • Equipment Cost. • Need for student/educator expertise in using emerging technologies. • Need for large amounts of data to train systems. • Separation and disengagement from the learning process. That results in isolated students.
Opportunities	**Threats**
• Availability of state-of-the-art equipment at more accessible cost (i.e. interactive screens, cameras, microphones, VR and AR headsets and glasses). • External factors, like the COVID-19 pandemic, dictate the use of technology in teaching as a means of supporting remote teaching. • Trend towards on-line virtual environments (i.e. META, METAVERSE (Mystakides, 2022) in line with smart-class technologies. • Latest development in AI that results in accurate algorithms, in the form of deep learning. Availability of 'public' ML tools (i.e. lobe.ai, that allows not trained individuals to set up and use ML models).	• Privacy issues, ethics and GDBR regulations regarding data collection required by smart systems. • AI systems and large server stations that store data regarding vital research, may be threatened by hackers. • Educators tend to avoid or face difficulties using AI systems due to their inadequacy to adapt to new forms of technology and refuse to accept new technologies as a new norm. • Cheating-based AI tools may give an unfair advantage to students over their classmates during exams and assessments (Abd-Elaal et. al., 2019). • Bias in ML systems that may cause unfair student treatment.

2.6 Discussion - Future Directions

In this section we outline the main issues in the dimensions of technology infrastructure, personnel, and data handling that need to be addressed by the research community in order to maximize the impact of AI in enhancing smart classes.

2.6.1 Technology infrastructure

To enhance the capabilities of a smart classroom it is necessary to integrate all technologies, hence a combination of emerging technologies and AI is essential. A central AI system that can manage the use of different technologies, suggest optimum ways of integrating each technology in specific classes, and provide a comprehensive evaluation of students and the educational process will be a highly desirable feature of future smart classes.

Since the teaching process is a highly dynamic process where educators need to adapt to the changes in student attitudes and overall class requirements, it is important to deploy AI-based systems that continuously monitor the student requirements and adjust to respond to all changes. While this can take the form of reinforcement learning (Liu et al., 2018) dedicated techniques for AI systems that deal with in-class scenarios, need to be devised.

The integration of special technical equipment is usually an issue due to the expensive cost. As a result, it is critical to adopt new low-cost technical equipment that students may use anywhere, at any time. Experts should develop techniques and technologies that can run on personal equipment rather than dedicated machines, for example using smart phones or low-end personal computers. When it comes to AI-based systems that need to be re-trained continuously, efficient training methods that allow the training process to be completed using ordinary computer systems, need to be employed, so that costs associated with the purchase of dedicated equipment or the purchase of computational time, are decreased.

2.6.2 Personnel

The need to adopt in practice appropriate educator training programs regarding the use of technology in education has become urgent. Apart from training for using emerging technologies, educators should also receive adequate training for AI related issues, so that they learn how to harness the power of AI systems for the benefit of the education process. Thus, it is imperative that dedicated AI courses for educators are created, so that smart class educators are well aware of the potential and risks of using AI empowered emerging technologies. Furthermore, dedicated user-friendly tools that will allow educators to train and use Machine Learning modules should be developed.

Classroom overlays for educators that incorporate grades, special arrangements, and medical and social information are probably among the educational applications of the future. As technology advances, it will be able to alert educators to students' learning needs and behavioral issues in real-time and provide solutions. Educators are sometimes untrained to handle the technical challenges that may occur when a device does not function as planned. As a result, for educators to succeed, there may be a significant amount of assistance required. To prevent the design of learning from being largely the responsibility of computer scientists who have a limited understanding of successful pedagogy, it is essential that educators learn how to integrate technology into their teaching (Krüger et al., 2019). With the recognition that students' abilities can be impacted by their cognitive, motor, and spatial capabilities, technology also makes it easier for educators to teach content and learning objectives. Students can become more actively involved in the learning process as they develop their motivation and foundational knowledge (Liono et al., 2021).

Empathy is the ability to recognize somebody's emotional reactions and motives, care for them and their sentiments (Srinivasan et al., 2022). It is vital to develop specialized AI systems that take into consideration the unique characteristics of each student, through an empathetic nature. The topic of producing “empathetic” AI systems can open up several research directions.

2.6.3 Data Management

One of the most crucial issues of the future of smart classes is ethics in the use of data in AI systems (Borenstein et al., 2021). It is vital to address the way data are collected and used by those systems in order to avoid the violation of privacy. Regulations regarding the collection of data must be established and adopted by the scientific community. Data can also be encrypted and anonymised, so in case a hack occurs it won't be feasible to find correlations between provided data and individuals. Within this scope, new methods that guarantee data security, but at the same time allows the access to the necessary information by different stakeholders, within a smart-class needs to be developed.

Bias in AI is an issue that needs be addressed while using advanced technological systems. More precisely, there is worry about how fair AI systems can be to all students, regardless the attributes of each student such as ability level, race, religion, appearance, or gender (Li and Leite, 2021). Developers must consider all the biases that may rise due to their personal beliefs and eliminate them. In this way, any form of discrimination towards minorities will be alleviated and students will be able to attend education and receive fair feedback compared to their peers. Furthermore, since supervised AI systems often rely on annotated data, techniques that ensure that any form of bias in the annotation process is eliminated, so that the resulting AI systems are not subjected to any kind of discrimination. AI systems should include machine learning techniques with explainable AI to analyze the educational factors that lead to more fair and effective decision making for students since the ML-based black box model is more understandable to educators (Guleria et al., 2022).

Using data collection, user profiling, and adaptive learning can be useful in creating a more personalized and effective learning experience, and artificial intelligence can play a role in supporting these efforts. However, it is important to carefully consider the ethical implications of collecting and using data, and to ensure that students' privacy is protected. The use of AI in education can also raise questions about the role of technology in learning and the potential for it to replace human educators. While AI can certainly be a useful tool for supporting and enhancing education, it is important to consider the limitations of technology and the value of human interaction and guidance in the learning process.

Overall, it is necessary to carefully evaluate the potential benefits and risks of using AI and other technology in education, and to strike a balance between the use of technology and more traditional teaching methods.

2.7 Conclusions

Throughout this literature review we have analysed a range of AI-assisted emerging technologies, their implementation in smart classrooms and provided useful insights. More specifically technologies related to the class management, teaching aids and performance assessment have been presented. For each smart class technology presented the role of AI was discussed, allowing the in that way the determination of the role of AI in smart classes. Furthermore, through the analysis of advantages and disadvantages of smart classes, along with a SWOT analysis, the prospects, and trends related to the use of AI on smart classes have been discusses, allowing in that way the definition of several future research directions. The future directions presented can provide motivation to the AI, and educational technology research communities to engage in research activities that aim to deal with the identified challenges. Since the new era of technological advancement and the proliferation of digital devices and applications that are routinely used in everyday life has been integrated in education, there is a continuous need to invest in improving the services offered to students and the further development of AI-based smart classes definitely leads those efforts in the right direction.

Chapter 3

Student Action Recognition During Tele-Education

Strong interaction between instructors and students during online course delivery is essential for supporting the educational experience. As part of the efforts to maximize the interaction between educators and students, a pilot application that monitors the actions of the students in online courses while protecting as much as possible students' privacy was developed. In this chapter the process of designing, implementing and evaluation the proposed student action monitoring system are described. The work described in this chapter is an extended version of the work described in Dimitriadou et al. (2021, 2022, 2023).

3.1 Introduction

Technological advances in recent years led to the introduction of several emerging technologies in educational environments that aim to upgrade the overall student experience while maximizing the education impact. Among other technologies tele-education has been an area of continuous development (Ulum et al., 2021; Pandit et al., 2022). The COVID-19 pandemic, during which most schools, from kindergartens to universities, were forced to replace face-to-face with online education, accelerated the process of adopting tele-education models for class delivery. Dedicated tele-education tools like Zoom, Microsoft Teams, etc. made it possible for students to attend classes, take exams, get grades, and pass classes. This, however, raised several questions in relation to the effectiveness of tele-education as a number of students tend to be inactive during the delivery of on-line courses (Abdurrahmansyah, et al., 2022; Selvaraj et al., 2021; Borup et al., 2019). This trend is reinforced by the fact that in several countries, due to privacy violation concerns, the use of cameras is not allowed during tele-education (especially when younger students are involved) and as a result, there is no optical contact between educators and students. In this chapter, we explore the possibility of adopting an action recognition framework used for recognizing actions performed by students during teleconferencing, so that the educator is informed in real time about the actions performed by students, without having direct optical contact with the students. The main motivation behind the development of this system is to maximize student awareness and involvement during tele-education, while preserving as much as possible student privacy. The aim of our work is the scientific contribution arising from the overall system evaluation rather than the development of a market ready application. We anticipate that the findings presented in this chapter will reinforce efforts in developing efficient and user-accepted systems for student action recognition.

The proposed system recognizes a set of student actions related to the quality of attendance of students during online class delivery (Dimitriadou et al., 2022). All actions considered belong to the categories of "Absent", "Present but not participating", "Present and actively participating", "Present and performing a relevant activity" and "Present and performing a non-relevant activity". These actions considered are related to the three categories "Physical Presence" (Raddon 2006), "Active Participation" (Pratton and Hales, 1986), and "Distraction" (Baron, 1986). Based on the proposed system, real-time feedback is provided to educators through a 3D virtual class visualization, to inform them if the students are adopting any of the actions considered, so that educators get an indication of the level of student engagement. In the current implementation, the system provides the educator with the information about student activity but on par with a real setting, the educator can judge if a certain student activity at a given time is appropriate. This is in line with circumstances in a real class, where educator may observe a certain student's action (i.e. a student writing), but it is in his/her discretion to decide if the specific action is appropriate at the specific lesson instance.

The work presented in this chapter involves a description of the development of a pilot student action recognition system, a quantitative performance evaluation, and an extensive user evaluation where the stakeholders involved in the educational process express their opinions and views about the proposed application allowing in that way the derivation of conclusions related to the acceptance and effectiveness of the proposed application during remote teaching activities. The term 'stakeholders' refers to those who are closely involved in the educational process: educators, students, and parents who usually have a strong interest in their children's progress. The main contribution of our work is the system design, modelling, and user evaluation with stakeholders. Stakeholder needs, elicited from interviews, led to the proposed system design. An integrated AI-based system including 3D virtual classroom and animated avatars was developed. Subsequently, the impact of application was assessed with stakeholders. The research questions under investigation are:

RQ1: How learners, educators and parents *perceive* the feasibility of using privacy-protecting methods for monitoring student actions during tele-education?

RQ2: How is the acceptance of using privacy-protecting methods for monitoring student actions during tele-education *perceived* by the learners, educators, and parents?

RQ3: How learners, educators and parents *perceive* the impact of using privacy-protecting methods for monitoring student actions during tele-education?

Previous studies focused on recognizing students' actions in the smart classroom. Li et al. (2019) used multiple cameras which had been fixed on the front and back wall of the classroom to capture the students' actions from different angles. Similarly, Rashmi et al. (2021) proposed an automatic system, which monitors student activities in real time in a computer lab on a smart campus. The work of Bian et al. (2019), is closely related to our work since they study the problem of facial expression recognition during the delivery of online courses. In all studies stated above, authors perform quantitative evaluations to assess the performance of their systems, but the issue of evaluating the acceptance of action recognition technologies by the stakeholders is not considered. To the best of our knowledge, this is the first time that a systematic evaluation process is performed that includes both quantitative evaluation and evaluation by the stakeholders involved in the educational process.

In the remainder of the chapter, a literature review on the topics of Artificial Intelligence in education and action recognition in tele-education is presented. Subsequently, the methodology adopted to develop the proposed application is presented. The experimental evaluation and the results obtained are presented in Sections 3.4 and 3.5, respectively. In the final section, a discussion followed by plans for future work with concluding comments is outlined.

3.2 Literature Review

This section presents a brief literature review on the topic of student action recognition and user-acceptance of tele-education.

3.2.1 Student Action Recognition

The implementation of action recognition applications in a classroom can be really useful. One of the first benefits of action recognition systems is that they can analyse students' behaviour during the course and estimate their engagement (Thomas and Jayagopi, 2017). These systems are able to identify if students are active or not through the eye detection and face movements and provide feedback to educators accordingly. This can assist educators in their work, especially when they have many students, and it is difficult to monitor each one of them individually.

Unwanted events in the classroom could include situations such as bullying, aggressive behavior, or students experiencing extreme emotional distress. For example, if a student is exhibiting behaviors such as slouching, fidgeting, or avoiding eye contact, a human action recognition system may detect signs of discomfort or anxiety. If left unaddressed, these behaviors could potentially escalate into unwanted events, such as the student becoming disruptive or acting out. With the assistance of action recognition systems, educators can identify and support students who may need additional assistance or intervention to prevent such events from occurring (de Carvalho et al., 2022; Dhiman and Vishwakarma, 2019; Dimitriadou and Lanitis, 2023; Zheng et al., 2021). By alerting educators to these behaviors, they can take steps to intervene and prevent further negative interactions (Escobanez and Comendador, 2022).

More detailed descriptions regarding previous work related to student action recognition systems reported in the literature systems are provided in Chapter 2, Section 2.3.1.4.

3.2.2 Action Recognition in Tele-education

Image processing can be used in online education for monitoring students' facial expressions during classes (Arciniegas et al., 2021; Neelakantappa et al., 2022; Zacharis, 2016). Analysis of the facial expressions of students can give professors feedback on students' moods in real time. Know (2020) states that in addition to facial expressions heart rate and brain waves were used for better analysis of students' moods. Applications based on AI can offer real-time information about each student's activity in online classes.

Even though student actions recognition has been examined before, there is a lack of research concerning the development of applications that recognize the students' actions during online lessons. To address the gap, Bian et al. (2019), developed a database for an Online Learning Spontaneous Facial Expression (OL-SFED) regarding automatic inference of academic emotions. This OL-SFED database included five academic emotions of confusion, neutral emotion, distraction, fatigue, and enjoyment. OL-SFED included videos and facial images captured from a Web-camera during online courses. Facial expression algorithms for the prediction of emotions consisted of a VGG16 algorithm and different CNN architectures together with data augmentation techniques. According to the results, CNN using data augmentation techniques achieved an emotion recognition accuracy of 91.6%.

3.2.3 Evaluation of the acceptance of Tele-education

This subsection is considered important because it focuses on the evaluation of the systems that are used in tele-education, as our study in which we evaluate the acceptability of the suggested system. It is essential to assess the acceptance of systems, among those directly involved as it provides insights into how satisfied users are, and their perceptions and behavior towards the technology. By understanding user satisfaction with systems, we can identify areas for improvement. Furthermore, the system acceptability evaluation by the users enhances their experience, their trust and ensures the application of the systems.

The research community has recently paid a significant amount of attention to the evaluation process of e-learning applications as regards user experience, contentment, and acceptability so as to both gauge and quantify the level of satisfaction and effectiveness for academic users. According to Garrison (2011), the effectiveness, scope, and depth of the assessment of student learning and engagement for utilizing the e-learning system are key to the evaluation process. However, concerning technology adoption, the majority of methods for evaluating an application are based on using a questionnaire, including the appropriate answers in the form of a Likert scale.

Previous studies (Chen et al., 2022; Han and Sa, 2022; Pal and Vanijja, 2020; Prasetyo et al., 2021; Vlachogianni and Tselios, 2021) have evaluated the acceptance of well-known e-learning platforms such as MOOC, Microsoft Teams, Mobile Learning System, Zoom, Google Meetings etc., by users based on the Technology Acceptance Model (TAM) and the SUS (System Usability Scale) questionnaire, which are mainly recommended for evaluating online applications. A broader perspective has been adopted by Simoes and de Moraes (2012), where three different evaluation methodologies were used, including the SUS questionnaire, so as the usability of the Moodle e-learning platform is examined to estimate user satisfaction. In light of the COVID-19 pandemic, O'Pal and Vanija et al. (2020) presented an assessment of Microsoft Teams' usability using it as a benchmark, using both TAM and SUS approaches. Recently, Al-Maroof et al. (2021) explore the effect of Google Meet acceptance among Arab students during the pandemic. Data has been collected from 475 students and the results have shown that Google Meet is a useful tool.

There is a growing number of research that has been conducted to examine the perspectives of the individuals involved in the education process, the main focus of them remains on specific applications that students and educators use. For example, Marachi and Quill (2020) present the results of a User Satisfaction survey from LMS "Canvas", Heap et al. (2020) presents a study about the impact of AI-driven discussion platforms, and Chounta et al. (2022) examines the educator's perceptions in Artificial Intelligence as a tool to support their practice in Estonian K-12 education. Based on the findings from the literature review, it is evident that the issue of user evaluation of systems for monitoring student actions in online courses was not addressed before in the literature.

3.3 Action Recognition during Tele-education

In this section, the proposed Action Recognition system that can be used during tele-education is presented. This study outlines a systemic approach following a multiphase research design which includes six steps as outlined in subsequent sections.

3.3.1 Proposed System Overview

The purpose of this study is to provide a computer vision-based tool that can be used for examining the behavioral participation and behavioral disaffection of primary school students' during tele-education. Behavioral participation involves: effort, attention, initiation of action, involvement, intensity, persistence, and absorption, while behavioral disaffection involves: withdrawal, giving up, passivity, being inattentive, distracted, not engaged mentally and not prepared (Skinner et al., 2008, 2009). Behavioral participation and behavioral disaffection are considered as the main factors for students' participation (Skinner et al., 2009). The selection of behavioral participation and behavioral disaffection as factors for examining student behavior in online classes is warranted due to their significant impact on the learning process. These factors can be measured through visual information, providing researchers and educators with a valuable tool for evaluating teleconferencing effectiveness. However, it is crucial to acknowledge the multidimensional nature of these constructs and consider the complex interplay of various factors that affect teleconferencing (Ally, 2004; Picciano et al., 2002). To fulfil the requirements, a system was developed requiring lower computational power, where images are processed locally and only information related to attendance status is transmitted to the instructor rather than transmitting images of students to the instructor. In line with the taxonomy listed below (see Table 3.1), we aim to develop a method for recognising student's actions related to student's attention to the lesson, their absence from the lesson, their active participation, and their distraction.

Table 3.1 : Taxonomy of student actions.

Category	Class	Description
Absent	Absent	Not being present in the camera point of view.
Present but not participating	Looking Elsewhere	Not looking at the camera
Present and actively participating	Attending	Looking towards the camera.
	Hand Raising	Raising the left or the right hand.
Present and performing a relevant activity	Writing	Student writing notes on a pad.
Present and performing a non-relevant activity	Telephone Call	Using a smartphone for making a call.
	Using Phone	Using a smartphone for texting or playing games.

To deal with this problem, we propose to employ a machine vision-based approach that can be used for monitoring student's actions during the class delivery process and report to the instructor the status and level of concentration of the students. For this purpose, the use of different network architectures including faster R-CNN, SqueezeNet, GoogleNet, and Inception-v3 was investigated. More details regarding the CNN architecture-based image classification are presented in Appendix B. Figure 3.1 shows a block diagram of the proposed student monitoring system. An important aspect of this approach is that images of students captured during the process are processed locally and only information about the actions of the students is transmitted to the instructor so that issues related to privacy violation are minimised. When the proposed system is used in real classes, it is assumed that both parents and students should give their prior consent, ensuring that no ethical considerations related to privacy protection arise.

Under the European General Data Protection Regulation (GDPR), the use of cameras in a video conferencing system for an online class, in order to monitor the students, does not violate privacy, as long as certain conditions are met. The GDPR requires that institutions should have at least one lawful purpose for processing personal data and objectives such as monitoring attendance are considered lawful purposes. The collection of data should be limited to this purpose. In the case that the proposed system is used in real applications, it will be ensured that the GDPR provisions are met, by ensuring that all data collected are transferred solely to the educator and deleted at the end of a class. In addition, before a possible commercialization of the proposed system, all aspects regarding privacy, data handling, and other issues related to the operation of the system will be thoroughly investigated to ensure compliance with ethical and legal requirements.

Since the computation is done locally on the computers or smart devices of each student, it is imperative to adopt approaches that require minimum computational power, to ensure the smooth operation of the system regardless the specifications of the equipment that each student uses for the purpose of tele-education. Although the recognition of student's actions has been addressed in the literature before, to the best of our knowledge, the proposed formation of the application within the domain of tele-education has not been considered before.

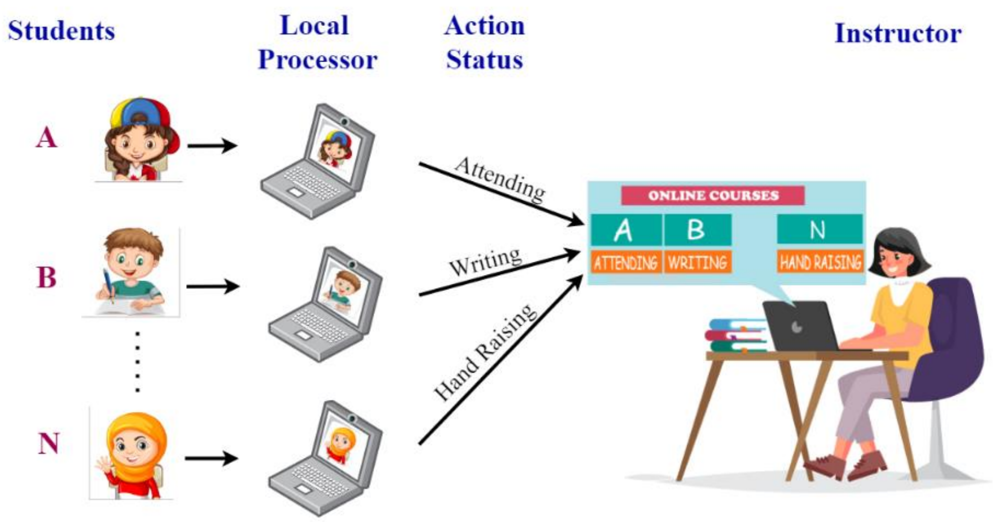

Figure 3.1 : Schematic diagram of the proposed student monitoring system during online courses.

The main phases of the proposed methodology include the steps of User Requirements Analysis, Data Collection, Activity Recognition (ML training), Performance Evaluation, System Development, User Evaluation. The proposed study covers a thorough procedure that includes six crucial steps (see Figure 3.2) to guarantee the efficient creation and assessment of a system based on Machine Learning (ML).

Phase I : Requirements analysis

In order to determine the needs of students and educators, the latest technological developments are analyzed, using questionnaires, interviews with educators, students and parents.

Phase II : Data Collection

In this phase, necessary datasets are collected that include various examples of students actions for training the machine learning models. The datasets are exposed to a variety of cases (e.g. gestures, postures etc.) so it is capable of learning effectively.

Phase III : Activity Recognition

In this crucial phase, the gathered data is processed, appropriate ML models are selected and trained, so the system starts to learn and adapt based on its inputs. The goal is that the model will develop the capabilities to predict based on the system requirements.

Phase IV : Performance Evaluation

The fifth step is the assessment of the training performance and the quantitative results. More specifically, the accuracy and the efficiency of the models to recognize students' actions during online courses is taken into account.

Phase V : System Development

In this phase, the ML models are integrated into a user-friendly application, appropriate for real-time analysis. The main objective here is ensuring that the system operates seamlessly and effectively during online courses.

Phase VI : User Evaluation

Finally, the system is evaluated for its real-world applicability and its overall performance by its actual end-users. Valuable feedback regarding the effectiveness and usability of the system is gathered, in the form of qualitative data for analysis. The results of the analysis can be used for future refinement of the system.

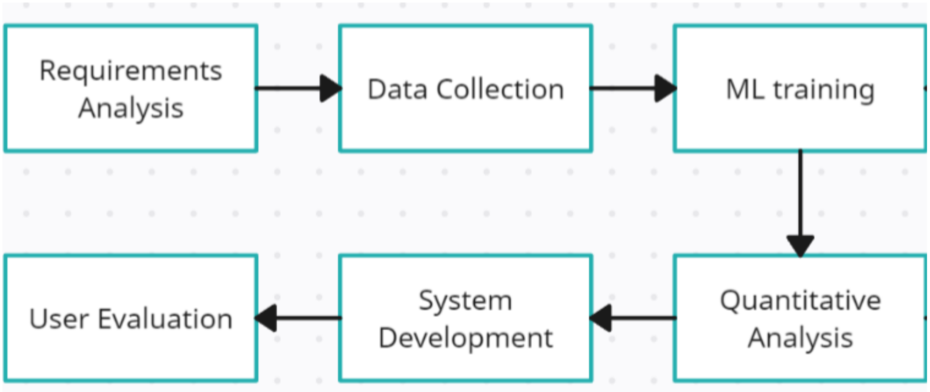

Figure 3.2 : Block Diagram of the Research & Development Process.

In the following sections, we describe each step of the methodology.

3.3.2 User Requirements Analysis

Prior to the application development, opinions of three educators, three students and three parents have been recorded, in order to register their feedback towards the proposed class monitoring tool. During the interviews the main features of the proposed system were presented to the participants, so that they could provide feedback on issues related to the system design, the impact of the system in the educational process and also state possible advantages and disadvantages. All the data were collected through semi-structured interviews since this method constitutes the most appropriate tool for recording detailed opinions and other related feedback (Barriball and While, 1994). Moreover, interviews constitute the most appropriate research tool when the sample involves students.

Data analysis was performed with the use of qualitative techniques (CRESWELL et al., 2002) where the words, sentences and phrases that had similar conceptual meaning and were important for the research, were classified in groups, while the data of secondary importance have been split from the aforementioned contents. This process is called codification and refers to the process of departmentalization and labelling of texts occurring from interviews (CRESWELL et al., 2002) so as to derive descriptions regarding the system requirements. This process has been repeated to confirm the validity and credibility of codification. The following table (see Figure 3.3) demonstrates a summary of the main views of educators, parents, and students, as derived from the codification method.

The analysis of the feedback received shows that the participants were enthusiastic about the system of recognizing students’ actions in online lessons. With regards to the disadvantages, the educators and parents characterized the application as excellent in contrast with the students, where the majority declared that they would have difficulties in accepting the application of the system as it will prevent them from engaging in activities not related to the class delivery. At the end of the interviews, the participants had the opportunity to suggest what they wanted more from the system and most of the participants found the application complete except for two educators arguing that it could involve more actions (e.g., sleeping) and more features so that the prosed system can also be used during the delivery of artistic lessons, such as art and music. Based on the feedback received from the stakeholders, the development process was carried out, as exemplified in the following subsections.

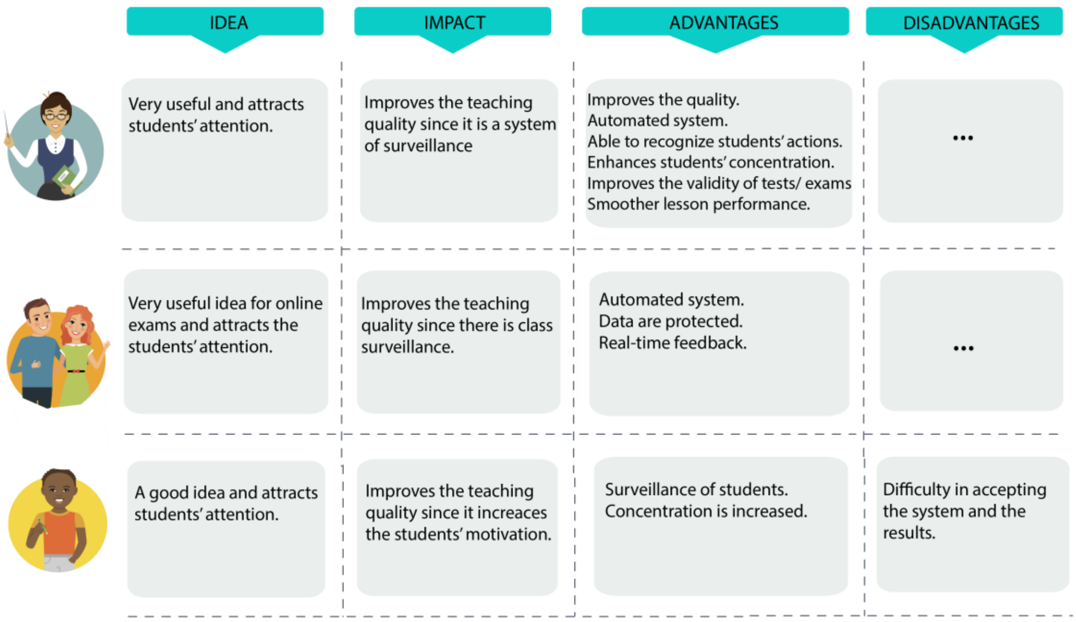

Figure 3.3 : Opinions of educators (top row), parents (middle row), and students (bottom row) regarding the proposes class surveillance system.

3.3.3 Training Data Collection

An important part of the study is the collection of training data required for training machine learning models for the action recognition task. Training data have been collected using a laptop camera, from 15 primary school students while they were using a laptop in a style that is usually adopted during the attendance of on-line courses from their homes. Students who took part in the data collection process were asked to perform the actions of "Absent", "Attending", "Hand Raising", "Writing", "Telephone Call", "Using Phone - texting, playing games" and "Looking Elsewhere" (see Figure 3.4). All the actions considered, are associated with the five categories of "Absent", "Present but not participating", "Present and actively participating", "Present and performing a relevant activity" and "Present and performing a non-relevant activity" (see Section 3.3.1, Table 3.1). Additionally, the definition of the exact actions considered was based on educator's suggestions and relate to the quality of attendance of students during on-line class delivery.

For each of the actions stated above, a 10 second video that demonstrated each class of actions was recorded. For every student, two set of videos (Session A and Session B) were recorded, in which the students wore different clothes and the background changed. Each session has 605 images and videos for different students had different backgrounds. In total, the dataset contains 194 videos with a total of 9700 image frames, where Session A contains 5200 frames and Session B 4500 frames. An example of typical images depicting different actions considered are shown in Figure 3.4. More details regarding the video capture protocol are presented in Appendix A.

Figure 3.4 : Typical students' images regarding the seven actions. (a) Telephone Call (b) Attending (c) Hand Raising (d) Looking Elsewhere (e) Writing (f) Using Phone (g) Absent.

Prior to students' performance of the actions that are illustrated on Table 3.1, the researchers guided the students by giving clear guidelines regarding the actions that they have to perform and the time duration of each action. The students were constantly being informed, and they had the right to withdraw their participation in the research at any time without giving any reasons or explanations. The actions executed by the students displayed a high level of realism, as they were routinely performed during class, thus necessitating no additional preparation since they are not complicated actions.

3.3.4 Action Recognition

Action recognition is performed using deep networks. In order to select the most appropriate network architecture for the given problem several deep network architectures that include a GoogleNet (Szegedy et al., 2015) SqueezeNet (Iandola et al., 2016) Inception-v3 (Szegedy et al., 2016) and faster R-CNN (Ren et al., 2015) were trained and evaluated. The selection of the four different machine learning architectures was based on the fact that the proposed application should require minimal memory requirements in order to be able to run in real-time on each student's machine, and therefore networks were used that required as little computational resources as possible. Furthermore, the selected networks were chosen as they have been previously used effectively in similar applications (Putra et al. 2023; Tereikovska et al. 2021; Dukić et al. 2022; Farooqi et al. 2022). Figures 3.5, 3.6 and 3.7 show the training procedure of the second experiment (see Section 3.4.2) for the GoogleNet, SqueezeNet and Inception-v3 respectively.

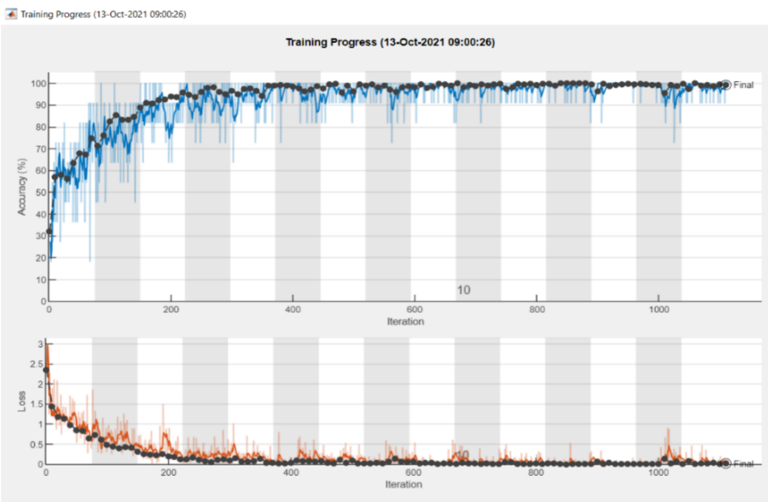

Figure 3.5 : Training procedure (accuracy, training loss) of the second experiment for the GoogleNet.

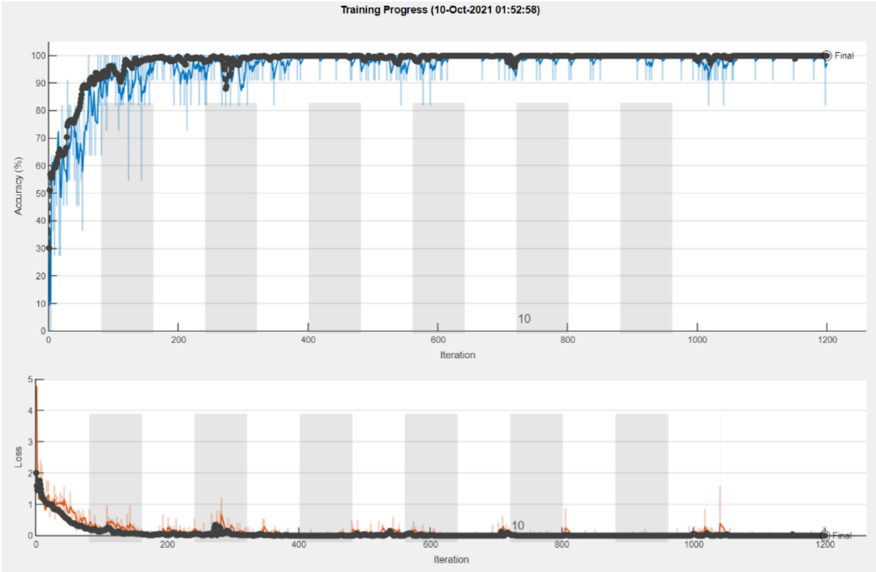

Figure 3.6 : Training procedure (accuracy, training loss) of the second experiment for the SqueezeNet.

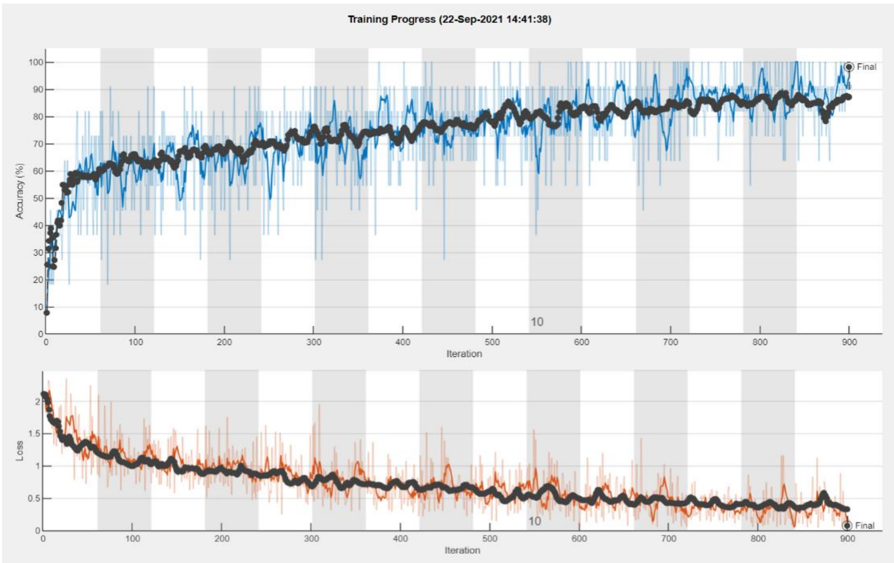

Figure 3.7 : Training procedure (accuracy, training loss) of the second experiment for the Inception-v3.

To solve the problem of limited data, we used data augmentation to augment images in the training dataset. In the present work, augmentation algorithm included reflection, rotation, scale and translation of all training images. During the training procedure, transfer learning was adopted where starting from a pre-trained version of the networks trained using images from the ImageNet database (www.imagenet.org), the network weights of certain layers are adapted based on the train data and the classification task in question. To train the networks, we used the Adam optimizer (Kingma and Ba, 2014) with a momentum value of 0.9 and weight decay of 0.0001 to minimize a cross-entropy loss function. In the training options, we set the learning rate 0.0001, defined the size of batch 11 while training involved 15 epochs.

3.4 Quantitative Performance Evaluation

From the initial stages of the experimental evaluation, it was evident that the faster R-CNN architecture was the least appropriate network for the proposed application framework, due to the computational load required during the classification stage, that would prevent the real time operation of the system on student's machines. Therefore, the experimental evaluation was focused on the comparative evaluation of the GoogleNet, SqueezeNet and Inception-v3 architectures.

Based on the taxonomy in Table 3.1 (see Section 3.3.1), results are reported both for the seven-class classification problem, where the exact student action is recognized, and for the five-class classification problem where student's actions are classified into the states of "Absent," "Present but not participating," "Present and actively participating," "Present and performing a relevant activity," and " Present and performing a non-relevant activity". Two experiments were performed :

3.4.1 Experiment 1: Using New Instances of Previously Enrolled Students

For this experiment image frames from Session A were used for training the system and image frames from Session B (see Section 3.3.3) for testing the system, allowing in that way the assessment of the ability of the proposed system to recognize actions in new videos of students who provided training data.

The results obtained from the proposed CNN architectures for the performance evaluation of the seven-class classification problem are presented in Table 3.2. The errors of the GoogleNet, SqueezeNet and Inception-v3 are 0.022, 0.059 and 0.374 respectively.

GoogleNet and SqueezeNet are proved as the most suitable networks in the classification of the students' actions in Experiment 1, in contrast to Inception-v3. However, the SqueezeNet needs less computational time and memory requirements in comparison with the other networks. The low performance measures in Inception-v3 are due to the fact that more data are required for training.

Table 3.2 : Accuracy metrics for experiment 1.

Performance Measures	GoogleNet	SqueezeNet	Inception-v3
Accuracy(%)	97.81	94.15	62.61
Recall	0.964	0.910	0.601
Precision	0.964	0.926	0.510
F1-score	0.963	0.912	0.542
MCC*	0.960	0.907	0.479
Cohen's k	0.910	0.761	0.345
Classification time (s)	0.089	0.039	0.258
Memory requirements (MB)	21.3	2.60	77.1

**MCC=Matthews Correlation Coefficient*

Based on the results it is evident that the algorithm can classify students' actions almost with perfect accuracy for GoogleNet. From the GoogleNet confusion matrix for the seven-class problem (see Figure 3.8), we observed that the images were recognized correctly in class 1 (Absent), class 6 (Using phone) and class 4 (Looking Elsewhere) while the accuracy is greater than 90% for class 2 (Attending), class 5 (Telephone Call), class 3 (Hand Raising) and class 7 (Writing). For the five-class classification problem, GoogleNet achieves correct recognition rates of 98.05%. Absent and present but not participating are perfectly classified while present and performing a non-relevant activity, present and performing a relevant activity, and present and actively participating has an accuracy of 98.3%, 90.7% and 95.7%, respectively (see Figure 3.9). Figure 3.10 represents the ROC curve for each class for the GoogleNet.

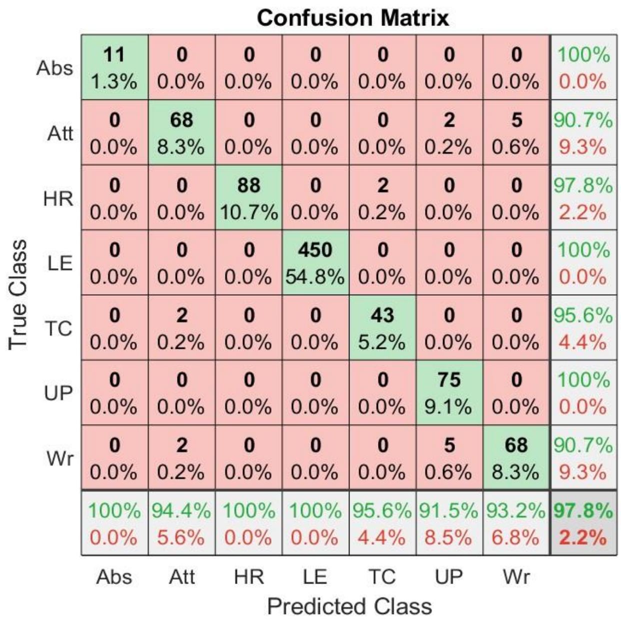

Figure 3.8 : Experiment 1: Confusion matrix for the 7-class classification problem when GoogleNet was used. Classes involved are Absent(Abs), Attending(Att), Hand Raising(HR), Looking Elsewhere(LE), Telephone Call(TC), Using Phone(UP) and Writing(Wr).

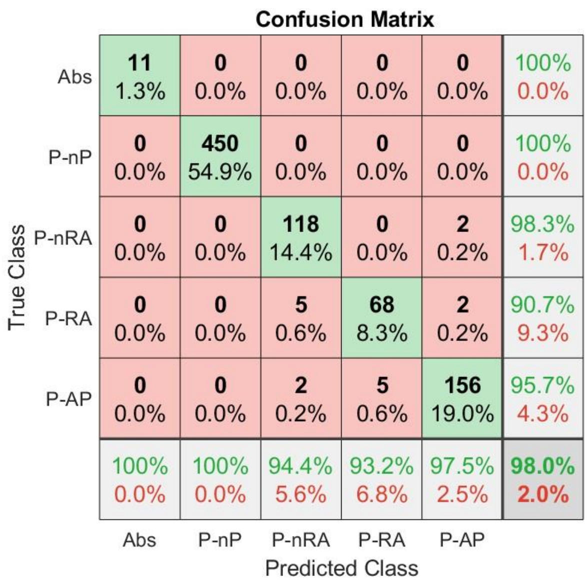

Figure 3.9 : Experiment 1: Confusion matrix for the 5-class classification problem when GoogleNet was used. Classes involved are Absent(Abs), Present but not participating(P-nP), Present and performing a non-relevant activity(PnRA), Present and performing a relevant activity(P-RA), Present and actively participating(P-AP).

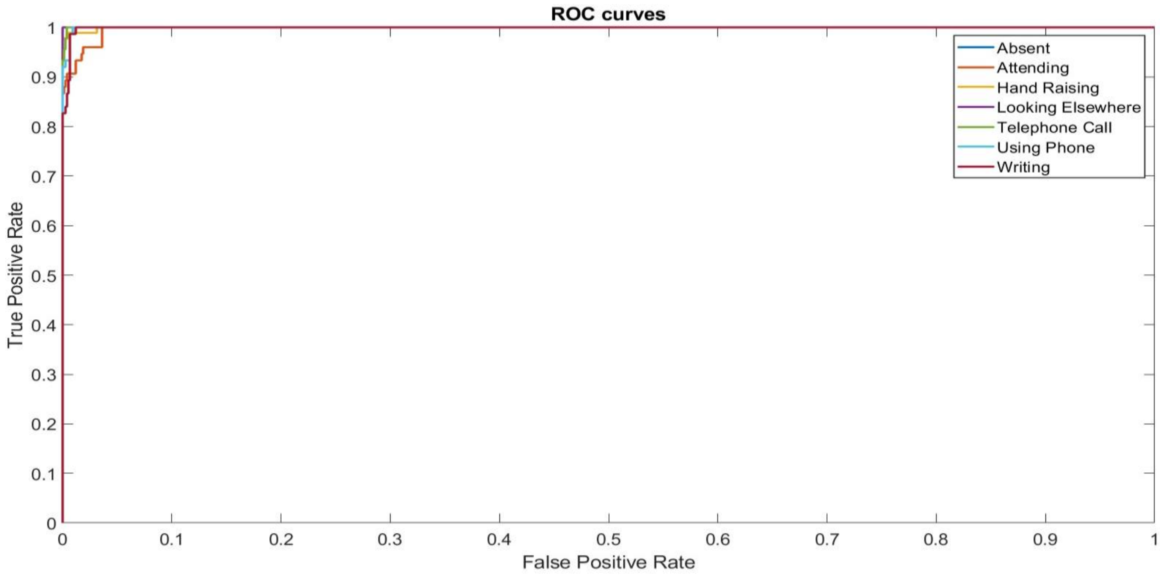

Figure 3.10 : ROC curves for GoogleNet for the seven-class classification problem for experiment 1.

3.4.2 Experiment 2: Recognizing Actions of Previously Unseen Students

All images of eight students (from both session A and Session B) were used for training the system and images of the remaining seven students were used for testing the system, so that recognition performance is tested on previously unseen students.

Table 3.3 presents the performance measures obtained from the suggested CNN architectures for the seven-class classification problem. For Experiment 2, the errors of GoogleNet, SqueezeNet, and Inceptionv3 are 0.057, 0.127 and 0.551, respectively.

Among all networks considered, GoogleNet had the highest correct recognition rates (see Table 3.3). From the GoogleNet confusion matrix for the seven-class problem (see Figure 3.11), the images were recognized 100% correctly in class 1 (Absent), class 5 (Telephone Call), class 4 (Looking Elsewhere), class 6 (Using Phone) and the remaining classes, class 2(Attending), class 3(Hand Raising) and class 7(Writing) have accuracy 78.6%, 98.8% and 61.4%, respectively. According to our findings, GoogleNet misclassifies the classes ”Attending” and ”Writing” with the class “Using phone” by 1.9% and 3.4%, respectively. Aggregating the seven actions into five more general categories we get the confusion matrix presented in Figure 3.12, which illustrates that the network classifies the five general categories related to student status with a correct recognition rate of 94.32%. The classes relating to absent, present but not participating, present and performing a non-relevant activity are perfectly classified with 100% accuracy, whereas the present and performing a relevant activity, present and actively participating categories have 61.4% and 89.6% accuracy, respectively. According to our findings, we conclude that GoogleNet can recognize with increased accuracy behavioral disaffection rather than behavioral participation in primary school students, which is significant for educators to know during teleconferences. Figure 3.13 represents the ROC curve for each class for the GoogleNet.

Table 3.3 : Accuracy metrics for experiment 2.

Performance Measures	Googlenet	Squeezenet	Inception-v3
Accuracy(%)	94.32	87.32	44.91
Recall	0.913	0.820	0.540
Precision	0.939	0.812	0.369
F1-score	0.911	0.804	0.361
MCC*	0.911	0.790	0.325
Cohen's k	0.768	0.482	0.555
Classification time (s)	0.082	0.038	0.234
Memory requirements (MB)	21.3	2.60	77.1

**MCC=Matthews Correlation Coefficient*

We observe that in both Experiments, GoogleNet confuses the aforementioned classes with minimal errors. Otherwise, SqueezeNet mostly overestimates the phone usage of students during active participation by 3.4%. On the other hand, Inception-v3 overestimates phone usage and class "Looking elsewhere" during active participation by 6.4% and 13%, respectively. Error percentages for the three networks are higher in Experiment 2 than in Experiment 1, since the size of the train set in Experiment 1 is larger than the size in Experiments 2. In the future, in order to minimize the error rates, the overall experimental evaluation will be implemented using several recorded videos of online lessons of larger duration.

The use of the GoogleNet model ensures that the computational requirements for the classification process are kept low, allowing the real-time operation on almost any machine. More specifically the trained networks require only 0.089 seconds on a standard laptop to classify an action from an image, while only 21.3MB of memory is required to store the trained network on a smart device. The students' actions were captured using the camera of a laptop with Intel(R) Core™ i7-7500U CPU @ 2.70GHz(4CPUs) processor and 8192MB RAM memory. The aforementioned laptop was employed solely for the training of the application, rather than its execution. The application is compatible with any standard hardware commonly accessible to the public, as it demands low computation power, hence the selection of GoogleNet as the architecture. Although the use of more intricate architectures could potentially enhance network performance, it may hinder their execution on standard hardware.

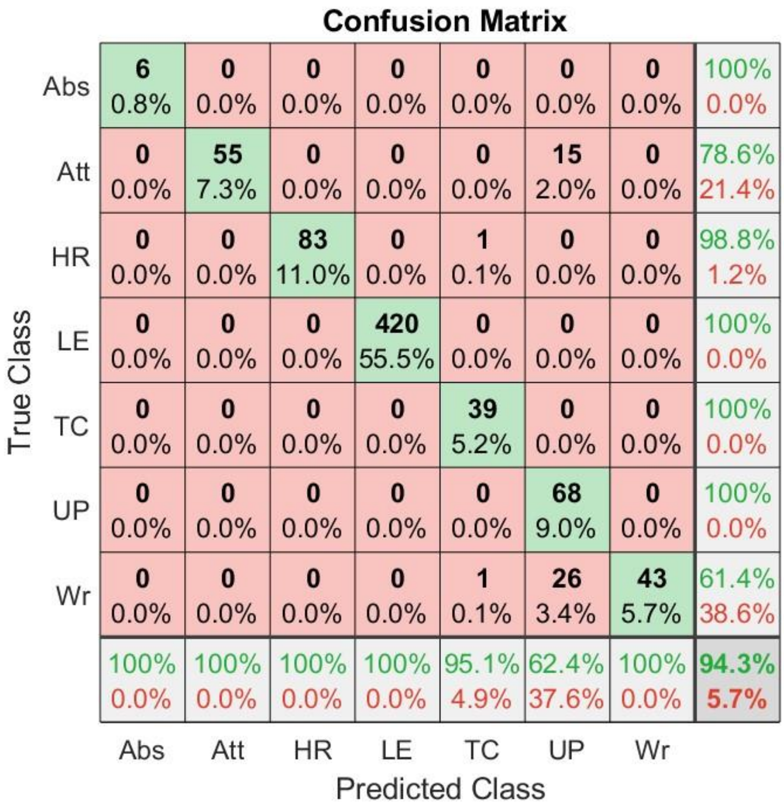

Figure 3.11 : Experiment 2: Confusion matrix for the 7-class classification problem when GoogleNet was used. Classes involved are Absent(Abs), Attending(Att), Hand Raising(HR), Looking Elsewhere(LE), Telephone Call(TC), Using Phone(UP) and Writing(Wr).

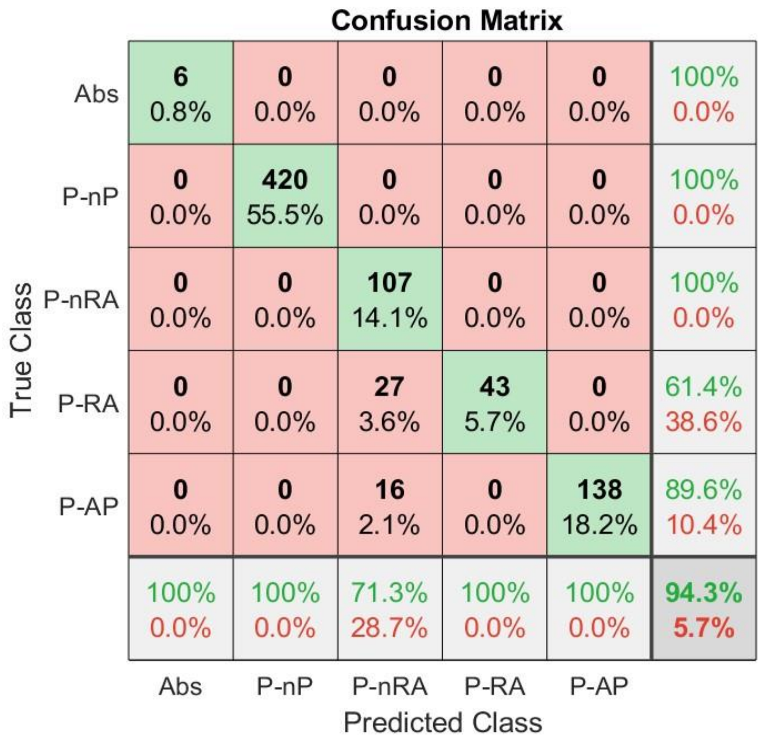

Figure 3.12 : Experiment 2: Confusion matrix for the 5-class classification problem when GoogleNet was used. Classes involved are Absent(Abs), Present but not participating (P-nP), Present and performing a non-relevant activity(PnRA), Present and performing a relevant activity(P-RA), Present and actively participating(P-AP).

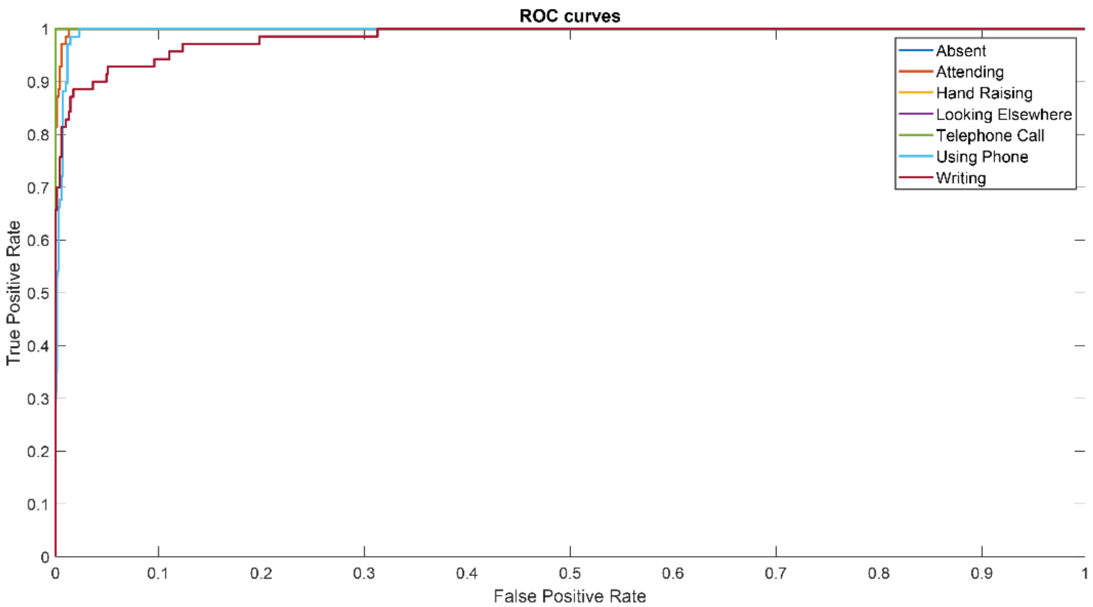

Figure 3.13 : ROC curves for GoogleNet for the seven-class classification problem for experiment 2.

3.4.3 Conclusions

In our study, we developed a deep network model which can provide to educators real-time video analysis of young students, providing in that way information about the behavioral participation and behavioral disaffection of their students during the delivery of online courses.

Initial results demonstrate high classification rates for the five class and seven class classification problems, both when dealing with new images of previously enrolled students or when dealing with previously unseen students. The results indicate the feasibility of this approach that can be used as the basis for implementing an integrated system that helps educators to monitor actions of participants during remote class delivery. An important aspect of the system is the fact that the privacy of students is protected since educators receive only real-time information about students' actions rather than receiving images of the students. To eliminate any additional ethical considerations regarding student privacy, in the final system students and parents will be thoroughly informed about the operation of the action recognition system, and they will be required to approve its use during the delivery of online courses.

Since in the proposed system, the action recognition process will take place locally, on the device of each student, it is imperative to use classification methods that require minimal computational load. In the final system implementation, students who possess devices with low computational capabilities will be using the SqueezeNet network for classification, as in that case the computational and memory requirements are minimized, allowing real-time operation, and a reasonable recognition accuracy. Otherwise, if the students have a powerful device, then it is more appropriate to use the GoogleNet network so that we take advantage of the increased recognition accuracy achieved by this architecture.

In future work, we aim to explore different network architectures, extend the dataset to include more students and additional actions, perform an exhaustive user evaluation with all stakeholders, and investigate practical issues of integrating the proposed action recognition system in tele-education teaching sessions.

3.5 Integrated System

An integrated system was developed using Unity software (www.unity.com) in which the students' actions were used to animate corresponding avatars in a virtual classroom.

Figure 3.14 shows a block diagram that demonstrates the function of the proposed integrated system. The system consists of the client (student) and the server (instructor). The images of the students are recorded by Web cameras and are processed locally on their personal computers in order to determine their actions. The application is compatible with any standard hardware commonly accessible to the public, as it demands low computation power. Information related to student actions is sent to the server (instructor). The instructor's interface contains a 3D view of the classroom where every student is represented by an animated avatar that demonstrates their activity. A video demonstrating the operation of the system can be found here:

https://youtu.be/R_NZCu_6ysk?si=54SgiMAzZc4GJF7e.

The 3D model that was used for the 3D virtual classroom was obtained from turbosquid.com. The avatars were created using the Autodesk character generator (https://charactergenerator.autodesk.com/) and their movements were incorporated using the Autodesk Maya software (see Figure 3.15). Animated avatars allow the instructors to visualise the activities of the students during teleconferencing without having access to actual videos showing the students (see Figure 3.16). The students' actions in the three-dimensional classroom synchronize with the students' actions in reality during online lessons.

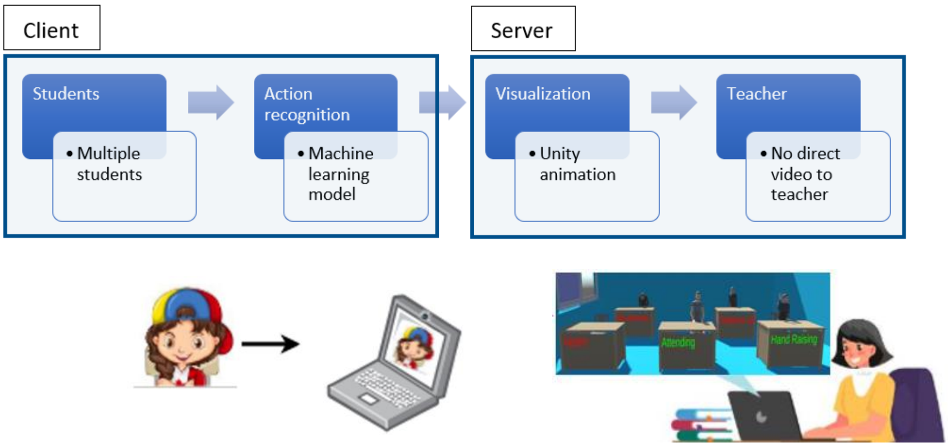

Figure 3.14 : System Overview.

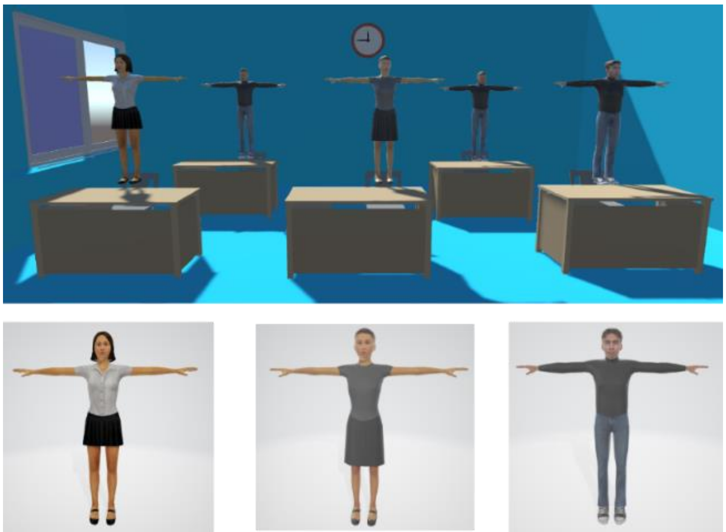

Figure 3.15 : Typical screenshots of the avatars corresponding to students attending the class remotely.

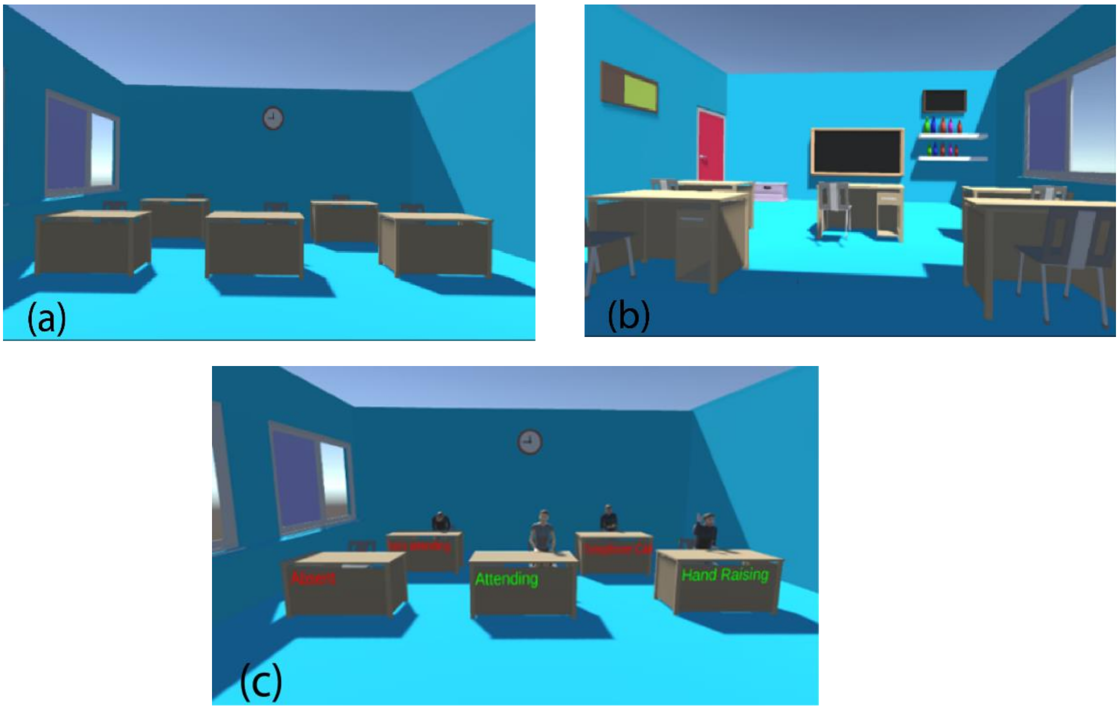

Figure 3.16 : Screenshot of animated students in virtual 3D class. (a) Front view of the virtual classroom. (b) Back view of the virtual classroom. (c) Animated students in virtual 3D class.

3.5.1 Technical details

The client side of the proposed system (see Figure 3.14) incorporates a machine learning model trained to classify the following seven student actions: absent, attending, hand raising, looking elsewhere, telephone call, using phone and writing (see Section 3.4 for details about the action recognition process).

Both the student and the educator side use a python script for sending and receiving information about student actions. This is done using python socket (https://docs.python.org/3/library/socket.html) which provides a way for two nodes to communicate on a network. On the client side, classifications are performed constantly, sending information to the server side about the student action in each image frame captured. This is done at a rate of approximately 90 frames per 10 seconds. On the server side, the classifications are saved and on every iteration (10 seconds) a majority voting strategy within the selected time interval, is used to determine the exact student action to be written in a log file for each student.

At the server (educator) side a Unity3D program reads the log file for each student, and activates the corresponding animation of each student avatar that matches the recognized student action. This process is done simultaneously for all students in class, so that the educator visualizes the actions of all students taking place in a class in a similar way that he/she visualizes students in a real class. Figure 3.17 shows a screenshot of animated students in the virtual 3D class, where the actions of the student avatars correspond to the actions of each student at the client sides.

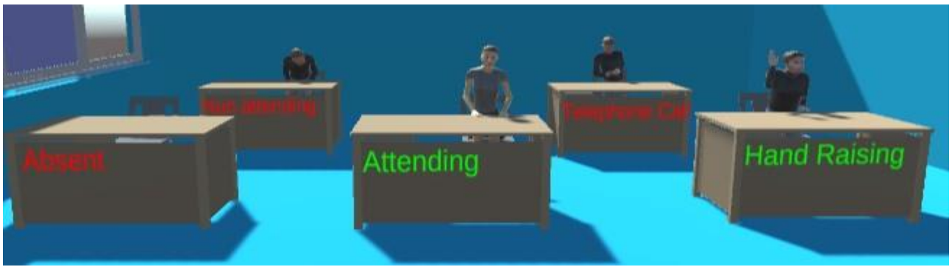

Figure 3.17: Screenshot of animated students in virtual 3D class.

3.5.2 Experimental User Evaluation

While the quantitative results demonstrate the potential of the method to correctly classify student actions, it is imperative to assess the acceptance of the application by the main stakeholders involved in the educational process. The evaluation of user perspectives plays a critical role in the development of integrated interactive applications. An examination of end users' views on the efficacy and acceptance of a system is imperative to ensure that it aligns with the desired objectives (Shneiderman et al., 2016). By gathering valuable insights into the user experience and overall usability of the system and leveraging user feedback, developers can optimize their design. In this regard, user evaluation serves as a vital step to ensure that the system aligns with the needs and expectations of the intended user demographic, which can result in increased user satisfaction and engagement (Virzi, 1992). In this section a user-based evaluation process used for examining the reactions of educators, students and parents toward the proposed application is presented.

3.5.2.1 Overview of the evaluation procedure

The purpose of this study is to investigate the acceptance of using an experimental machine-vision based application that can be used for monitoring student's actions during the class delivery process and report to the instructor the status and level of concentration of the students. Main motivation for this study is to investigate if it is feasible to use the proposed application during real educational activities. Our study aims to address the three research questions :

RQ1: How learners, educators and parents *perceive* the feasibility of using privacy-protecting methods for monitoring student actions during tele-education?

RQ2: How is the acceptance of using privacy-protecting methods for monitoring student actions during tele-education *perceived* by the learners, educators, and parents?

RQ3: How learners, educators and parents *perceive* the impact of using privacy-protecting methods for monitoring student actions during tele-education?

The experimental procedure consisted of two stages. The first stage of the research focused mainly on the completion of an online questionnaire used as a means of evaluation of the suggested system. During the evaluation process participants completed a pre-questionnaire, then watched a video that demonstrated the operation of the application, and afterwards, they completed post-questionnaires similar as the ones in the pre-questionnaire. To further validate the results obtained, during the second stage of the experiment a number of participants had the chance to use the application, rather than just watching a video of the application, and answer questions as part of a semi-structured interview process. More details about the evaluation process are shown below.

3.5.2.2 Sample

The size of the sample for the main research consisted of 75 participants separated in three groups: students, parents and educators. Students who participated in the experiment were 9-23 years old, while educators were of primary, secondary and higher levels. In our study, 34 male (45%) and 41 female (55%), 9-52 years old participated. Specifically, eight male educators, 10 male parents and 16 male students, 17 female educators, 15 female parents and nine female students. All participants were from Cyprus. Twenty-one (84%) of the parents' group were graduates of a higher education institution and four (16%) high school graduates. Eighteen (72%) of the parents stated that they have two years experience with online classes, while the remaining seven (28%) stated that they have one and a half years experience with online classes.

Concerning ethics, all the participants were acquainted about the purpose of this study both orally and in writing in order to obtain their informed consent. Furthermore, the participants were assured of the confidentiality and anonymity of their personal data. For students under the age of 18, there was a legal form of consent that was signed by their parents. The study underwent an ethics review process and was approved by the Cyprus National Bioethics Committee (CNBC) (Ref. number: ΕΕΒΚ ΕΠ 2022.01.203), ensuring that the research was conducted in accordance with ethical standards.

3.5.2.3 Phase I : Questionnaires

All participants were given an online questionnaire. The first part of the questionnaire contained closed type questions in which personal information of demographic interest was recorded (nationality, gender, profile), while the second part contained both closed and open type questions regarding the participants' experience with online education. In the beginning there was a definition for online education for those who weren't familiar with teleconferencing. There were questions regarding the participants' engagement in the use of online education, the difficulties they had to overcome, and questions related to the use of cameras in teleconferencing. All questions were in a Likert 6-level scale from "not at all" to "very much". In the end, there were two more open type questions. One was about actual incidents that had occurred to them during online classes, while the other was related to how those incidents were handled. The open type questions were not compulsory.

After the completion of the first questionnaire, volunteers from all three groups watched a video that illustrates the operation of the proposed application. Typical screenshots of the video are shown in Figure 3.18. Subsequently, the participants completed a post questionnaire, with questions similar as the ones in the pre-questionnaire.

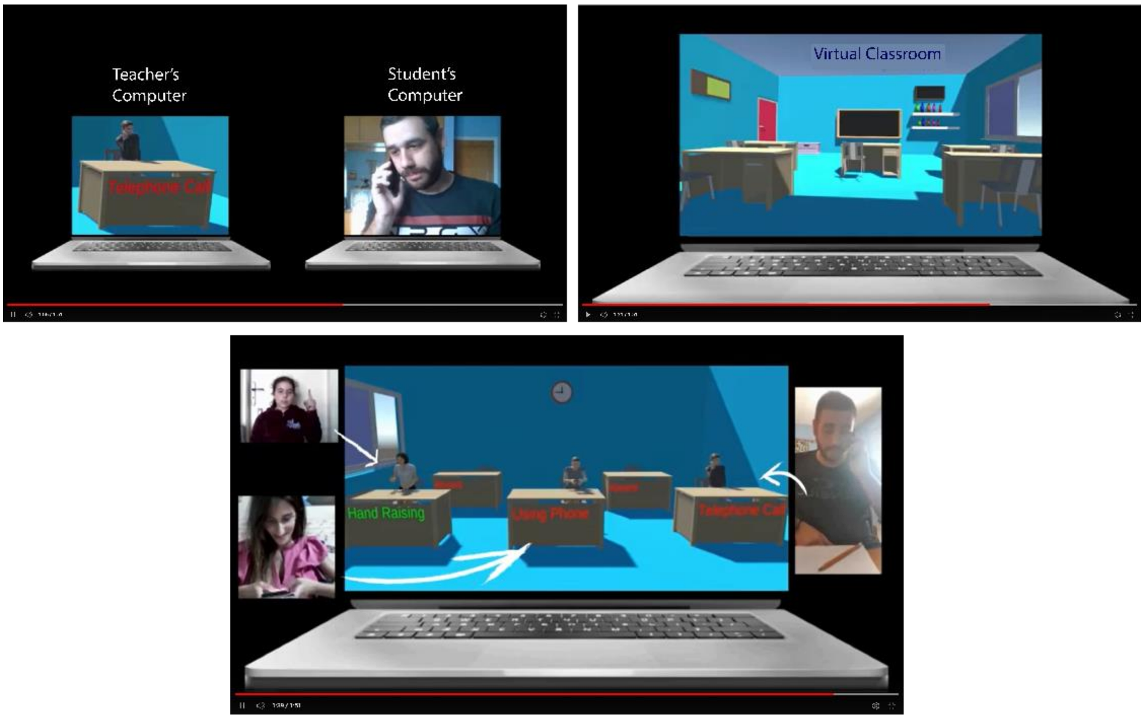

Figure 3.18: Typical screenshots of the video.

3.5.2.4 Phase II: Interviews

After the experiments ended, a semi-structured interview took place with six of the participants of the first experiment, two of each group, and a duration of 10 minutes in order to define the participant's reaction to the use of the proposed application in online education. Based on the availability of participants to attend an interview, six participants (two educators, two parents, and two students) were selected to take part in the interview sessions. Interviews constitute the most suitable tool for recording detailed views and other related feedback (Barriball and While, 1993) and moreover, the most appropriate research tool when the sample involves students.

During the interview sessions, participants had the opportunity to try the application in real time before answering the questions. Participants followed the author's guidelines for using the application. The server and client tools were running on the same laptop, allowing participants to test the application from both the student and educator sides (see Figure 3.19). The questions asked to the participants were based on part C in the post-questionnaire (included in the next subsection). The qualitative data that were collected were analyzed thoroughly using the grouping method (Creswell, 2002), where the findings led to further conclusions about the functionality of the system.

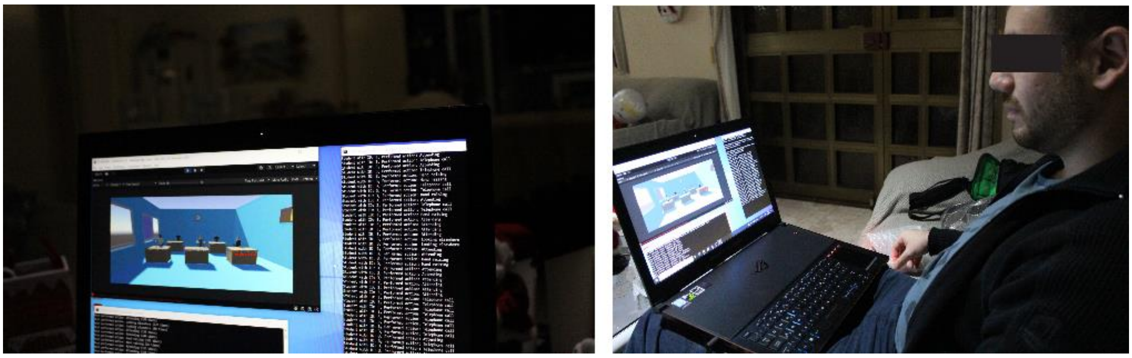

Figure 3.19: Participant (student) using the application**.**

3.5.3 Evaluation Results

This section presents the results of the online questionnaire as well as the interviews.

3.5.3.1 Questionnaire-based results

The objective of this study is to answer RQ1, RQ2 and RQ3 regarding for the groups of students, parents and educators and regarding their view of the efficiency of the system. Hence, in order to assess the validity of our hypotheses, statistical analysis is necessary. Statistical analysis constitutes a fundamental tool in user evaluation studies, particularly in the context of Human-Computer Interaction (HCI). As highlighted by MacDonald and Atwood (2013), HCI is concerned with the design, implementation, and assessment of interactive computer systems and their related products (MacDonald and Atwood, 2013). As system efficiency and performance are crucial, user evaluation studies aim to enhance the overall efficacy of the system and to ascertain its suitability for its intended purpose. In this regard, summative evaluation represents a valuable method to assess the success of a system at the end of the product development phase, with the active participation of project stakeholders (Shneiderman et al., 2016). Statistical analysis is crucial for understanding user behavior and system performance. It allows researchers to analyze user feedback, identify trends, and draw meaningful conclusions. It is an essential part of user evaluation studies, providing a rigorous and systematic approach to assess interactive computer systems (Lewis, 1995; MacDonald and Atwood, 2013).

For the analysis, both Descriptive and Inferential Statistics were applied for exploring the differences among the groups, and for testing the hypothesis. For the data analysis, the package SPSS was used. The reliability of the questionnaires has been tested with Cronbach's alpha reliability index and, according to the results, the index varied between $0.737 \leq a \leq 0.780$. These values show the reliability of the questionnaires used in the experiment (Nunnally, 1978). Prior to the statistical analysis, the sample normality within and between groups was tested. Therefore, the statistical inference was conducted using nonparametric tests such as Wilcoxon signed rank test and the Chi-square test so as to answer the research questions which were defined for the aim of this research based on statistically significant results. Furthermore, the reliability of the questionnaires with the index Cronbach's alpha has been tested. The results of the questionnaires were cross-validated with interviews as the participants had the opportunity to try the application in real time. The statistical analysis of the interviews was conducted using the grouping method. This process has been repeated to confirm the validity and credibility of codification, so that the validity of this study is guaranteed.

Research Question (RQ) 1: How learners, educators and parents *perceive* the feasibility of using privacy-protecting methods for monitoring student actions during tele-education?

Table 3.4 shows the results of the non-parametric Wilcoxon signed rank test for the students, educators, and parents' group of the differentiation before and after the interference. This test is used because the samples are paired, and the data are in an ordinal scale since it has to do with the same persons in different circumstances (before and after the interference). The null hypothesis (Ho) is that there is no significant statistical difference regarding the views about the usage of a web camera before and after the interference and the alternative (H_1) is that there is a statistically significant difference with regard to views about the usage of a web camera in online classes. Furthermore, the below table shows the results of the Chi-square test for the comparison between groups regarding their opinion on whether the use of the camera is necessary. This test is used because the samples are independent and the data are in ordinal and nominal scale. The null hypothesis (Ho) is that there is no difference between groups and the alternative (H_1) is that there is a statistically significant difference between groups. The null hypothesis is accepted when $p\text{-value} \geq 0.05$ and is rejected when $p\text{-value} < 0.05$.

Table 3.4 : Mean, Standard Deviations for each group and group comparison results regarding the use of cameras (N = 75).

	Students		**Parents**		**Educators**		**Comparison**
	M (SD)	p-value	M (SD)	p-value	M (SD)	p-value	p-value
Q1 (pre-test)	2.72 (1.54)	.096	3.00 (1.44)	**.004***	2.72 (1.51)	**.002***	.342
Q1 (post-test)	3.72 (1.77)		4.80 (1.50)		3.96 (1.74)		**.029***

Q1: Do you think that the use of camera is necessary?

SD: Standard deviation

*** Statistically significant change (p-value<0.05)**

There was found statistically significant difference between before and after the intervention to the responses of parents on whether the usage of a web camera is necessary for the online classes (p=0.004). Moreover, there is a statistically significant difference between the educators' answers of before and after whether the use of camera is necessary(p=0.002). Specifically, after the video, educators denoted that the use of cameras is necessary while parents declared that the use of a web camera is more necessary to the courses as compared to what they declared earlier. Between the groups, there is a statistically significant relationship in the post-questionnaire (p=0.029). Specifically, educators and students agree much with that statement (48% and 36% respectively), and parents agree very much (48%). In conclusion, all groups agree on the necessity of the use of cameras required by the application for identifying the actions of the students in online classes. The proposed application protects the privacy of students. For this reason, after the intervention, participants stated that the use of a camera is required in online classes.

Table 3.5, shows descriptive statistics (Mean, SD) about the feasibility of the proposed application. There is no statistically significant difference between the groups and the different opinions whether it is possible to use methods to protect students' privacy.

Educators and parents strongly disagree that the application affects the students' privacy (56% and 60% respectively) while students mostly agree (20%). Overall, the three groups believe the use of the application in online classes is feasible at a grade ranging from mediocre to high without raising confidentiality issues.

Table 3.5 : Mean, Standard Deviations for each group and group comparison results concerning participants' views on the protection of students' personal data and the feasibility of the application in online courses (N=75).

	Students	**Parents**	**Educators**	**Comparison**
	M (SD)	M (SD)	M(SD)	p-value
Q2 (post-test)	4.36 (1.22)	5.36 (.757)	4.88 (1.30)	.058
Q3 (post-test)	3.20 (1.66)	5.04 (1.27)	5.04 (1.27)	**.001***

Q2: Do you think that the proposed application during online lessons is feasible?

Q3: Do you think that the proposed application affects your privacy?

SD: Standard deviation

*** Statistically significant change (p-value<0.05)**

Research Question (RQ) 2: How is the acceptance of using privacy-protecting methods for monitoring student actions during tele-education *perceived* by the learners, educators and parents?

In each one of the following situations, the null hypothesis (Ho) is that there is no major difference statistically before the interference and the alternative hypothesis (H_1) is that a statistically significant difference exists.

Table 3.6 shows the results for the usefulness of the application functionality. The results indicate that there is a statistically significant difference between the answers before and after the intervention regarding whether the students consider as useful the fact that the educator has to be informed regarding their actions during online lessons. More specifically, all the groups denoted that the educator should be informed about the student's actions as compared to what they declared earlier. Specifically, educators and parents agree much with that statement (48% and 36% respectively), students totally disagree (28%) while after the interference educators and parents agree very much with that statement (52%) whereas students agree much (28%). The results showed that the application is useful since all three groups agree that it's important for the instructor to be informed about the student's actions in online classes.

Table 3.6: Mean, Standard Deviations for each group and group comparison results on whether it is useful to inform the educator about student actions in online courses.

	Students		**Parents**		**Educators**		**Comparison**
	M (SD)	p-value	M (SD)	p-value	M (SD)	p-value	p-value
Q4 (pre-test)	2.84 (1.63)	**.004***	3.92 (1.35)	**.001***	4.00 (1.38)	**.002***	**.023***
Q4 (post-test)	3.80 (1.58)		5.44 (.71)		5.28 (1.10)		**.001***

Q4: Do you think that it is useful for the educator to be informed about the students' actions?

SD: Standard deviation

* **Statistically significant change (p-value<0.05)**

There is a statistically significant relationship in the parents' and educators' groups concerning whether the students were satisfied with the online lessons ($p<0.001$). More specifically, after the interference, they denoted that the application is useful through teleconferencing as compared to what they declared earlier. There is no statistically significant relationship between the groups and the different opinions to whether they are satisfied with online lessons before and after the interference (see Table 3.7). Students, parents, and educators agree much to very much with that statement (88%, 90% and 68% respectively). All groups believe that they would be more content with online education if this application were to be used in online classes.

Table 3.7: Mean, standard deviations for each group, and group comparison results on satisfaction with online courses.

	Students		Parents		Educators		Comparison
	M (SD)	p-value	M (SD)	p-value	M (SD)	p-value	p-value
Q5 (pre-test)	3.84 (1.52)	.648	3.32 (1.25)	**.000***	3.20 (1.23)	**.000***	.192
Q6 (post-test)	4.00 (1.61)		5.24 (.78)		5.28 (1.10)		.227

Q5: Are you satisfied with online lessons?

Q6: Will you be satisfied if the application is used in online lessons?

SD: Standard deviation

*** Statistically significant change (p-value<0.05)**

Research Question (RQ) 3: How learners, educators and parents *perceive* the impact of using privacy-protecting methods for monitoring student actions during tele-education?

The below Table 3.8 shows the results of the non-parametric Wilcoxon signed rank test for the educators, students and parents' group of the differentiation of the extent they believe that the application facilitates tele-education regarding the active participation, level of concentration, learning results, educator-student interaction, student interest and student evaluation before and after the interference. This test is used because the samples are paired, and the data are in ordinal scale since it has to do with the same persons in different circumstances (before and after the interference). The null hypothesis (Ho) is that there is no significant statistical difference regarding the active participation, level of concentration, learning results, educators-student interaction, student interest and student evaluation before and after the intervention and the alternative (H_1) is that there is a statistically significant difference. Furthermore, Table 3.8 shows the results of the Chi-square test for the differences between groups. This test is used because the samples are independent, and the data are in ordinal and nominal scales. The null hypothesis (Ho) is that there is no difference between groups and the alternative (H_1) is that there is a statistically significant difference between groups. The null hypothesis is accepted when p value≥0.05 and is rejected when p value<0.05.

There is a statistically significant difference between the answers before and after concerning the degree of difficulties the students and the educators faced during tele-education with regards to active participation and educator-student interaction. All the groups, after the interference, declared that the application facilitated active participation and educator-student interaction to a great extent in contrast to what they declared before the interference. There is a statistically significant relationship between the groups and the different opinions to what extent they have difficulties with active participation during tele-education ($p<0.001$). More specifically, educators mostly have difficulties to a moderate degree (36%) whereas parents have very much (44%) and students little (44%). However, there is no statistically significant relationship between the groups and the different opinions to what extent they have difficulties with the educator-student interaction during tele-education ($p=0.060$) and the different opinions to what extent the application facilitates tele-education concerning the educator-student interaction ($p=0.243$). Most students, parents, and educators strongly agree that the application facilitates educator-student interaction (76%, 72%, 56% respectively). All groups believe the application facilitates active participation and educator-student interaction in online classes.

There is a statistically significant difference between the answers before and after the intervention regarding the degree that the educators faced difficulties during tele-education in relation to the concentration level ($p=0.001$), learning results ($p=0.003$), class control ($p=0.009$), presence of the students ($p=0.010$), students' interest ($p=0.005$) and student evaluation ($p=0.009$). Regarding the students' group there is a statistically significant difference between the answers of before and after regarding the degree of difficulty that the students faced during tele-education in relation to evaluation ($p=0.031$) while concerning the parents' group there is a statistically significant difference between the answers of before and after with regards to the learning results ($p=0.007$). After the interference, the educators declared that the application facilitates the concentration level, learning results, class control, students' interest, educator-student interaction, active participation and student evaluation. On the other hand, students claim that the application facilitates only the evaluation, active participation and educator-student interaction while the parents claim that the application facilitates learning results, educator-student interaction and active participation.

There is a statistically significant relationship between the groups and the different opinions to what extent they have difficulties with the level of concentration and learning results during tele-education (p=0.002 and p=0.038 respectively). More specifically, concerning the level of concentration educators mostly have very much difficulties (44%) whereas parents and students have much (48% and 36% respectively) and regarding the learning results educators mostly have difficulties to a moderate degree (44%) whereas parents have very much (36%) and students have much (32%). There is no statistically significant relationship between the groups and the different opinions to what extent the application facilitates tele-education concerning active participation, level of concentration, learning results, educator-student interaction, student interest, and student evaluation. All the groups believe that the application improves the efficiency of tele-education regarding active participation, level of concentration, learning results, educator-student interaction, student interest, and student evaluation.

Table 3.8: Mean, standard deviations for each group, and comparison of groups concerning difficulties during on-line courses before and after the intervention.

	Students		**Parents**		**Educators**		**Comparison**
Difficulties	M(SD)	p-value	M(SD)	p-value	M(SD)	p-value	p-value
Q7 (pre-test)	3.56 (1.16)	**.027***	2.32 (1.65)	**.002***	3.24 (1.36)	**.002***	**.000***
Q7 (post-test)	4.48 (1.48)		5.08 (1.12)		4.84 (1.25)		.695
Q8 (pre-test)	3.44 (1.36)	.052	2.72 (2.09)	.064	2.80 (1.32)	**.001***	**.002***
Q8 (post-test)	4.28 (1.54)		4.88 (1.20)		4.92 (1.35)		.893
Q9 (pre-test)	3.40 (1.56)	.383	2.56 (1.69)	**.007***	3.12 (1.39)	**.003***	**.038***
Q9 (post-test)	4.12 (1.36)		4.88 (1.33)		4.68 (1.31)		.063
Q10 (pre-test)	3.20 (1.08)	**.007***	3.24 (1.51)	**.002***	3.24 (1.51)	**.002***	.060
Q10 (post-test)	4.32 (1.55)		4.76 (1.17)		4.76 (1.17)		.243
Q11 (pre-test)	3.60 (1.47)	.167	-	-	3.12 (1.45)	**.005***	.201
Q11(post-test)	4.20 (1.58)		-		4.80 (1.38)		.693
Q12 (pre-test)	3.56 (1.42)	**.031***	-	-	3.56 (1.66)	**.009***	.232
Q12 (post-test)	4.36 (1.41)		-		4.88 (1.30)		.536

Q7: Active Participation
Q8: Level of Concentration
Q9: Learning Results
Q10: Educator-Student Interaction
Q11: Student Interest
Q12: Student Evaluation
SD: Standard deviation
*** Statistically significant change (p-value<0.05)**

3.5.3.2 Interview results

The participants stated that the application improves the performance of teleconferencing to the greatest extent, and they consider it useful in online courses as they believe that it is very useful to inform the educator about the actions of the students in the online courses. In the questionnaires, some students were hesitant to apply it in online courses as they feel it prevents them from being distracted. Nevertheless, participants had a more complete picture of the application as they had the opportunity to test the application in real-time. In the questionnaires, the same participants did not consider the use of a camera very necessary, while during the interviews they understood the value of the application in the online courses and stated that the use of a camera is very necessary. In addition, the participants stated that the application does not affect the students' privacy. Therefore, the interviews further reinforced the conclusions related to the usefulness of the proposed student action recognition system.

3.5.4 Discussion

The aim of the current study is to assess the acceptance of an application based on artificial intelligence to the stakeholders that are directly involved (students, parents, educators). For this reason, the stakeholders, who were directly involved, completed an online questionnaire about the test of research hypotheses before and after watching a video regarding the functionality of the application. The first research question was whether the use of protection methods for monitoring the students' actions in private life during tele-education is feasible. The second research question was whether the use of protection methods for monitoring the students' actions in private life during tele-education is acceptable from all the stakeholders involved and the third research question was whether users believe that monitoring the students' actions improves the efficiency of tele-education.

Regarding RQ1 (*"How learners, educators and parents perceive the feasibility of using privacy-protecting methods for monitoring student actions during tele-education?"*) all groups consider the use of privacy-protecting methods of the students' actions feasible in online classes after viewing the explanatory video regarding the function of the application since the use of a camera is deemed necessary and doesn't interfere with the student's personal data. The results showed that there was no statistical significance relationship among the groups before the intervention, while after the intervention, they denoted that the use of a camera is necessary. Specifically, the majority of educators and students agree while parents strongly agree. Most parents and educators disagree that the application affects their privacy, while only a small percentage of students agree. Hence, the use of protection methods for students' private life for monitoring the students' actions during online lessons is feasible. The answer to RQ1 arises from whether the users believe that the use of protection methods of data in the surveillance of students' actions during online lessons is feasible. The feasibility of RQ1 is related to the user acceptance of those who are directly involved.

Concerning RQ2 (*"How is the acceptance of using privacy protecting methods for monitoring student actions during tele-education perceived by the learners, educators and parents?"*) all groups regard the application as useful in online classes since it informs the instructor about the actions of the students. There is a significant statistical relationship among the groups before and after the intervention with regard to whether it is useful for the educator to be informed about the students' actions during online lessons. Parents and educators agree a lot before the intervention, while they strongly agree after the intervention. In contrast, the majority of students disagree before the intervention, while after the intervention the majority of them agree a lot. The participants of all groups consider the application as very useful to absolutely useful. On the whole, the use of application does not substitute the role of the educator as it combines the expertise of the educators and neuro-fuzzy synergism for students' diagnosis by monitoring students' actions (Stathacopoulou et al., 2007). There was no significant statistical relationship among the three groups with regard to whether the students are satisfied with the online lessons before and after the intervention. The students' attitude shows indecisiveness as they consider that the application is useful, but on the other hand, they deny its use during online lessons. According to Barrett et al. (2021) the use of surveillance systems is based on the conviction that the students might not be reliable and the refusal to accept the system by pupils is due to the stress that might occur with regards to the practices of collection and data use, something which is denoted in our research through their answers to the open-type questions. Thus, the use of protection methods of private life for monitoring the students' actions during tele-education is mainly acceptable by parents and educators, while students have a neutral attitude about it. The current research question comes in contrast to previous studies in which parents and educators expressed their concerns regarding the surveillance applications (Barrett, 2021; Lederman, 2020). As a result, the RQ2 demonstrates the importance of application functionality in online courses. The analysis of the results proves that the application is well-received by parents and instructors due to the fact that the student's personal data are protected with the proposed system. In RQ2 we examine whether the use of surveillance systems of students' actions during online lessons is acceptable by those who are directly involved. The answer to research question 2 arises from the fact that the participants had the opportunity to watch how the application worked and answer questions with regard to its function. Moreover, the interviews complete and assure the participants' answers since the volunteers who took part in the interviews, had the opportunity to try the application in a real-time. Interviews were conducted to cross-validate the findings of the questionnaires.

Regarding RQ3 (*"How learners, educators and parents perceive the impact of using privacy-protecting methods for monitoring student actions during tele-education?"*) all three groups believe that the application improves the efficiency of tele-education concerning active participation and instructor-student interaction. After the interference, the educators declared that the application facilitates the concentration level, learning results, class control, students' interest, educator-student interaction, active participation, and student evaluation. On the other hand, students claim that the application facilitates only the evaluation, active participation, and educator-student interaction, while the parents claim that the application facilitates learning results, educator-student interaction, and active participation. There was a statistically significant relationship among the groups before the intervention with regards to the difficulties that occur during the online lessons as for active participation, concentration level, and learning results. The educators believe that these difficulties occur to a greater extent, while students believe that they occur to a less extent. After the intervention, the three groups agree that the experimental application improves the efficiency of tele-education with regards to active participation, concentration level, learning results, educator-student interaction, students' interest, and assessment. In RQ3 we examine whether the users think that the surveillance of students' actions can improve the efficiency of tele-education. The third research question aims to cover the research gap that exists in the current bibliography regarding the benefits of surveillance systems for students in online lessons.

The results presented in this Section were derived from the questionnaires (with 75 participants), and they reflect participant's opinions regarding the possible contribution of the proposed system in improving students' attention, concentration level, learning results, class control, students' interest, educator-student interaction, active participation, and student evaluation. Further experiments will be required to deduct conclusions related to the actual impact of the proposed system in relation to the factors quoted above.

The results of the interviews show the positive impact of the application during online courses. The participants had a more complete picture of the application since they had the opportunity to use the application in real time. The participants stated that the interviews helped them understand the value of the application in relation to the online questionnaire. Overall, the participants agree this is an innovative application and educators will use it extensively. Therefore, in relation to the RQ2 where the results showed that the application is mainly acceptable by parents and educators, the interviews suggest that the application is also acceptable by the students.

For the aims of our study, we developed an innovative system based on artificial intelligence for the surveillance of students during online lessons that attempts to protect students' private data and give feedback to educators in real-time. The stakeholders who are directly involved (parents, students, educators) denoted that the use of the experimental application is feasible and improves the efficiency of tele-education.

3.6 Limitations of the study

This study is considered significant mainly because it aims to offer the best possible solution to the major problem of lack of visual contact that instructors face in online classes. Furthermore, it aims to cure the lack of research concerning the benefits of monitoring systems of students' actions in online classes while protecting their privacy and personal data. However, there are some restrictions concerning the present research, such as the size of the sample because of which the results cannot reach a generalization status. Nevertheless, the proposed framework will set the basis for future research which will define the impact of monitoring systems in education, while promoting new ways of approaching education and learning. Additionally, the results of this research may have been affected by the limited amount of time available. The total time that the participants dedicated to the research was 10 minutes. Therefore, the factor of time could have interfered with the results of the research, which might have led to different conclusions if the participants had more time. The 75 participants in this research were chosen through random sampling. In the future, data from different regions will be collected. Another limitation of the present study can be considered the selection of the sample of participants. Due to the small, and non-representative sample, the results of this study only concern the specific students/educators/parents and may not generalize to the entire population. In future research, participants can be selected using random sampling and from different regions. Furthermore, another limitation of the first case study is that the participants in the first phase during the evaluation process assessed the impact of the application through a video simulation of the application. Therefore, the results might have been different if the 75 participants had the opportunity to directly interact with the real application. Although a small number of participants in the interviews had the opportunity to try the application, in the future we aim to evaluate the acceptance of the system based on the operation of the application in real time and with a larger number of participants. Furthermore, collecting samples throughout different regions and dedicating more time might allow constructive comparisons and further analysis concerning the factors influencing the efficiency of monitoring systems in online classes.

The work done in this chapter, presents the initial effort for proofing the viability and acceptance of the proposed system. In this case an indicative set of actions were used. In future implementations that will target operation in real settings, the set of actions will be redefined in order to ensure that the actions considered reflect in a better way the requirements. For example, in the case where students are typing notes rather than writing notes on a pad, there is a high probability that the algorithm recognizes this action as "attending" instead of "writing". Although both actions are related to the active participation of students in online courses, we will deal with this limitation by including more actions in the action set. Furthermore, in the case in which a student uses a mobile phone not within the camera range, there is a high probability that the algorithm recognizes this action as "looking elsewhere" instead of "using phone". Although both actions are related to distraction in online courses, in the future we plan to deal with issue by adding more actions in the action set. Another limitation of the study is apparent when a student uses two or more screens on his computer. To address this limitation, a protocol will be provided prior to using the application in online courses stating that if the student is using two or more screens the camera should be placed on the screen facing the student and the student should avoid moving the window of the conferencing tool from the main monitor. In addition, the use of the "hand raising" metric is included in the proposed system to enhance the teaching quality. However, in the case that a conferencing tool already has the virtual hand action, the 'raise hand' indication will be triggered both by physically raising a hand or by pressing the virtual hand button. Furthermore, in future implementations, the set of recognizable actions will be enriched with additional actions, and the educator will have the ability to choose adaptively the actions he/she wants to consider as positive/negative, according to the class level, the nature of the class, and the teaching style adopted in each class.

3.7 Conclusions

This study refers to development, quantitative performance evaluation, and user evaluation that aims to define the efficiency of online education through the proposed experimental application. The results of the quantitative evaluation validate the performance of the method. For the user evaluation, data were collected through an online questionnaire from students, parents and educators who at first expressed difficulties concerning online classes. Nevertheless, after the presentation of the proposed application through interviews, they formed the opinion that the application was both useful and necessary in online classes since it can give feedback to the instructors about the actions of the students. Parents, students and educators were positive regarding the use of the application in online classes. It is essential to mention that in the bibliography there has been no similar study on this matter which explores the benefits of monitoring systems in online classes. Hence, this study gives insight into the acceptance of monitoring tele-education.

Chapter 4

An automated lecture style assessment system

This chapter presents an integrated system that provides automated lecture style evaluation, allowing educators to get instant feedback related to the goodness of their lecturing style. The proposed system aims to promote quality improvement of lecture delivery, that could upgrade the overall learning experience of students. Furthermore, this chapter includes the performance evaluation of the proposed system, the evaluation of the acceptance of the system by the end users, and the evaluation of the impact of the application in improving the teaching style of educators.

4.1 Introduction

Teaching style is an important aspect in educational settings, directly influencing educators' effectiveness in message delivery, classroom management, and student interactions (Benzer et al., 2012). Automated lecture quality assessment tools can provide objective and timely feedback on the quality of lecture delivery, assisting in that way educators to improve their lecture quality that will eventually lead to an improved learning experiences for students. As part of an effort to assist educators to improve their teaching style, a Teaching Style Assessment (TSA) application that provides automated feedback regarding the quality of educator's teaching styles was developed (see Figure 4.1) (Dimitriadou et al., 2023).

Figure 4.1 : Automated TSA tool. A video of a lecture captured by an ordinary camera is analysed to extract lecture style quality indicators.

The TSA application relies on a set of measurable biometric features through video and audio recordings, to estimate lecture style quality, providing in that way an easy to use and low-cost alternative for performing a task that usually requires human expertise. The biometric characteristics used for assessing the lecture style quality were defined through a systematic multi-phased process that involves the definition of a set of lecture style quality indicators that reflect the goodness of a lecture presentation, as outlined in Figure 4.2.

Figure 4.2: The systematic approach for developing a lecture quality assessment tool**.**

The biometric features considered relate to facial expressions, body activity, hand movements, facial pose, speech rate and speech tone which can be retrieved from video recordings of lectures in real time or in a batch processing mode. So far, few models have been proposed that combine hand and facial pose features due to the challenges that exist in tracking human faces from video (such as hand and head tilt) (Rastgoo et al., 2021).

Although, in theory the lecture quality could be estimated with deep networks that extract automatically features associated with good lecturing, the lack of suitable training data, requires the intermediate step of formulating a set of measurable biometric characteristics necessary for this task. The main steps in the process of defining suitable quality metrics include the step of requirements analysis where through a literature review and interviews with stakeholders, a set of biometric features associated with lecture delivery quality are defined, followed by the development of dedicated methods for extracting the features from a video stream. The extracted features are then used for estimating an overall lecture delivery quality score.

Due to the importance of high-quality teaching style in the educational process several attempts to evaluate and provide feedback about teaching styles were recorded in the literature. In some cases, questionnaire-based methods are used for teaching style evaluation. For example, Selma et al. (2015) explores the differences in body language usage between prospective elementary mathematics and social sciences educators based on data gathered using a 21-item "Body Language Questionnaire (BLQ)". Findings show a difference in body language usage between the two groups of educators, with positive attitudes towards body language utilization in teaching. Kucuk et al. (2023) explores educators' perceptions of the role and importance of body language in the educational setting. The user evaluation was conducted through a questionnaire distributed to educators and in-person interviews. The questionnaire was designed to gather insights into the educators' opinions on the significance of body language in teaching. On the other hand, Tai et al. (2014) explores the utilization of body language in English teaching to foster a more engaging and effective learning environment. It delves into how educators use gestures, facial expressions, and eye contact to enhance communication and understanding in the classroom. The approach relies on observational insights and existing literature to argue the benefits of using body language in English teaching, without specifying a concrete user evaluation method. Rosen et al. (2015) promotes the "educator-as-researcher" paradigm, encouraging sign language educators to engage in action research to enhance teaching and learning experiences in their classrooms. User evaluation is executed through action research, a stepwise process where educators identify gaps in the current teaching approach, develop interventions, and assess the outcomes. This hands-on approach to research is grounded in real classroom experiences, aiming to bridge the theoretical and practical aspects of teaching.

Although there are some existing tools that use automated methods to assess lecture quality and/or educator's body language (Mohammadreza et al., 2021; Zhao et al., 2019), they have limitations in terms of the accuracy and range of attributes measured. Mohammadreza et al. (2021) presents a novel approach to assessing lecture quality based on audience reactions, specifically focusing on students' engagement levels. They developed a system that analyses students' facial reactions, captured in real-time, to infer engagement. This research is significant in the educational field as it shifts from traditional assessment methods, such as questionnaires or external observers, to an automated system trained using Machine Learning (ML). However, the proposed system relies on videos showing students, hence the implementation of the system in real situations may not be acceptable due to data privacy issues. Furthermore, Zhao and Tang (2019) developed a classroom teaching quality evaluation model using a BP (Back Propagation) neural network algorithm. The model uses student evaluations and teaching team assessments as input data, in order to evaluate teaching quality. This model improved on existing methods by reducing subjectivity, avoiding overfitting, and increasing accuracy. Dimitriadou et al. (2023), focus their attention on developing an integrated lecture quality evaluation application for lecture quality assessment, as well as performing a performance evaluation experiment for determining the accuracy of the system in estimating lecture style quality scores.

Compared to previous work reported in the literature, in our approach we adopt a systematic approach for obtaining a comprehensive set of lecture quality indicators and then derive an integrated set of features associated with a good lecture rather than choosing features arbitrarily. Furthermore, the combination of quality scores from all features both at frame rate, and for the whole lecture, allow educators to get useful feedback regarding the lecture delivery quality both at real time, and as a report concerning the whole lecture. In relation to the biometric features used, when compared to previous efforts, in our work a more integrated set of features that includes facial pose, activity-related metrics, speech intonation, word density and hand movements, are considered. These measurable biometric characteristics of a good educator have been defined based on the current bibliographic material and the interviews of the persons directly involved in class delivery. The main difference with previous studies is that the metrics are defined based on the stakeholders, allowing the proposed application to better reflect the needs and requirements of the target user group. Using a combination of speech recognition and computer vision technologies, we aim to provide a more accurate and reliable assessment of the quality of educators' lectures that captures both verbal and non-verbal cues. Furthermore, previous work reported in the literature does not include quantitative performance evaluation. In this work performance evaluation results of the proposed system are presented, and most importantly the results of a comparison of the performance of humans against the performance of the proposed automated lecture style evaluation system is also presented.

Furthermore, there is a lack of studies focusing exclusively on the automated evaluation of educators' body language, its acceptance by educators, and most importantly there is lack of studies that assess the impact of such applications in improving teaching style. The present study aims to fill the gap in the literature concerning the acceptance and impact of such systems by the stakeholders. Evaluating the acceptance of an application that assesses body language by educators, who are directly implicated, is paramount for several reasons. Firstly, educators are the primary users and thus, their comfort, ease of use, and trust in the application will directly influence its successful implementation. Secondly, their first-hand experience in the educational setting enables educators to provide valuable feedback on the practicality and relevance of the application in real-world teaching scenarios. Lastly, ensuring that such an application is well-received and valued by educators not only enhances its credibility but also fosters a positive attitude towards technology-assisted teaching methodologies, thereby facilitating a smoother integration of such technologies in educational settings. This, in turn, can pave the way for more data-driven and evidence-based teaching strategies, enhancing the overall educational experience for both educators and students.

The main contributions of our work are:

- Utilizing human expertise for defining lecture style quality features.
- Use of an extended set of lecture style quality features.
- Performance evaluation and comparison with performance of humans.

- Evaluation of the impact and acceptance of the proposed system by educators.
- Operates in real time without the need for dedicated equipment.

In the remainder of the chapter, we present a literature review on the topic of educator performance assessment (Section 4.2) and in Subsection 4.3, we outline the process of defining lecture quality indicators. In Subsection 4.4, we present technical details for each biometric features while in Subsection 4.5, the performance evaluation of our proposed system is discussed. In Subsection 4.6 the experimental evaluation procedure and results of the evaluation is presented followed by a discussion and concluding comments (Section 4.7).

4.2 Literature Review

Performance assessment of educator is highly important as a means of safeguarding the quality of lectures delivered to students. Traditional educator performance assessment, based on lecture observation or student feedback, has been a quite complex and time-consuming process that does not provide instantaneous and seamless feedback. In this literature review a brief description of the importance of body language and educator performance assessment, and also presents methodologies used for assessing educator performance during class delivery.

4.2.1 Educator Performance Assessment

Educator performance assessment can be defined as a framework utilized in a classroom to assess and evaluate the performance of educators (Jensen et al., 2020). Traditional assessment methods are usually based on the observation of educators by experts during course time something that can be expensive, time consuming, not accurate and usually the feedback provided is infrequent and is related to the daily performance and does not provide useful information that would allow educators to enhance their techniques (Archer et al., 2016). Furthermore, the use of student feedback to evaluate the educator's performance is not a reliable method, as the data is not collected in real-time and responses can be manipulated (Winarno et al., 2017). To overcome this crucial impediment in educator development, new technologies can be used to produce high quality and meaningful automatic lecture quality feedback for educators. Within this context lecture quality assessment refers to the evaluation of the lecturing style, rather than an overall teaching performance of educator that includes other aspects, such as teaching methodology, and subject knowledge.

In the context of assessing teaching quality in schools, colleges and universities, a variety of evaluation categories are often considered to provide a comprehensive view of the educational experience (see Table 4.1). These categories may include the subject knowledge (Schempp et al., 1988), knowledge of learners (Dubinsky et al., 2022), teaching methodology (Darling-Hammond et al., 2013), curriculum knowledge (Behar et al., 2013), general pedagogical knowledge (Liakopoulou et al., 2011), knowledge of contexts (Darling-Hammond et al., 2010), self-knowledge (Schussler et al., 2010), lecture style, and audience interaction (Short et al., 2011). In essence, the effectiveness of a educator is determined by the interconnectedness of these knowledge categories, with the ability to integrate and apply them holistically to facilitate optimal student learning and development.

Table 4.1 : The evaluation categories for educator.

Educators' evaluation categories	**Description**
Subject Knowledge	An educator's in-depth understanding of the subject matter they are teaching, including its content, principles, and methodologies.
Knowledge of Learners	Educators should possess knowledge about students' biological, social, psychological, and cognitive development.
Teaching Methodology	A skilled educator is well-versed in various teaching methods, strategies, and approaches.
Curriculum Knowledge	Educators need to be familiar with the curriculum, textbooks, and educational policies relevant to their subject and grade level.
General Pedagogical Knowledge	Encompasses broader principles of classroom management, organization, and learning theory that extend beyond subject-specific content.
Knowledge of Contexts	Effective educators are aware of the broader educational, social, and cultural contexts in which they work.
Self-Knowledge	Educators should have a reflective understanding of their role, responsibilities, values, and professional development.
Lecture Style and Audience Interaction	A skilled educator can deliver lectures clearly and engagingly, employing various teaching methods to maintain student interest and understanding.

4.2.2 Educators' Body Language During Class Delivery

Body language, refers to nonverbal cues and behaviors, communicating emotions, intentions, and thoughts. This includes facial expressions, gestures, posture, eye movements, touch, and even aspects of speech such as tone and volume (Fast, 1970; Pease, 1981). According to Kucuk et al. (2023), body language in education is defined as the use of non-verbal signs (such as posture, facial expressions, gestures and body language) by educators and students to convey information and express emotions during the learning process.

Body language plays a vital role in education as it can influence learning and teaching dynamics. Educators' non-verbal cues can enhance clarity, keep students engaged, and establish a positive classroom environment. For students, their body language can reflect their level of understanding, engagement, and emotions, providing educators with feedback. Recognizing and responding to these cues can significantly enhance the educational experience (Miller 2005; Kucuk et al., 2023; Hussain et al., 2022). Educators who effectively use body language create a positive and attractive environment (Kucuk et al., 2023) and students showing higher levels of satisfaction for the lesson (Caswell & Neill, 2003).

Educators' body language can be evaluated either in an automated way or in a non-automated way. The use of automated methods requires technological tools (Abdulrahman et al., 2020; Turaev et al., 2023), while the use of non-automated methods is based on observations, surveys (Tai et al., 2014), questionnaires (Kucuk et al., 2023), and interviews (Denham et al., 2013). Specifically, non-automatic measurement of body language relies on meticulous human observation, including coding behaviors from videos, gathering self-reports, and expert observation in real-time. Despite drawbacks like intensive labor and observer biases, these methods yield invaluable insights through keen attention to details.

4.2.3 Non automatic methods for body language evaluation

The following studies are focused on evaluating body language using non-automated methods. Hattie and Timperley (2007) examined effective methods of feedback without specifically focusing on body language. They linked evaluation to effective teaching and explored how educators could use feedback to improve their teaching practices. While this study does not exclusively focus on body language, it underscores the importance of effective evaluation and feedback in enhancing teaching and learning. Although several studies examine body language in the educational sphere, only few studies focus exclusively on the evaluation of educators' body language and the acceptance of these evaluation systems by other educators or students. Woolfolk and Brooks (1985) investigated the impact of non-verbal cues, including body language, on students' perceptions of educators. Their findings indicated that students' perceptions of educators are significantly influenced by non-verbal cues, which, in turn, can impact their acceptance of educator evaluation systems.

Mehmet and Temel (2014) deal with the quantification of educators' body language proficiency. Within this context, they designed a 23-item scale through a rigorous process that incorporated feedback from educators, analysis of existing research, and pilot testing. When applied to a sample of 503 pre-service educators, the scale demonstrated reliability, backed by significant statistical indicators. Building on this foundational work, Karaca and Filiz (2019-2020) employed Tok and Temel's scale to assess the body language competencies of Physical Education Teachers (PETs), surveying a total of 347 PETs. Their findings indicated that those PETs who had received training in communication skills displayed more advanced body language proficiency.

Bower et al. (2013) undertook a study to understand how various communication elements could impact pre-service educators' presentations. Their research highlighted the importance of alignment between body language, voice, and verbal content. To assess the presentation abilities of pre-service educators, they contrasted two assessment models: the "Constructed Impression" model and the "Modes of Communication" model. The former focused on aspects such as confidence and clarity in communication, while the latter emphasized the integration of voice, words, and body language. Results from Bower et al. (2013) indicated that the "Constructed Impression" model provided a more accurate representation of presentation skills, but the "Modes of Communication" model was more predictive of overall performance scores. Furthermore, Kucuk's (2023) employed a mixed-method approach to gain insights into educators' perspectives on body language. Utilizing both a questionnaire and subsequent interviews with 30 educators, Kucuk's findings consistently underscored the critical role that body language plays in effective instruction.

4.2.4 Automated Educator Performance Evaluation

In few cases attempts for automating the process of educator performance evaluation were recorded. Yang et al. (2012) proposed a teaching assessment model to address the complexities involved in evaluating teaching quality. In the proposed teaching model, the aim of using back propagation is to quantitatively measure the concept of teaching evaluation index, using specific data as input and teaching effectiveness as the output. The features used for teaching quality evaluation are related with guiding ideology, educators, teaching conditions, teaching construction and reform, construction of study style, teaching management, teaching effectiveness, classroom teaching effectiveness, and others. The results reported were satisfactory, indicating that the model has a broad applicability in assessing teaching effectiveness. While the research presents positive outcomes, several aspects of their approach warrant further scrutiny. One notable limitation is the absence of comprehensive performance metrics to objectively evaluate the model's effectiveness. Although the authors assert that the results were satisfactory and the neural network outputs closely align with actual target values, the lack of specific metrics such as accuracy, precision, recall, or mean squared error undermines the quantitative assessment of the model's performance. The study would benefit from a comparative analysis with other established teaching quality assessment methods or benchmarks to ascertain the model's superiority and unique contributions.

Barmaki and Hughes (2018) developed an automated educator body language evaluation system designed to detect and provide feedback on non-verbal "closed" gestures prevalent in virtual teaching sessions. Utilizing the kinect motion-capture device they created a gesture recognition method that analyzed full-body data. After training the system using annotated clips of five students, their Visual Gesture Builder (VGB) was employed to produce multiple classifiers for each gesture, culminating in an ensemble with a remarkable accuracy of 96.5% ± 2.1%. When tested in a case study, the system showed significant potential in enhancing the body language mindfulness of users through its visual feedback mechanism, with a follow-up study further indicating a positive reception to an added vibration feedback feature. In relation to our proposed system, Barmaki and Hughes (2018) required specialized equipment to evaluate educators' body language (such as Kinect). Furthermore, their study body language assessment method is based on gestures rather than a multitude of biometric features such as speech recognition.

The evaluation and acceptance of educators' evaluation systems are critical for enhancing the quality of education. While there is a vast body of literature on various aspects of educator evaluation, there is limited research specifically focusing on the impact of such applications to improving teaching style. In few occasions impact assessment with multi-phased experiments was performed (Barmaki and Hughes 2018). The work presented in this thesis aims to address the issues of impact and acceptance related to automated teaching style quality determination.

More detailed descriptions regarding the automated educator performance evaluation are provided in Chapter 2, Subsection 2.3.3.2.

4.3 Defining Lecture Style Quality Indicators

The first step in the proposed methodology for designing a lecture quality evaluation system involves the definition of indicators associated with high and low-quality lecture styles. To define the required features, findings from a thorough research in the existing bibliography in combination with information derived from educators, students and chief education officers were utilized.

As a result of the literature review (Azer 2005; Bambaeeroo et al., 2017; Miller 1988; Yadav 2022) a set of characteristics related to high and low-quality lecturing styles were gathered. For example, high quality lecturing styles include features related to level of commitment (Azer 2005), interaction and communication skills (Crosby 2010), promotion of critical thinking, teamwork, and creativity (Azer 2005), giving directions, helping and giving feedback, avoiding negative words (Bambaeeroo et al., 2017), and body gestures (Yadav 2022).

To further refine the set of initial features defined based on the related literature, interviews with stakeholders were staged. During the interviews, participants watched typical YouTube videos showing 'good' and ‘bad’ examples of lecturing, and they indicated specific educator actions regarded as indications of high and low-quality lecturing styles. More specifically participants were shown clips from two online videos with the characteristics of the "*bad* " educator [8,9] and two online videos with the characteristics of the "*good* " educator [10,11] . The criteria for selection of the online YouTube videos were based on the search keywords "*good educator*", "*good lecture*”, "*bad educator* ", "*bad lecture* " as well as based on rating, number of views and viewer comments.

Interviews were conducted with two chief education officers, two educators and two students who participated in the video observation action. The views of all three categories of participants are highly important as chief education officers perform the process of educator assessment, while educators and students are directly involved in the educational process. The total duration for each interview was about 30 minutes. After watching each video, participants rated the quality of the lectures they watched, and responded to questions related to the level of lecture quality, the specific actions observed that related to high and low-quality lecturing styles. In addition, participants provided comments on the body language, expression, and speech characteristics of the lectures. More specifically, participants responded to the following questions:

1) *How would you rate the quality of the lecture and why?*

2) *What do you think are the characteristics of a good/bad lecturing style?*

3) *Do you think that body language (non-verbal communication) plays an important role in the quality of the lecture and why?*

4) *What facial expressions (angry, disgust, fear, happy, neutral, sad, surprise) do you think a good educator and a bad educator have during a lecture?*

5) *Which actions do you think should be avoided by educators and which should be used by a good educator in the classroom?*

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[8] https://www.youtube.com/watch?v=7DY1e0Grwtw

[9] https://www.youtube.com/watch?v=3kgtpl4Q5OY

[10] https://www.youtube.com/watch?v=nLfFmYWjHtc

[11] https://www.youtube.com/watch?v=hGBNi4P9OfA

6) *What do you think are the characteristics of a good educator in verbal communication and what are the characteristics of a bad educator in verbal communication?*

Interview data analysis was carried out with the use of codification qualitative techniques (Barriball et al., 1994) in which words, sentences and phrases that had similar conceptual meaning and were important for the research, were arranged in groups whereas data of minor importance were taken apart. This procedure has been repeated to ensure the validity of the codification. Based on the interview findings, most of the participants expressed the view that effective educators are proficient in using technology, exhibit positive body language (such as facial expressions, head and hand movements), maintain an engaging tone of voice, actively move around the classroom, provide constructive feedback, motivate students, led by example in terms of their attitudes and behavior (such as refraining from using their phone, or drinking in class), are well-prepared, and utilize modern teaching methodologies.

All features defined from the literature and the interviews were assessed with respect to the feasibility of extracting them accurately, and non-invasively, from a video captured using a standard static camera pointing at the educator. Furthermore, based on findings from the literature and interview responses, the values corresponding to high and low-quality lecturing types were defined (see Table 4.2). More information about the features extracted is provided in Section 4.4.

Table 4.2 : Lecture quality metrics.

Modality	Values for High Quality Lecture Style	Values for Low Quality Lecture Style
Facial Expressions	Happy, Surprise, Neutral	Anger, Fear, Disgust, Sad
Body Activity	Attending, Writing, Hand Raising	Absent, Telephone Call, Texting, Looking Elsewhere
Speech	Word Density (35%-55%) Speaking Speed (150-250 words per minute) Speech Intonation (40%-60%)	Word Density (<35%, >55%) Speaking Speed (<150, >250 words per minute) Speech Intonation (<40%, >60%)
Hand Movement	Moving	Stationary
Facial Pose	Left, Right, Up, Down and Forward	Far-Left, Far-Right, Far-Up, Far-Down, Backwards.

4.4 Lecture Style Quality Score Estimation

The proposed methodology aims to perform automated recognition of specific measurable characteristics related to verbal and non-verbal communication which are presented in Figure 4.3. The intensity of the extracted metrics is used for estimating an overall lecture style quality score for each frame and providing feedback to the educator. Following the determination of the key features, dedicated techniques were used for extracting those features from video recordings and estimating lecture quality metrics, as shown in Figure 4.3, and exemplified in the following subsections. A detailed description of all considered parameters are presented in Appendix C.

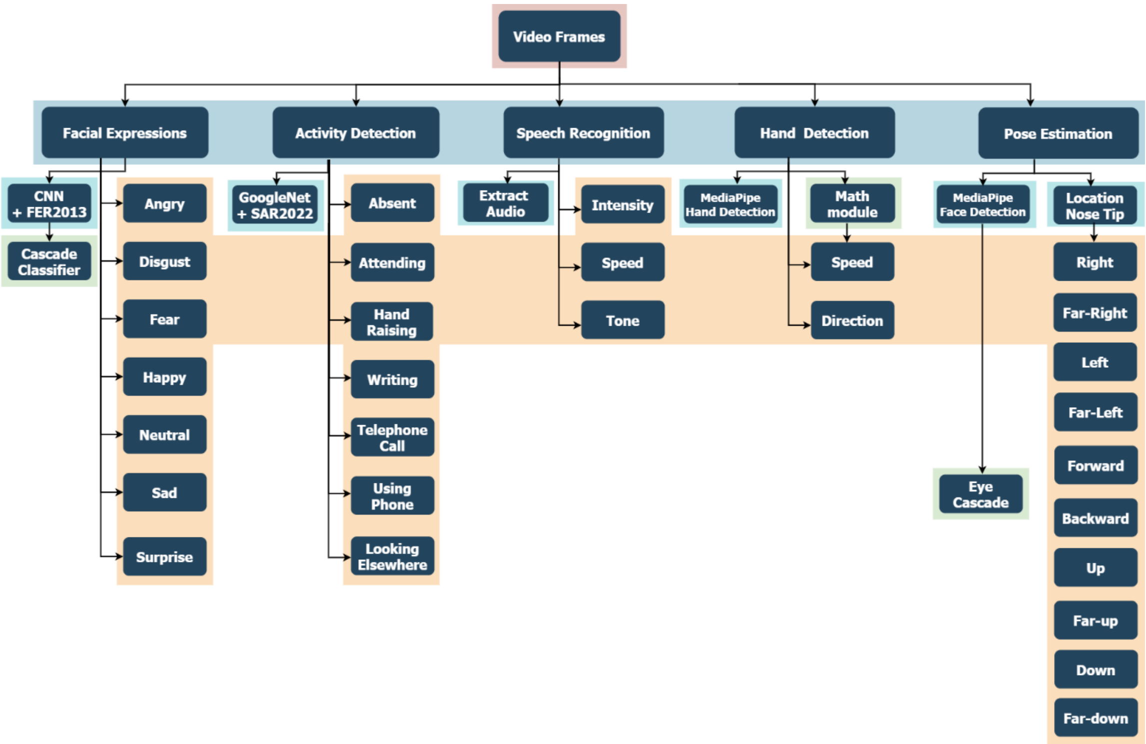


Figure 4.3 : Overview of lecture quality features and feature extraction methods.

4.4.1 Facial Expression Recognition

Facial expressions of educators are associated with the overall lecture quality, hence in the proposed system facial expression recognition is used. In order to choose the most appropriate method for recognizing facial expressions, a Convolutional Neural Network (CNN) (Amal 2022), AlexNet (Sekaran 2021), ResNet (Zhong et al., 2020) and VGG16 (Dubey et al., 2020) deep networks were trained, and evaluated in recognizing the seven basic emotions of anger, disgust, fear, happy, neutral, sad and surprise (see Figure 4.4). For the training and evaluation, the FER2013 dataset (Goodfellow et al., 2013) was used. Prior to training, data augmentation in the form of reflection, rotation, scale and translation were used to increase the size of our dataset. Regarding the training hyperparameters, a batch size of 64 was chosen, the learning rate was set at 0.0005 and the Adam optimizer was used. The train set included 28,709 images while the test set included 7,178 images. The results showed that CNN, AlexNet, ResNet have validation accuracy of 66.45%, 58.22% and 25.93% respectively (see Table 4.3). The results showed that CNN achieved the highest correct recognition accuracy among all networks considered. Figure 4.5 shows the confusion matrix for expression recognition results using the CNN.

Figure 4.4 : Typical screenshots from the FER2013 dataset.

Table 4.3 : Accuracy metrics for the facial expressions' algorithms.

Performance Measures	**CNN**	**AlexNet**	**ResNet**	**VGG16**
Accuracy(%)	66.45	58.22	25.93	24.71
Recall	0.664	0.582	0.259	0.247
Precision	0.653	0.586	0.167	0.061
F1-score	0.657	0.575	0.127	0.098
MCC*	0.595	0.494	0.064	-
Cohen's k	0.594	0.491	0.025	-

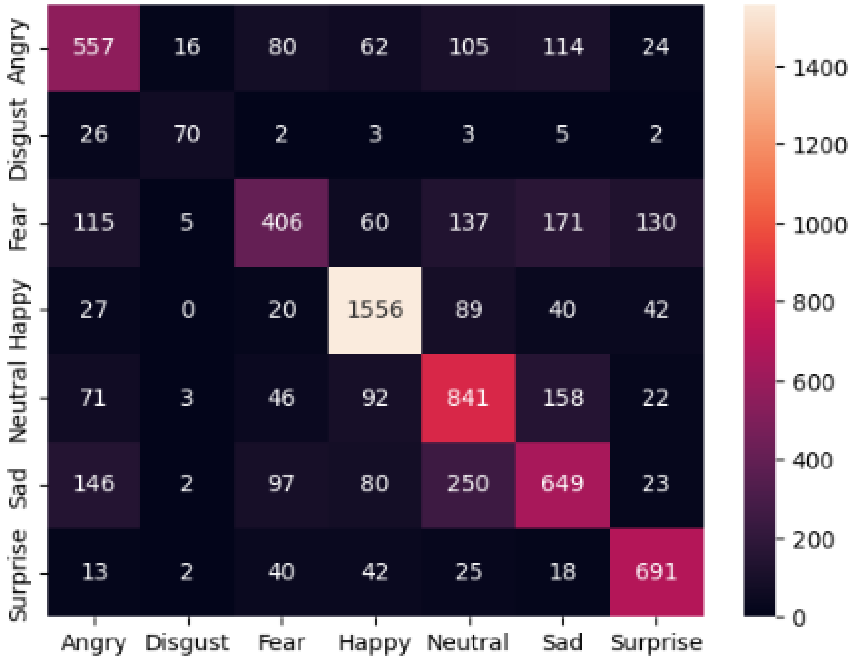


Figure 4.5 : CNN confusion matrix.

In the proposed application, expression recognition is performed using a cascade classifier (Amal et al., 2022) to detect the educator's face, and a Convolutional Neural Network (CNN) trained using the FER2013 dataset to classify the seven basics facial expressions (anger, disgust, fear, happy, neutral, sad, surprise) (Lasri et al., 2019). According to Hou et al. (2022) and based on the interviews with the stakeholders, anger, disgust, fear and sad are considered negative emotions while happy, surprise and neutral are considered positive emotions in relation to the teaching process. Therefore, when the expressions of happy, surprise, and neutral are detected a lecture quality score of 1 is assigned, whereas the detection of anger, fear, disgust, and sad expressions leads to a quality score of zero.

4.4.2 Activity Detection

Based on the literature (Bambaeeroo et al., 2017; Yadav 2022; Antes et al., 1996) and the views of the interviewed stakeholders, the activities performed by educator can contribute towards lecture quality. The proposed system recognizes seven key activities associated with low/high quality lecture styles. In particular the system recognizes the following actions: Absent from the camera point of view, attending, raising hand(s), writing, telephone call, texting, and looking elsewhere (see Figure 4.6). The classification of the seven classes was based on a tuned GoogleNet architecture (see Subsection 3.5) used for assessing in-class student activity (Dimitriadou et al., 2023). The proposed system classifies the activities attending, writing and hand raising as high-quality lecture styles and assigned a lecture quality score of one, while the activities absent, telephone call, texting, and not looking at the audience (looking elsewhere) are classified as low-quality lecture style (see Table 4.2), resulting in a lecture quality score of zero.

Figure 4.6 : Typical screenshot regarding the recognizing educators' activities in a recorded video.

4.4.3 Speech Recognition

Based on the interviews with the stakeholders, the speech speed, speech intervals and speech intonation are related to lecture speech quality, and for this reason audio characteristics extracted from video segments are utilized in the proposed application. The following features are extracted:

(a) Word Density: Non-silent audio intervals in a given speech segment are detected, and the percentage of non-silent against silent parts is estimated providing in that way a metric for Word Density. According to the literature (Rantala 1994), the average word density of educators is 35-55%, thus word density values between 35%-55% are associated with high quality lecture quality, whereas values outside the recommended range are associated with low quality lecture quality.

(b) Speaking Speed**:** Speaking speed is estimated by dividing the number of words detected in a speech segment over by the segment duration. The range of normal levels of human speech is between 150 and 250 words per minute (Lewandowski et al., 2016), hence the speaking speed (speed) is correlated with a high-quality lecture style if it is within the normal range, otherwise it is associated with low quality lecture style.

(c) Speaking Intonation: Speaking Intonation determines whether the sentence is a question or a statement (Eady 1986) allowing the derivations of information regarding the level of interaction between educator and the audience. Intonation is estimated as the root mean square (RMS) of the audio waveform. If the mean RMS is greater than 0.01, the intonation is classified as a question; otherwise, it is classified as a statement. The specific value of 0.01 was chosen as a threshold based on experimentation after consulting the librosa library documentation[12]. This approach allows the estimation of the percentage of questions against statements in a given audio segment. A percentage of questions among the 40%-60% in each interval denotes an adequate interaction between the educator and the audience hence in that case the quality of lecture is considered high (Almeida 2012), and otherwise it is associated with low quality lecture style.

Based on the three audio-based metrics extracted (Word Density, Speaking Speed, Speaking Intonation), a majority voting approach is employed to determine the overall speech quality. If the majority of the speech-related figures are associated with high-quality lecture style, the corresponding partial lecture speech-based quality score is set to one, whereas in the opposite case the speech-based lecture quality score is set to zero. For the proposed system, the time interval for audio segments was set to three minutes, hence speech metrics related to the intonation, speed and word density are updated every three minutes. An example of the extraction of speech characteristics and estimation of speech quality is shown in Figure 4.7.

```
MoviePy - Writing audio in C:/Users/jelen/Speech Recognition/test.wav

MoviePy - Done.
Loading Audio File..
Audio File Loaded..
Calculating..(time depends on file size)
Intensity(Speech Percentage): 96.19%
Speed: 249.00 words per minute
Tone: The recording consists of 94.83% question tone and 5.17% statement tone.
Intensity=  Bad, Speed= Good, Tone= Bad
```

Figure 4.7 : Examples of audio characteristics such as speech percentage, speaking speed, and speaking tone estimated from a speech segment.

---

[12] https://librosa.org/doc/latest/generated/librosa.feature.rms.html

4.4.4 Hand Movements

According to the literature (Abdulrahman et al., 2022; Bambaeeroo et al., 2017) hand movements is an important feature of a high-quality lecture. In the proposed system, hand detection is used for estimating the presence of hand movements. Hand detection is performed using Mediapipe Hand Detection (Veluri 2022) and the location of detected hands is used for estimating the speed and direction of hand movements.

If a hand is detected in the current frame, a set of landmarks on the hands are localized, and the center of gravity of the landmarks provides an estimate of the hand location. The hand location in each frame is used for estimating the distance and direction of movement of the hand (see Figure 4.8) . Hand speed is calculated as the distance between the current center and the previous center of the hand divided by the number of frames elapsed (see Figure 4.9). Hand direction is calculated as the angle between the current center and the previous center in degrees (see Figure 4.10). If the hands move in a given interval, hands are classified as “moving” and are considered as a high-quality lecture feature. Otherwise, hands are classified as “stationary”, and associated as a low-quality lecture style. The system analyzes hand movements, incrementing the hand movement score by one if hand movement is detected and assigned a score of zero when no movement is detected (see Table 4.2).

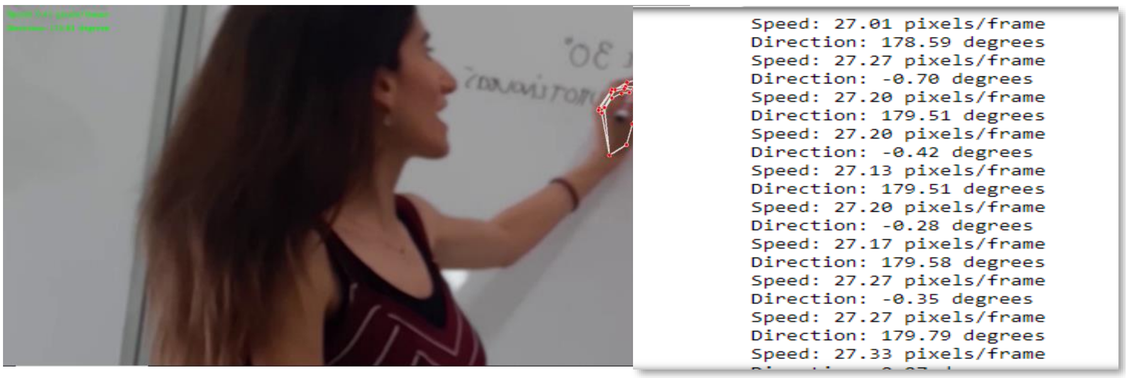


Figure 4.8 : Example of hand detection where speed and direction are printed on the console.

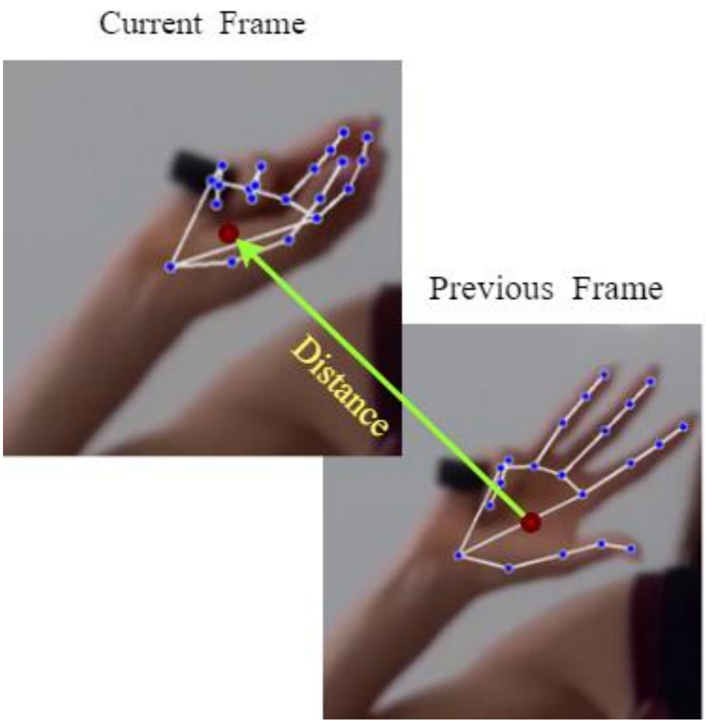


Figure 4.9 : Estimating the distance between hand locations, used for estimating speed of hand movement.

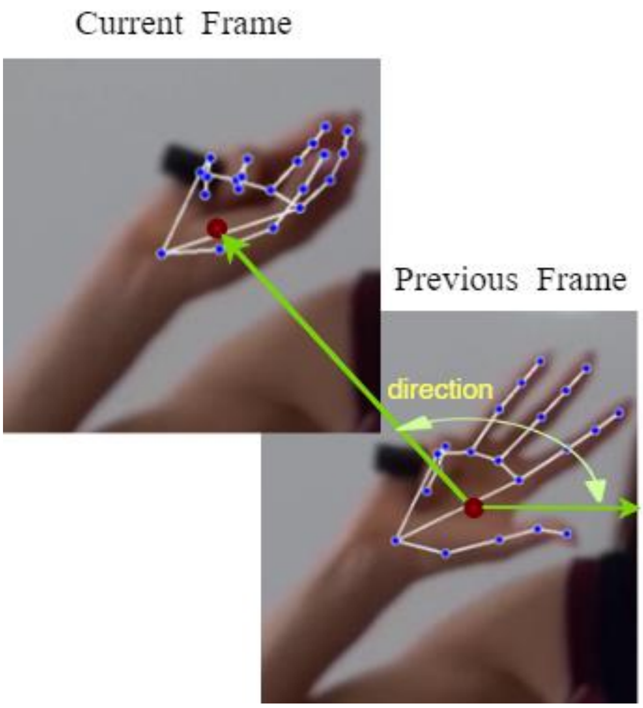


Figure 4.10 : Estimating the direction of hand movements based on hand location and orientation.

4.4.5 Facial Pose Estimation

Facial pose estimation is used for determining if educators have optical contact with the camera (Voit et al., 2007). Based on the interviews with the stakeholders, facial pose estimation is considered important in education due to its ability to maintain student engagement. Since the camera is positioned from the audience point of view, optical contact with the camera implies optical contact with the audience. Facial pose estimation is performed using Mediapipe Face Detection (Singh et al., 2022). The output of the face detector is used for determining if the educator is looking *right, left, up, down, far-left, far-right, far-up, far-down, forward and backwards* (see Figure 4.11). If a face is detected in the current frame, the nose tip is also located. The position of the nose tip relative to the bounding box around the face allows the calculation of the direction that the educator is looking (see Figure 4.12). In addition, an eyeCascade detector was used to detect eyes in a video frame. If the algorithm does not detect eyes, it assumes that the person is not looking towards the audience. Bearing in mind that the camera is positioned in front of the educator, when the educator is looking right, left, up, down and forward are classified as facial poses associated with high quality lecture style, as in that case it is implied that there is eye-contact between the educator and the audience. When far-right, far-left , far-up, far-down and backwards are detected the head direction is associated with a low-quality lecture style, as this implies that there is no optical contact with the audience (see Table 4.2).

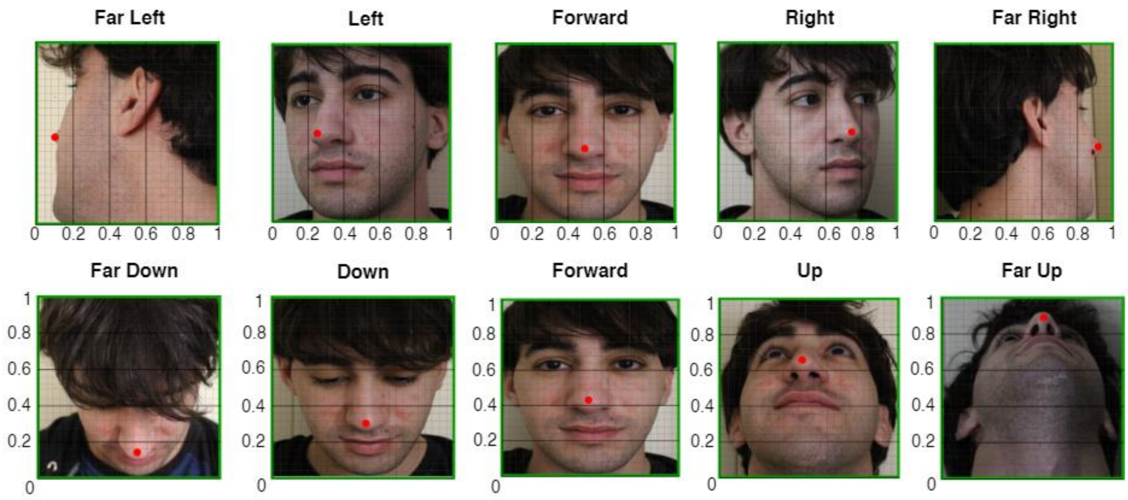


Figure 4.11 : Facial Pose Detection.

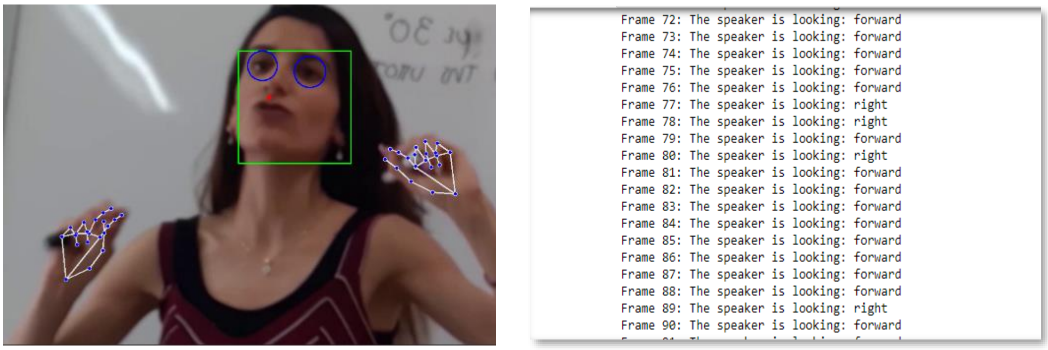


Figure 4.12 : Example of pose estimation where direction is printed on the console.

4.4.6 Merging Metrics

Overall, the proposed system utilizes five modalities (Facial Expressions, Body Activity, Speech, Hand Movement, and Facial Pose), and a positive measure for a given modality increases the total quality score by one. As a result, possible values for the quality score range between zero to five, where zero means that none of the modalities resulted in an acceptable score regarding lecture quality and a score of five indicates that all modalities produced a score associated with a high-quality lecture. The total score is calculated by summing the scores of each frame and dividing by the number of frames, and the total score is presented on the console providing real-time feedback to the educator. The process of estimating the overall quality score from partial scores is illustrated in Figure 4.13. Figure 4.14, shows an example of the overall lecture quality graph, activity score, facial expressions score, facial pose score, hand movement score, score per frame and speech score for a given part of a lecture.

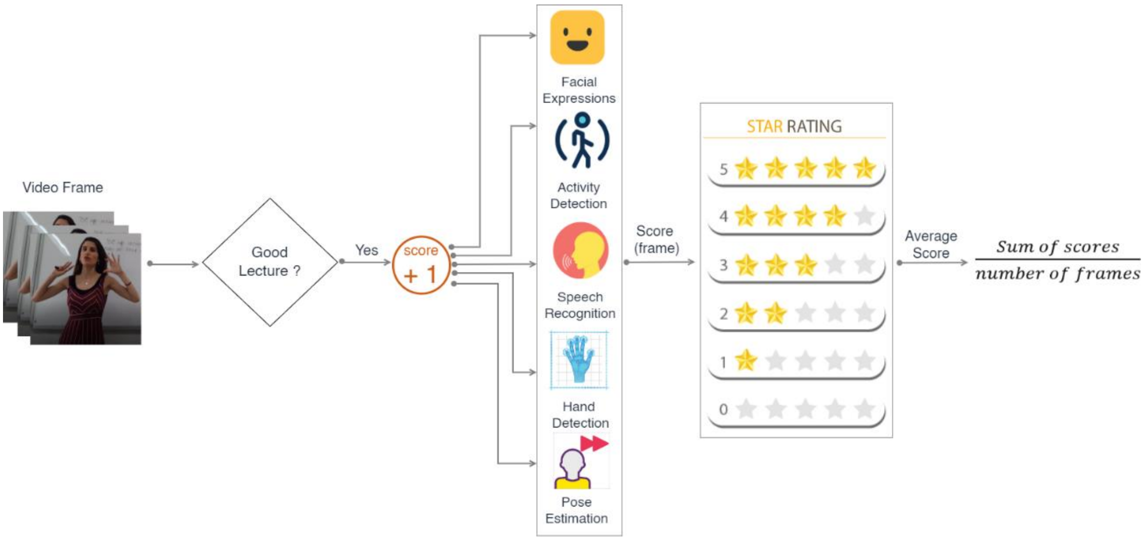


Figure 4.13 : Evaluation of the total quality score, based on modality-specific scores.

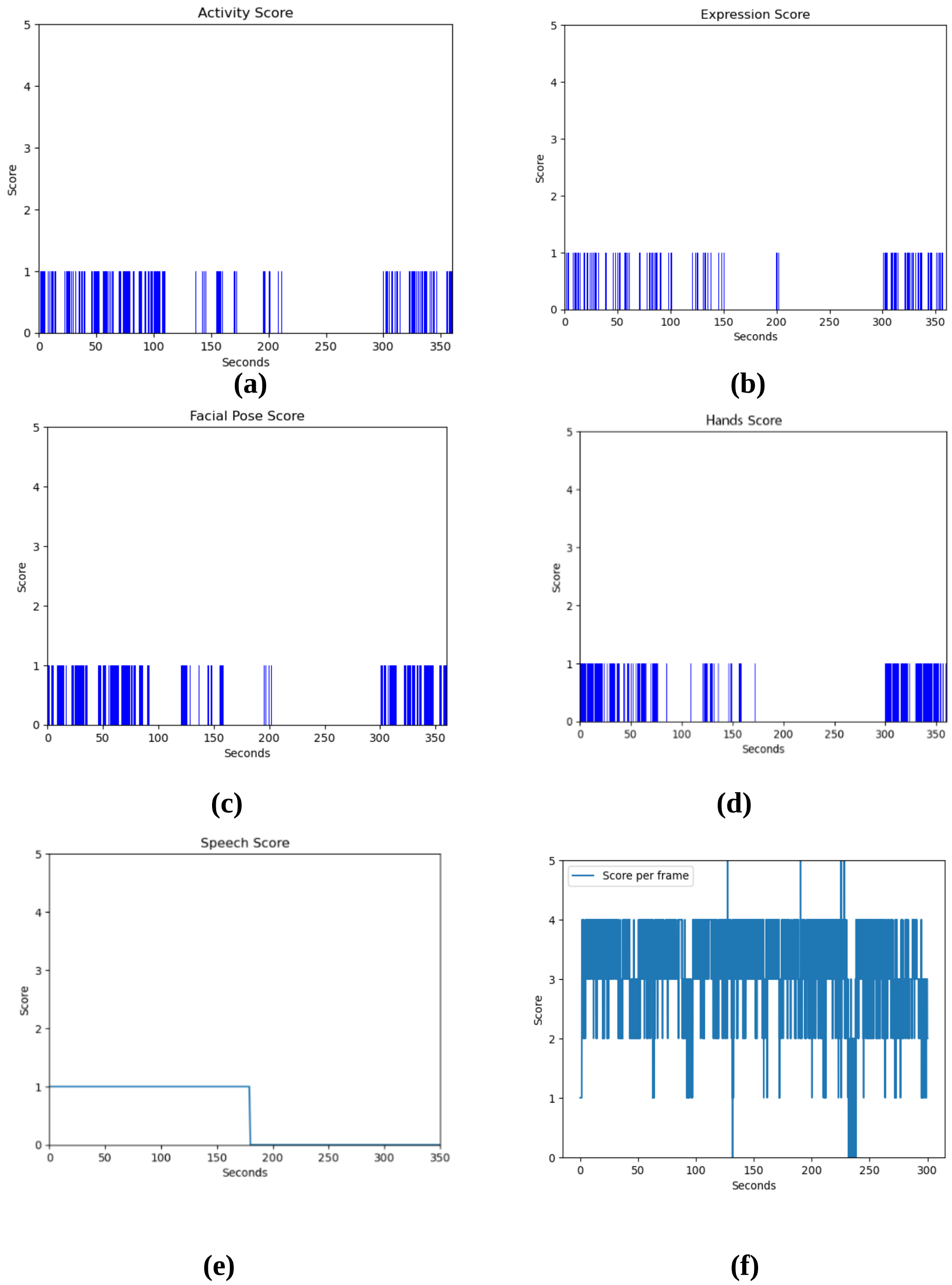


Figure 4.14 : Teaching style quality estimations. (a) Average Score up to the current frame (a) Score per frame for the "Activity" metric over a time period, (b) Score per frame for the "Facial Expression" metric over a time period, (c) Score per frame for the "Facial Pose" metric over a time period, (d) Score per frame for the "Hand Movement" metric over a time period, (e) Score per frame for the "Speech" metric over a time period and (f) Score per frame.

Indicative frames classified as high- or low-quality lecture style are shown in Figure 4.15. The image frame in Figure 4.15(a) is considered to show a high-quality lecture-style because it includes positive facial expressions (happy), positive activity detection (hand raising), hand movements, and facial pose (forward) that ensures eye-contact with the audience. For that interval speech features were not among the range of acceptable values, hence the overall score was four out of five. The image frame in Figure 4.15(b) was assigned a low lecture-style quality score because no positive facial expressions were detected, a negative action (looking elsewhere) and facial pose (backward) were detected, and the speech features were not among the range of acceptable values. However, since hand movements were detected, the score was assigned a score of one out of five. The image frame in Figure 4.15(c) was classified to a low-quality lecture-style quality style because a negative activity was detected (making a telephone call), while and facial pose (far-right), and the speech features were not among the range of acceptable values. However, since hand movements and a positive facial expression (neutral) was detected, the overall score was estimated to a value of two out of five.

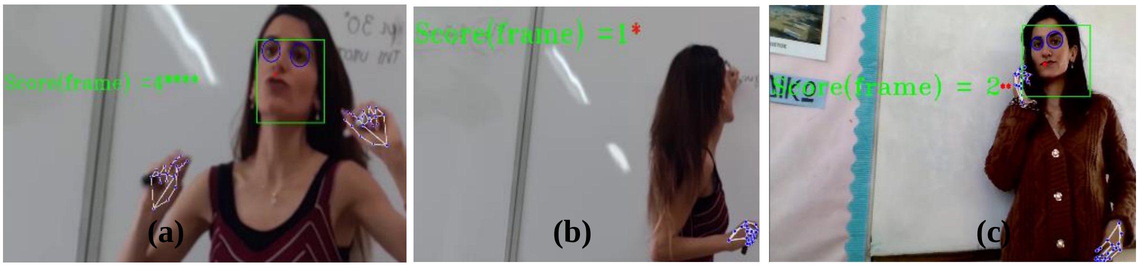


Figure 4.15 : Typical screenshots where high (a) or low-quality lecture styles (b)-(c) are detected.

The proposed system provides two options for providing feedback to the educator. The first option estimates the quantifiable metrics in real-time using the laptop camera to capture the video, so that low quality scores can be used for alerting the attention of the educator. The second option loads a recorded video of a lecture and produces quality score estimations for the overall lecture so that the educator can study and reflect about his/her performance at the end of a lecture.

The overall application operates efficiently in cases where the camera is located at a close distance from the speaker and the microphone is close to the speaker. In cases, where the speaker is at a far distance from the camera/microphone, proper detection of the body parts and extraction of audio features cannot be achieved accurately. Hence, in its current form the proposed system applies to cases where the educator does not move in a class, and the camera is located at a reasonable distance capturing images of the educator from the audience point of view. The use of suitable microphones attached on the educator is recommended so that speech-related features can be estimated more accurately.

The lecture style quality estimation techniques are incorporated into a user-friendly application that can be executed on standard personal computers without the need for dedicated equipment. The only requirements will be the existence of a mainstream personal computer with at least an intel I3 or equivalent processor, and at least 4GB RAM, and the existence of a web-camera and a microphone. The operation of the system on standard equipment, will allow the easy and large-scale utilization of the system.

4.5 Performance Evaluation

In this section a performance evaluation of the proposed lecture style quality evaluation system is presented. The evaluation focuses on examining the usefulness of the proposed system, and determining whether the lecture quality values generated by the proposed system are accurate and aligned with the views of human evaluators. In section 4.6 an evaluation of the potential of the proposed system to support the improvement of teaching style of educators is presented.

4.5.1 Preliminary Interview based-evaluation

To investigate the acceptance of the proposed methodology, a preliminary user evaluation using semi-structured interviews has been carried out with two chief education officers, two educators and two students. The interviews were conducted with the same participants who participated in the user requirements analysis step. One of the main tasks of a chief education officers relates to the guidance and evaluation of teaching staff in schools. Consequently, their opinion plays a crucial role in developing and completing the application.

Initially, the researchers demonstrated the application to the participants in real-time in order to receive more reliable feedback. Subsequently, participants answered questions regarding their impressions, about biometric features, and possible ways to improve the application. More specifically, participants responded the following questions:

1) *What are your impressions about the application*?

2) *Is the application considered useful, and if so, why*?

3) *Can you suggest possible ways to improve the application*?

The results showed that all participants consider the system to be an innovative idea as this system can provide real-time feedback. Participants also stated that features used accurately reflect the lecture style quality. Regarding ways to improve, participants mentioned that the camera may not only focus on the educator but also on the students so that student feedback is also considered as part of the evaluation process. Based on the positive outcome of the preliminary interview-based evaluation that ensures the usefulness of the proposed system, we proceeded to the process of quantitative evaluation of the performance of the system, as described in the following sections.

4.5.2 Quantitative Evaluation

In order to stage a quantitative evaluation of the system, ground truth data is required. Due to the lack of such data, an annotation process was staged with nine annotators aged from 18 to 62 years. Annotators included university students who study in public and private institutions and educators of elementary, secondary and tertiary levels. The average time needed for each annotator to complete the annotation process was approximately 60 minutes. More details about the process are provided below.

4.5.2.1 Data Annotation

The participants were asked to complete a three-stage annotation process. In the beginning, the participants were asked to carefully read the agreement form in order to give their consent regarding their answers which will remain confidential and will be exclusively used for the purposes of this research. The first part of the of the annotation process included a series of questions related to the annotators (ethnicity, gender, age, occupation) as well as open type questions, where annotators provided information about their educational experience (if any), field of expertise, while students were called to define the field, the level and the duration of their studies.

At the beginning of the other two parts (second and third) annotators were given instructions related to the five biometric features extracted by the system (i.e. facial expressions, activity performed, head direction, hand movements, speech recognition), in order to make their evaluation clearer and simpler. During the second part of the annotation procedure, annotators were presented with 100 image frames extracted from nine different lecture videos showing lectures with varying quality of presentation. Frames used were selected to portray a variety of different conditions reflecting different teaching styles. Each annotator had to evaluate the perceived lecture quality in each frame with respect to the following biometric features: Facial expression, educators' actions, hand movements, and head movements. Annotators also had to provide an overall evaluation of the lecture quality in each frame using the 4 level Likert scale, ranging from "very low" to "very high" lecture style quality.

The third part of the online questionnaire contained 100 sound segments with a duration of 15 seconds each, which were extracted from the nine videos used in part B of the evaluation. In this part, the participants listened each speech segment and provided an estimate of speech quality for each segment in the 4 level Likert scale ranging from "very low" to "very high" lecture style quality.

For the evaluation of the application, the data annotated was used as the ground truth. In this study, the average among all nine annotators was considered as the ground truth. The four-class problem for the facial expressions, activity detection, speech recognition and facial pose was transformed to a binary problem by considering annotations values of 1 and 2 as low-quality lecture, and the values 3 and 4 as high-quality lectures. The prevailing mode for every biometric feature and the total score per frame were calculated. The prevailing mode considered as the ground truth for each biometric feature is defined as the one that appears most often on the dataset.

The process of generating the ground truth data adopted in this work is not uncommon in domains where obtaining measurements is challenging, such as interpreting facial expressions or other non-verbal signals. Our methodology ensures that even though the data originates from observations the analysis remains completely objective and free from any biases. By drawing parallels with fields that rely on ground truth generated by humans

(Miceli et al., 2020; Wu et al., 2022) we emphasize the dependability and validity of this research methodology.

4.5.2.2 Performance Evaluation Results

For each visual/speech sample used, the output values given by the proposed system in every frame and the total score for every frame were calculated and compared with the ground truth obtained from the annotators (see Section 4.5.2.1). To evaluate the performance of the proposed model, specific performance measures for each biometric feature such as Accuracy, Precision, Recall, MCC, Cohen's kappa and F1-score were calculated. F1-score is a combination of the Precision (true positives / total predicted positives) and the Recall value (true positives/total actual positives) (see Table 4.4). Furthermore, the confusion matrix for every metric is shown in Figure 4.16.

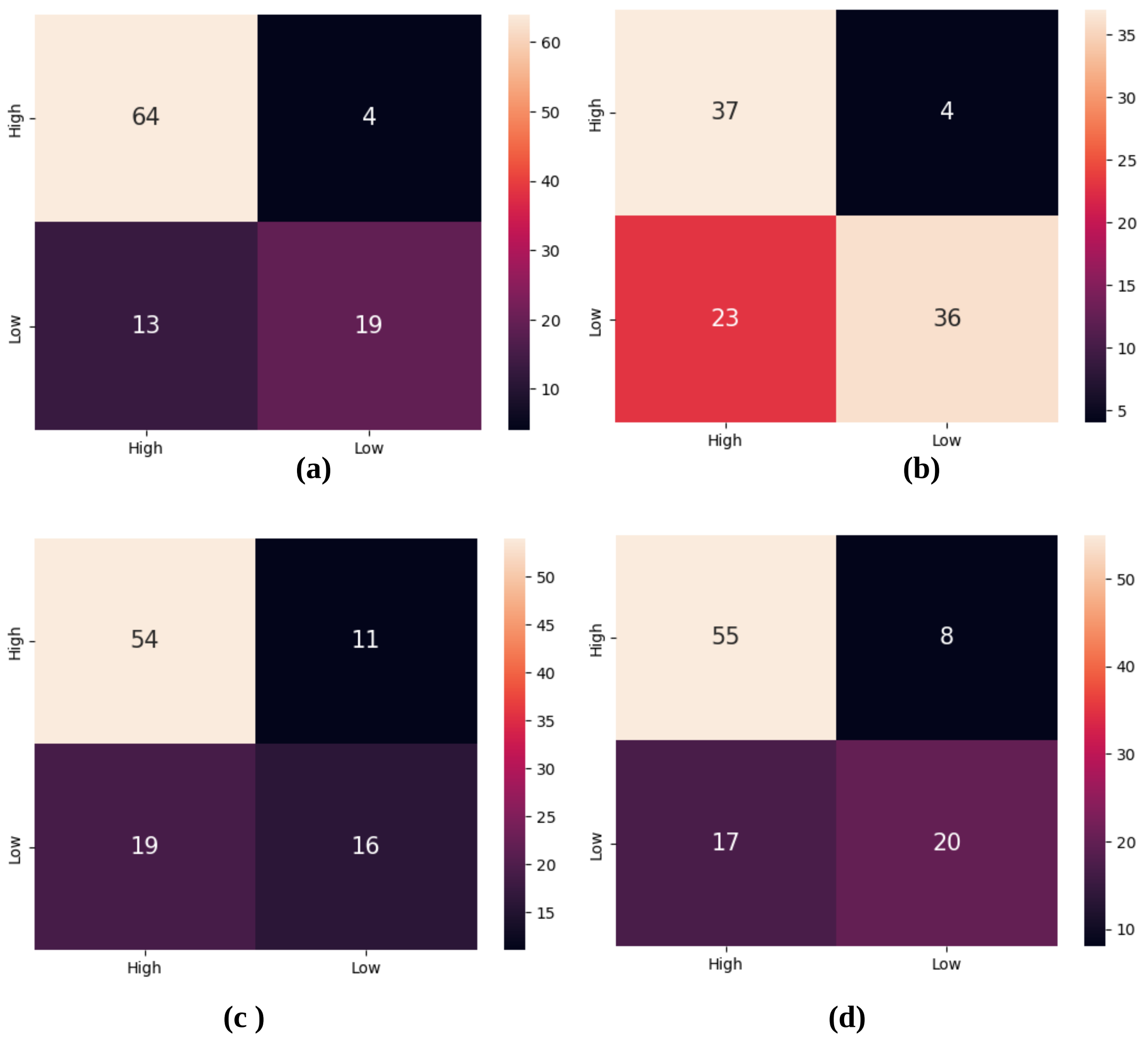
Table 4.4 : Accuracy metrics regarding the comparison between actual and output values.

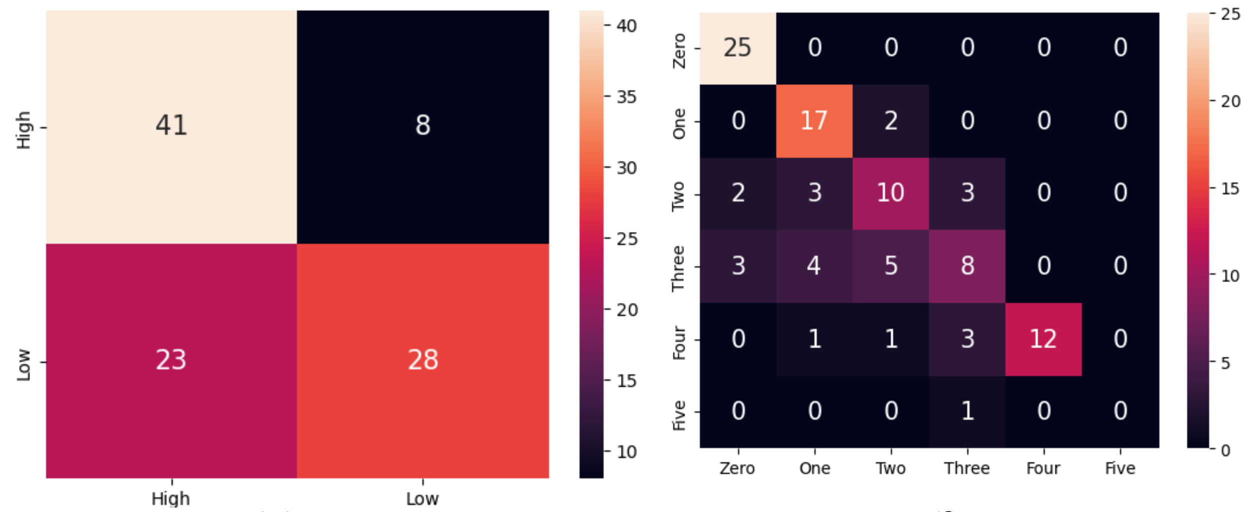
Performance Measures	Expressions	Body Activity	Facial Pose	Hand Movements	Speech	Score (frame)
Accuracy(%)	83.0	73.0	70.0	75.0	69.0	72.0
Recall	0.830	0.730	0.700	0.750	0.690	0.720
Precision	0.829	0.784	0.688	0.746	0.711	0.714
F1-score	0.821	0.729	0.689	0.741	0.684	0.706
MCC*	0.593	0.515	0.309	0.445	0.402	0.652
Cohen's k	0.578	0.479	0.304	0.435	0.383	0.648
Error	0.17	0.27	0.30	0.25	0.31	0.28
Mean Absolute Error (MAE)	N/A	N/A	N/A	N/A	N/A	**0.44**

MCC=Matthews Correlation Coefficient

Based on the results it is evident that the algorithm can classify educators' body language with an accuracy of 72% per frame. From the confusion matrices, the proposed system recognized the facial expressions with 83% accuracy, while the other metrics have accuracy higher than 69%. Figure 4.16 represents the confusion matrix for each biometric feature and score (per frame). In conclusion, the proposed method is doing better in recognizing expressions associated with high quality lecture styles rather than expressions associated with low quality lecture styles. Furthermore, the misclassification rates for image and audio frames are less than 5% and thus the proposed method rarely misclassifies frames and audio. The overall correct classification score per frame is 72%, which means that in 72 out of 100 cases, the method correctly classifies the teaching quality. The prediction error is relatively small therefore the performance satisfies the requirements for a practical application (Yang et al., 2012).

Furthermore, regarding the score per frame, the Mean Absolute Error (MAE) calculated as the mean of the sum of the absolute difference between the actual values and predicted values. The average difference between the actual values and predicted values by the model is 0.44 regarding the score per frame. This indicates that the predicted values will be off by an average of 0.44 units for measurements in the range of 0 to 5.





(e) **(f)**

Figure 4.16 : Confusion matrix for (a) facial expressions (first row-left), (b) body activity (first row-right), (c) facial pose (second row-left), (d) hand movements (second row-right), (e) speech (third row-left) and (f) score per frame (third row-right).

4.5.2.2.1 Assessing human performance

The task of lecture quality assessment is a subjective task, hence before concrete conclusions related to the performance of the proposed system are derived, it is essential to derive conclusions related to the level of conformity among the human annotators. For this purpose, leave-one-out experiments were carried out among the nine annotators where in turn the responses of the eight participants were considered as the ground truth and tested against the performance of the remaining annotator. The Mean Absolute Error (MAE) obtained among the nine leave-one out tests was 0.602. This indicates that the difference in responses among the participants will be off by an average of 0.602 units in the 1 to 4 scale. Each participant has their own opinion, so it is reasonable to expect differences in their responses for the subjective task of lecture style quality evaluation. The overall accuracy metrics were calculated by comparing the ground truth values to the values of the nine participants for each type of features and the overall quality score per frame (see Table 4.5).

Table 4.5 : Overall accuracy metrics for the nine annotators.

Performance Measures	Expressions	Body Activity	Facial Pose	Hand Movements	Speech	Score (frame)
Accuracy(%)	83.6	77.6	81.3	75.8	66.0	67.3
SD* (Accuracy)	0.07	0.07	0.12	0.09	0.02	0.07
Recall	0.836	0.776	0.813	0.758	0.660	0.673
Precision	0.837	0.793	0.819	0.766	0.670	0.725
F1-score	0.836	0.777	0.815	0.760	0.653	0.687
MCC*	0.626	0.561	0.600	0.496	0.327	0.602
Cohen's k	0.626	0.552	0.599	0.494	0.316	0.598
Error	0.16	0.22	0.19	0.24	0.34	0.33
Mean Absolute Error (MAE)	N/A	N/A	N/A	N/A	N/A	**0.60**

**SD=Standard Deviations, MCC=Matthews Correlation Coefficient,*

Based on the results it is evident that the humans can classify educators' body language with accuracy 67.3% per frame. From the confusion matrices, the humans recognized the facial expressions with 83.6% accuracy, while the other metrics have accuracy higher than 66%. The standard deviation of the nine annotators' accuracy was calculated, where the values were 0.07, 0.07, 0.12, 0.09, 0.02, and 0.07 for facial expressions, activity detection, facial pose, hand movements, speech recognition and score per frame respectively. It is observed that there is a variance between people in terms of classification accuracy in each metric due to the fact that each participant has their own opinion. The accuracy score regarding the score per frame is 67%, which means that in 67 out of 100 cases, the humans correctly classify the teaching quality.

Figure 4.17 represents the confusion matrix for each biometric feature and score per frame. In conclusion, expressions associated with low quality lecture styles rather than expressions associated with high quality lecture styles are recognized by humans with high accuracy. Furthermore, we observe that the misclassification percentages are less than 4% and thus our proposed system method rarely misclassifies frames and audio.

In addition to these results the Mean Absolute Error (MAE) calculated as the mean of the sum of the absolute difference between the actual values and predicted values was considered. Based on the results obtained, the average difference between the actual values and predicted values by the model is 0.60.

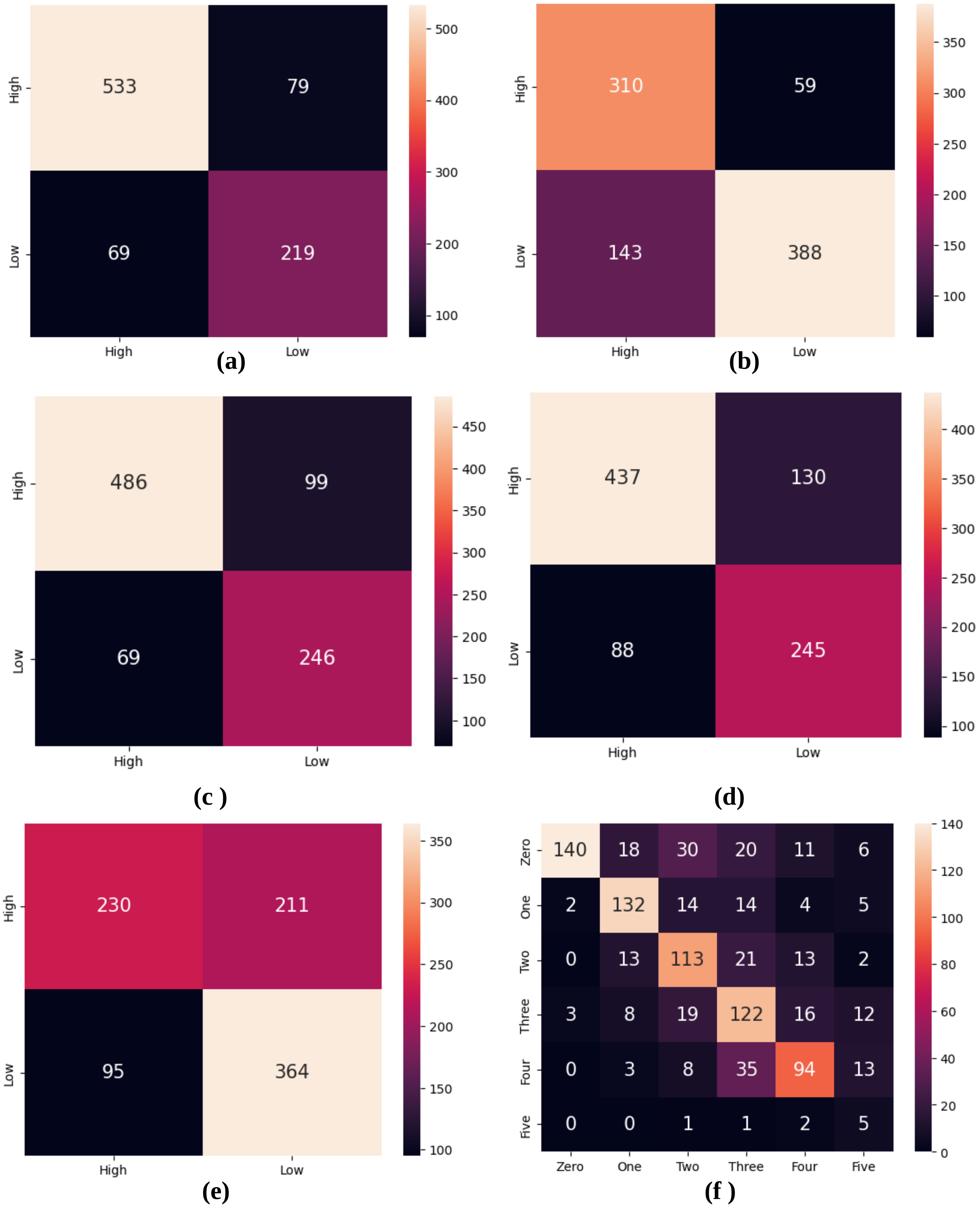


Figure 4.17 : Confusion matrix for (a) facial expressions (first row-left), (b) body activity (first row-right), (c) facial pose (second row-left), (d) hand movements (second row-right), (e) speech (third row-left) and (f) score per frame (third row-right).

4.5.2.2.2 Comparing machine and human performance

In this subsection, the goal is to compare the performance of the proposed system with human performance. In order to investigate differences between the mean accuracy of people and machine in variables “Expressions”, “Body Activity”, “Facial Pose”, “Hand Movements”, “Speech” and “Score per frame” the following hypotheses were examined.

Ho : Human performance is equal to the machine performance in the task of estimating lecture quality style.

H_1 : Human performance is different from machine performance in the task of estimating lecture quality style.

Inferential statistics were applied for exploring the differences between the groups and for testing the hypothesis using the Chi-square test, as the samples are independent, and the data are in ordinal and nominal scales. Subsequently, the Holm-Bonferroni method was used in order to deal with the problem of multiple comparisons. The significance level was set at 5%. The null hypothesis is accepted when p-value≥0,05 and is rejected when p-value<0.05.

Subsequently, the Holm-Bonferroni adjusted Chi-square test was used to compare the mean absolute errors for each modality. The results show that there is no statistically significant difference regarding the facial expressions (p=1.00), facial pose (p=0.696), hand movements (p=0.696), speech recognition (p=0.161) and overall score per frame (p= 1.00) (see Table 4.6). Therefore, human performance is equal to the machine performance for educators' body language assessment regarding the facial expressions, facial pose, hand movements, speech recognition and overall score per frame. Hence, the overall score per frame of the machine is the same with the overall score per frame of the human. On the other hand, there was a statistically significant difference regarding the biometric feature activity detection (p= 0.042<0.05). In Table 4.6, we can observe that the human's mean absolute error regarding the activity detection is 0.59 while the machine's is 0.40.

Table 4.6. Mean absolute error, standard deviations for each group, and comparison of groups for each biometric feature and overall score per frame.

Biometric Features	**Humans**	**Machine**	**Comparison**
	M (SD)	M (SD)	p-value
Facial Expressions	0.32 (0.469)	0.35 (0.479)	1.000
Activity Detection	0.59 (0.494)	0.40(0.492)	**0.042***
Speech Recognition	0.51(0.502)	0.36(0.487)	0.161
Hand Movements	0.37(0.485)	0.28(0.451)	0.696
Facial Pose	0.35(0.479)	0.27(0.446)	0.696
Score per frame	1.88(1.472)	1.54(1.374)	1.000

SD, standard deviation

***Statistically significant change (p value<0,05).**

Therefore, we conclude that the performance of the proposed system is similar to the performance of human annotators for lecture style quality estimation based on facial expressions, facial pose, hand movements, speech recognition and the overall quality score per frame. The only case that the performance between the machine and annotators was statistically different, was in the case of activity detection. However, even in that case the mean absolute error of the proposed application (0.44) (see Table 4.4) is lower and the mean absolute error for humans (0.6) (see Table 4.5), hence in the task of activity detection there is evidence that the proposed system outperforms humans. In conclusion, based on the results of statistical tests, the performance achieved by the proposed system is either similar or even better to the performance of human annotators.

4.5.3 Conclusions

A pilot automated system for evaluating the quality of the educators' lectures, based on the definition and extraction of a set of biometric features was presented. The proposed application extracts multiple features such as facial expressions, body activity, hand movement, facial pose, speech word density, speaking speed, and speech intonation, which are combined to provide a lecture style quality score for each frame as well as an overall score for the whole lecture. The acceptance of the application was evaluated by chief education officers, educators and students regarding the functionality, usefulness of the application, and possible improvements. The results showed that participants found the application novel and useful in providing automated feedback regarding lecture quality, so that the overall teaching process is benefitted.

In addition to the interview-based user evaluation, a quantitative performance evaluation was staged, where the accuracy of estimating lecture style quality using different modalities was evaluated. As part of the process, the performance of the system was tested against the ground truth obtained based on the opinions of several annotators. The performance of the system proved the feasibility of using it in real applications. Furthermore, the performance of the system was compared to the performance achieved by humans in the task of lecture style quality estimation. The results from the machine-human comparison showed that our proposed system achieves a similar performance to humans regarding the modalities of facial expressions, facial pose, hand movements, speech recognition and score per frame. Furthermore, human and machine performance analysis showed that the performance of our proposed system outperforms the performance of humans regarding the speech (69% and 66% respectively) and score per frame (72% and 67.3% respectively). The performance of our system differs little from that of humans regarding the biometric feature body activity. This is due to the fact that humans' performance evaluation was based on everyone's personal opinion, therefore, it is considered reasonable that there is some variation in the evaluation of metrics between humans and the machine. Nevertheless, the proposed system achieves smaller mean absolute error in estimating lecture style quality features associated with a educator's body language.

4.6 Evaluating the Impact of an Automated Teaching Style Assessment System

The impact of the teaching style assessment application is evaluated through a dedicated experimental investigation that involves comparative assessment of the impact of the application in improving lecture style quality. The steps adopted through the experimental evaluation, and the results obtained are described in this section.

4.6.1 Research Questions

The purpose of this research is to examine the impact of the teaching style analysis experimental application in improving the teaching style of educators. As part of the process, the following research questions were considered:

RQ1: Can this application potentially contribute to the improvement of the educators' teaching style?

RQ2: Does the application provide sufficient feedback regarding the teaching style of educators?

RQ3: Is the use of this application feasible in actual classroom conditions?

4.6.2 Overview of Experimental Procedure

The experimental procedure consisted of two phases (see Figure 4.18). In the first phase of the process, participants completed the first part of a questionnaire that contained closed type questions related to their demographic data such as ethnicity, gender, profile, age, field of expertise and years of teaching experience. Afterwards, the participants had the chance to present a short demo lecture and the teaching style analysis application (see Section 4.4) was used for analysing and estimating scores reflecting their teaching style during the lecture. After completing the first lecture, participants completed the second part of the questionnaire that included closed type questions regarding the user experience of the participants in using the TSA application. Following the completion of the second part of the questionnaire, short semi - structured interviews of the participants took place which had a duration of 10 - 15 minutes. The interviews were conducted by the researchers and contained information and a discussion related to the interpretation of results produced by the automated teaching style analysis application.

In the second phase of the experimental process, participants delivered another short demo lecture of the same duration as in the first phase. Then, they proceeded to the completion of the third part of the questionnaire that contained the same closed type questions as in the second part. At the end of the third part of the questionnaire the participants were given open type questions in order to provide additional feedback regarding the teaching style analysis application. At the end of the third part of the questionnaire a second short semi - structured interview of the participants took place. The interviews conducted by the researchers contained comments of the results of the application in order to determine whether at that point there was improvement concerning the comprehension of these results in comparison to the first phase of the research.

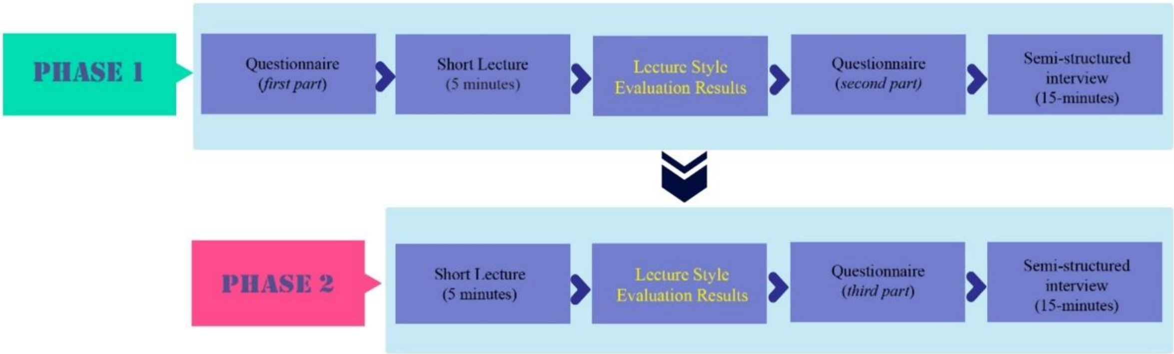


Figure 4.18 : Overview of the experimental procedure.

Before the beginning of the study, the participants were informed about the purpose of the study in order to guarantee that everyone follows the same steps towards its completion. Concerning ethics, all the educators were acquainted about the purpose of this study both orally and in writing in order to obtain their informed consent. Furthermore, the participants were assured of the confidentiality and anonymity of their personal data. Educators were informed that they could withdraw from the procedure at any time without giving any explanations. The study underwent an ethics review process and was approved by the Cyprus National Bioethics Committee (No. ΕΕΒΚ ΕΠ 2023.01.218), ensuring that the experimental investigation was conducted in accordance with ethical standards.

4.6.3 Sample

The sample of the main research contained nine educators of elementary, secondary, and higher education, from the age of 25 to 59. Table 4.7 presents a summary of the demographic characteristics of nine participants of current research. Considering experience in artificial intelligence technologies, the *22%* (*N=2*) are highly experienced and the *78%* (*N=7*) are not at all or little experienced.

Table 4.7 : Demographic characteristics.

Demographics	**Category**	**%**
Gender	Male Female	67.0% 33.0%
Grade of teaching	Primary school Secondary school Higher school	11.0% 78.0% 11.0%
Age	25-29 30-39 50-59	56.0% 22.0% 22.0%
Teaching experience (years)	1-5 20-22	78.0% 22.0%
Teaching specialty	Mathematician Information technology Design and Technology Psychology	56.0% 22.0% 11.0% 11.0%

4.6.4 Analysis of Teaching Style Scores

The overall teaching style score, and scores for different modalities were recorded for both lectures delivered by each participant (see Figure 4.19). The comparison of the scores between the two lectures, allows the derivation of information regarding the impact of the teaching style analysis application in adjusting the teaching style of the participants. Figure 4.20 shows the average quality score per frame for the two participants with the lowest improvement in lecture style scores, and the two participants with the highest improvement in lecture quality style score. Even for the cases with the lowest improvement, there is noticeable improvement in the quality scores.

Table 4.8 shows the results of the non-parametric Wilcoxon Sign Rank Test for the educators' group of the differentiation of the scores obtained between the first and the second phase. This test is used because the samples are paired, and the data are in ordinal scale since it has to do with the same persons in different circumstances. The null hypothesis (H_0) is that there is no statistically significant difference for the scores between the first and the second phase. The alternative (H_1) is that there is a statistically significant difference for the scores between the first and the second phase.

Table 4.8 : Mean, Standard Deviations, and p-value for the first and second phase regarding the biometric features.

Biometric Features	**Mean (*Standard Deviations*)**	**p-value**
Average Overall Score (first lecture)	.871 (*.346*)	**.011***
Average Overall Score (second lecture)	1.786 (*.764*)	
Speech Score (first lecture)	.000 (*.000*)	.317
Speech Score (second lecture)	.125 (*.354*)	
Hands Score (first lecture)	.125 (*.133*)	**.012***
Hands Score (second lecture)	.396 (*.288*)	
Facial Expressions Score(first lecture)	.165 (*.093*)	**.036***
Facial Expressions Score (second lecture)	.341 (*.164*)	
Facial Pose Score (first lecture)	.291 (*.315*)	**.025***
Facial Pose Score (second lecture)	.405 (*.349*)	
Body Activity Score (first lecture)	.271 (*.148*)	.069
Body Activity Score (second lecture)	.366 (*.208*)	

**Statistically significant difference ($p<0.05$)*

Based on the results, there is a statistically significant difference regarding the average score, facial expressions, hand movements, and body activity. The information provided about the application, and the automated evaluation results presented to the participants after the first lecture, have helped the participants to understand exactly which parameters have been considered ‘good’ or ‘bad’ for their teaching. As a result, they have managed to improve the specific metrics of average score, facial expressions, hand movements, body activity and score per frame. Concerning the speech and body activity score, the participants achieved better performance in the second lecture, but there was no statistically significant improvement when compared to the scores of the first lecture.

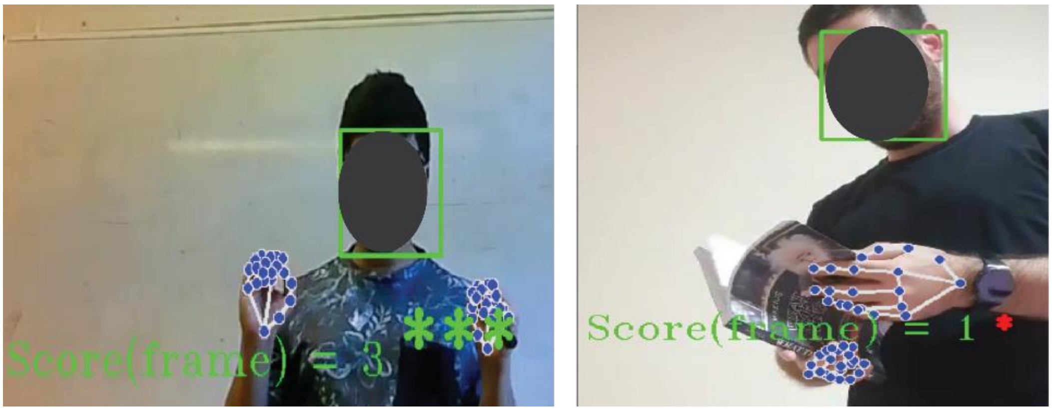
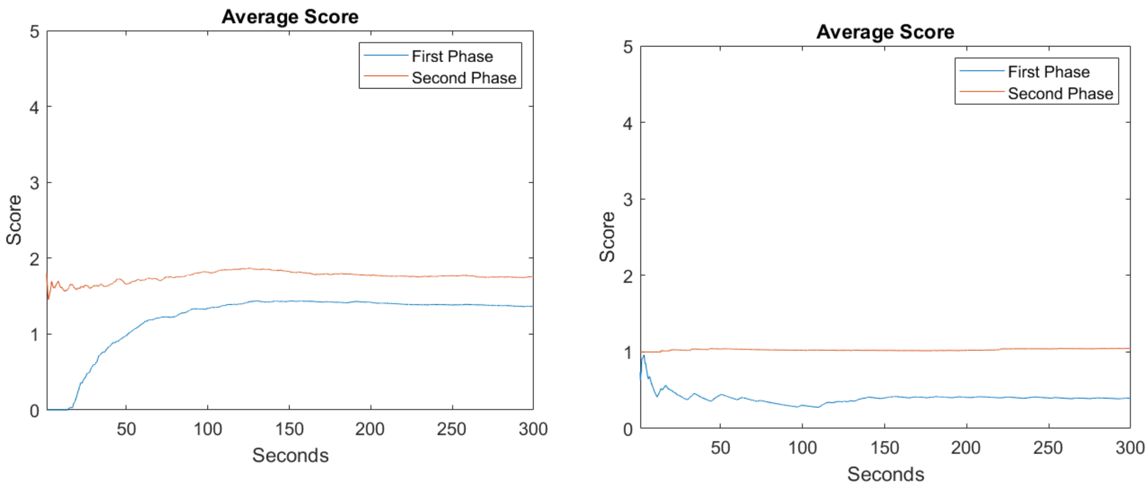


Figure 4.19 : Screenshots for the participants during the experimental procedure.



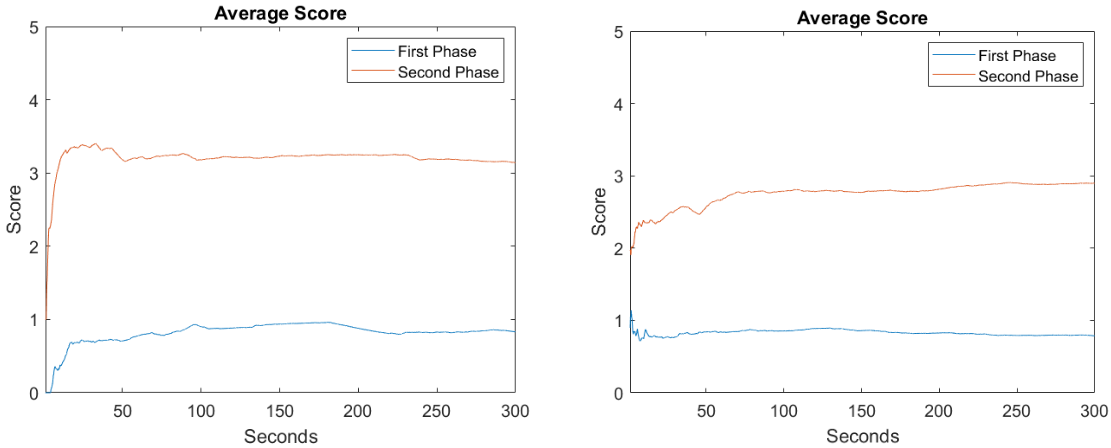


Figure 4.20 : The average score for two participants with the lowest improvement in lecture style scores (top row) and two participants with the highest improvement in lecture style using the TSA application (bottom row).

4.6.4.1 Questionnaire Results

Table 4.9 presents the results of reliability analysis for the factor "Satisfactory Feedback" between the first and the second phase, using the Cronbach Alpha coefficient to test internal consistency. Satisfactory values are considered those in the interval [*0.7*,*0.8*) high in the interval [*0.8*, *0.9*) and perfect in the interval [*0.9*,*1.0*] (Nunnaly & Bernstein, 1994). The "Satisfactory Feedback" factor analysis was conducted for the same six questions in both cases (first and second phase). Reliability was perfect for the first phase ($a=0.946$) and high for the second phase ($a=0.866$). To test the normality of variables, between the first and the second phase, the Shapiro Wilk test was used, which is considered to have the best results (Razali and Wah, 2011). Normality is accepted only for the factor "Satisfaction from feedback" for the first phase ($p=0.100$) and second phase ($p=0.175$).

Table 4.9 : Reliability analysis for factor "Satisfactory Feedback" before and after intervention.

Factor	Items	Cronbach Alpha	Reliability
Satisfactory Feedback (before)	6	0.946	Perfect
Satisfactory Feedback (after)	6	0.866	High

To test the mean differences between the first and the second phase in related samples (same participants in different conditions), the non-parametric Wilcoxon test was used, in cases that normality was not accepted between the first and the second phase. On the other hand, for the factor "Satisfaction from feedback", the paired samples t-test was used to test mean differences between the first and the second phase because factor is normally distributed in both cases and samples are related. Significance was set at 5% (Field, 2017). According to Table 4.10, participants agreed more about the application usefulness for improving the quality of the lecture after the intervention than before ($M_{before}= 4.78$ *vs* $M_{after}=5.67$, $p=0.011$).

Table 4.10 : Comparisons of application usefulness for improving the quality of the lecture before and after intervention.

Question	**Mean (*Standard Deviation*)**	**p-value**
Do you think the application is useful for improving the lecture quality?	4.78 (.67)	**.011***
Do you think the application is useful for improving the lecture quality?	5.67 (.50)	

Statistically significant difference (p<0.05)

There is a statistically significant difference between the first and the second phase regarding feedback about the facial expressions, body activity, hand movements, facial pose, and average score. According to Table 4.11, participants presented higher levels of satisfaction from feedback after intervention than before more particular considering facial expressions ($M_{before}=4.44$ *vs* $M_{after}=5.78$, $p=0.014$), body activity ($M_{before}=4.44$ *vs* $M_{after}=5.67$, $p=0.041$), hand movements ($M_{before}=4.56$ *vs* $M_{after}=5.78$, $p=0.041$), facial pose ($M_{before}=4.44$ *vs* $M_{after}=5.56$, $p=0.047$) and average score ($M_{before}=4.44$ *vs* $M_{after}=5.67$, $p=0.026$). All the participants agree that the proposed application provide sufficient feedback regarding the facial expressions, body activity, hand movements, facial pose, and average score. There is no statistically significant difference regarding the speech metric. In the first phase, 33% of educators stated that the system provides much to very much satisfactory feedback, while in the second phase 67% of the participants stated that the system provides much to very much satisfactory feedback.

Table 4.11: Comparisons of application satisfactory feedback on the educators' teaching style before and after intervention.

Question	**Mean (*Standard Deviation*)**	**p-value**
Facial Expressions (before)	4.44 (*1.42*)	**.014***
Facial Expressions (after)	5.78 (*.44*)	
Body Activity (before)	4.44 (*1.51*)	**.041***
Body Activity (after)	5.67 (*.50*)	
Speech Recognition (before)	4.11 (*1.17*)	.276
Speech Recognition (after)	4.67 (*1.41*)	
Hand Movements (before)	4.56 (*1.59*)	**.041***
Hand Movements (after)	5.78 (*.44*)	
Facial Pose (before)	4.44(*1.51*)	**.047***
Facial Pose (after)	5.56(*.53*)	
Average Score (before)	4.44(*1.42*)	**.026***
Average Score (after)	5.67(*.50*)	
Satisfaction from feedback (before)	4.41(1.34)	**.044***
Satisfaction from feedback (after)	5.52(.46)	

Statistically significant difference (p<0.05)

Even though the mean value related to the participant's impression of the usefulness of the system, increased after the intervention, there is no statistically significant difference between the first and second phase regarding the usefulness of the application in improving lecture quality (see Table 4.12). Since participants realized that this is a highly useful application even before the intervention, this specific metric received high responses from the first phase of the experiment, the improvement in the score after the intervention was not enough to make the difference statistically significant.

Table 4.12 : Mean, Standard deviations regarding whether the feedback provided by the application improves the lecture quality.

Question	**Mean (*Standard Deviation*)**	**p-value**
Do you believe that the application's feedback is useful to improve the lecture's quality? (Phase 1)	4.10 (.74)	.063
Do you believe that the application's feedback is useful to improve the lecture's quality? (Phase 2)	4.70 (.48)	

According to Table 4.13, participants agreed that the application is easy to use in real classroom ($M_{after}=5.44$). Regarding the open-type questions in the questionnaire, the majority of the participants claimed that they preferred the upload option rather than running the application in real time.

Table 4.13 : Comparisons of application easy to use before and after intervention.

Question	**Mean (*Standard Deviation*)**
Do you think that the application is easy to use in actual classroom? (Phase 2)	5.44 (*.73*)

Although a small sample was used, the results of the interviews are important as they provide useful feedback regarding the views of the participants about the teaching style evaluation system.

4.6.4.2 Semi-structured interview results

In this subsection, the analysis of semi-structured interviews is presented, which was carried out using thematic analysis. Thematic analysis was selected because is considered important to summarize key features. According to Braun and Clarke (2006), thematic analysis is described as "*a method for identifying, analyzing and reporting patterns (themes) within data*".

Table 4.14 presents the results of participants' views regarding the use of the application. All educators stated that they were satisfied with the use of the application and the vast majority improved their understanding of the results of the application between Phase 1 and Phase 2.

Table 4.14: Application contribution to the improvement of educators' teaching style.

Themes	Codes - Quotes
1. App usage opinions	**Satisfaction with its use (1, 2, 3, 4, 5, 6, 7, 8, 9)**
	"Yes, very satisfied." (R1)
	"I am satisfied although the results of my lecture were again not as good as I wished." (R2)
	"Yes, it's okay. I really enjoyed the app… I have tried to fix the mistakes I realized I made last time. I did better" (R3)
	"Yes, I am satisfied. Very nice app……. Maybe it could also evaluate the quality of the lesson not just the body language. If only there was an app that could correct our writing even better." (R4)
	"I liked it. I find it a very useful app. " (R5)
	"Yes, I am very satisfied. I definitely have room for improvement..." (R6)
	"It is fine. (R7)
	"Your idea is very nice..." (R8)
	"I am very satisfied. It is a great application." (R9)
	Improved understanding of results between Phase 1 and Phase 2 (1, 3, 4, 6, 7, 9)
	"Yeah, much better than the first time." (R1)
	"*My results are too low. I didn't know what the system evaluates in order to get better results…………Yes I have understood them now, but what exactly can I do to get a perfect score?!."* (R3)
	"I liked that it brings out the score in every frame. But it is not clear what the number 0 and the number 1 mean… Yes. I tried to improve based on the graphics from last time." (R4)
	"The first time I made the video I didn't understand what 0 was and what 1 stands for." (R6)
	"*I can read the results better this time."* (R7)
	"*Compared to the first phase, I can better understand the graphics. "* (R9)
	Understanding results from Phase 1 (2, 5, 8)
	"I have understood them and I will try to work on the points that I had bad results."(R2)
	"I have understood the results. Where my movements were not correct, I got a low score" (R5)
	"As soon as I saw the graphics I understood exactly what the system was measuring because when I saw the asterisks in the video it wasn't clear." (R8)
2. Application contribution to educators' teaching methods	**Improving facial expressions (2, 3, 4, 5, 6, 7, 8, 9)**
	"Yes it was clear at which seconds the facial expressions were not correct." (R2)
	"I did better on the facial expressions compared to the first video." (R3)
	"The app helped me to understand my mistakes……….. I did better on the facial expressions compared to the first video." (R3)
	"I tried to have good expressions this time" (R4)
	"I improved here" (R5)
	"I've improved a lot." (R6)
	"Much better results. Basically, it helped me a lot to be able to improve my expressions." (R7)
	"I find it difficult in a class to have good expressions all the time because there are students who make a fuss…………Very good facial expressions." (R8)
	"My facial expressions have improved." (R9)
	No enhancement of facial expressions (1)
	"I can read the graphic but what exactly I did wrong I don't know though." (R1)
	Hand Movement Improvement (2, 4, 5, 6, 7)
	"Yes I understand." (R2)
	"I need to move my arms more." (R4)
	"I did better here too." (R5)
	"Very useful graphics. I didn't know how to move my hands. … Yes I am satisfied with the graphic." (R6)
	"My hand movements are better because now I was moving my hands." (R7)
	"Yes, I understand, I just have to watch the video again to understand even better why in those seconds the hand movements were not so good..." (R8)
	"Quite satisfied." (R8)
	" My performance in hand movements has improved in the second phase. " (R9)
	Improve speech recognition (1, 3)
	"Yes, I understand." (R1)
	"Here I was fine because I managed to make the score 1." (R3)
	Poor speech recognition performance (2, 4, 5, 6, 7, 8, 9)
	"I could probably speak more slowly this time." (R2)
	"Here I didn't understand why I scored 0." (R4)
	"I expected better " (R5)
	"I am not satisfied" (R6)
	"I tried but I had to improve my speaking rate" (R7)
	*" It could be better " (*R8)
	" I would like it to include more statistics about the voice." (R9)
	Action Improvement (2, 3, 5, 6, 7, 8, 9)
	"*Yeah it's clearer now."* (R2)
	"*I did better*." (R3)
	"Much better than last time." (R5)
	"*I was good. No complaints.* (R6)
	"*My actions are more refined."* (R7)
	"*I was fine compared to the first time*." (R8)
	" *My performance has improved, but I can do even better.* "(R9)
	No Actions improvement (1, 4)
	"*I can read the graphics but what exactly I did I don't know though."* (R1)
	"I will try next time to be more focused on the camera" (R4)
	Score improvement for each frame (2, 3, 4, 5, 6, 7, 8, 9)
	"I'm happy compared to the first time..." (R2)
	"*And here the score is much better. In some cases I score 4/5."* (R3)
	"My score is much better now..." (R4)
	*"My score is better now."(*R5)
	"Yes, very good" (R6)
	"My score was more improved." (R7)
	"It was fine." (R8)
	"*I'm happy compared to the first time."* (R9)
	No score improvement for each frame (1)
	"*I read the graphic but what exactly I did wrong I don't know though." (*R1)

Table 4.15 presents the results regarding the implementation feedback on educators' teaching style. The majority of educators state that there is satisfactory feedback. The rest of the participants mentioned that the feedback provided by the application needs to be presented in a better way.

Table 4.15 : Implementation feedback on educators' teaching style.

Themes	Codes - Quotes
3. Application feedback	**Satisfactory feedback (1, 2, 6, 7, 8, 9)**
	" The application is useful and a good idea. It's a good idea to use graphs for feedback." (R1)
	" Yes, I'm satisfied. " (R2)
	" Yes, I'm very satisfied. I can improve sure. " (R6)
	" I understand the results and I am satisfied. Where my activities were incorrect, I received a low score. " (R7)
	" I liked that it displays the score in every frame. The feedback it provides is useful. " (R8)
	"I'm satisfied with the feedback. " (R9)
	Lack of feedback (3, 4, 5)
	"Yes, I have understood them, but what exactly can I do to get a perfect score?! It would be helpful if you could provide specific feedback." (R3)
	"The app is very useful but it could provide feedback by saying specifically what was wrong without me having to think………… It would be good I think if it also gives feedback which actions are considered good and which are not……… I would like but to provide feedback as to what exactly led me to get a score of 0." (R4)
	"Maybe if there was some feedback to know exactly what to improve." (R5)

Table 4.16 presents the results regarding the usefulness of application in real classroom conditions. Five out of nine participants answered that it needs improvement before the application can be used in real classrooms.

Table 4.16 : Usefulness of application in real classroom conditions.

Themes	Codes - Quotes
4. Usefulness of application in real classroom conditions	**Needs improvement in actual classroom conditions (1, 2, 4, 8, 9)**
	"The app is useful and a good idea but it needs an explanation of what is good and what helps the lesson. I noticed that my outfit of wearing short pants in class didn't take it into account." (R1)
	"I think if the app recognized the legibility of the educator's letters it could provide better feedback." (R2)
	"The app is very useful but could provide feedback by specifically stating what was wrong without me having to think." (R4)
	"Quite satisfied……………….I find it difficult in a class to have good expressions all the time because there are students who make a fuss" (R8)
	"The use of the application is feasible because 0 and 1 make sense...... It would be more useful if colors were added. " (R9)

The results of the interviews showed that the majority of educators are satisfied with the results of the application. In particular, they stated that they had a better understanding of the results of the application in the second phase as opposed to the first phase. Furthermore, the educators agree that the application improves facial expressions, hand movements, body activity and score per frame. In addition, the majority of educators state that there is satisfactory feedback with the graphs. Apart from the positive comments, the majority of participants stated that the application needs improvement in order to be used in real classroom conditions, and provided highly useful feedback regarding the required modifications.

4.6.5 Discussion

This research examines the differences regarding the teaching style of educators between two lectures when using an automated teaching style evaluation application. For this purpose, the experimental procedure consisted of two phases. In the first phase of the experiment, the educators carried out short lectures. During this lecture the teaching style of the presenters was evaluated based on the automated teaching style analysis application. Afterwards, participants answered the questions of an online questionnaire that evaluated their experience with the application. Then, a short semi-structured interview followed, a procedure of approximately 15 minutes with each of the participants in order to discuss the results of the application, and explain to them the operation of the application. During the second phase of the experiment participants, they repeated the same procedure as the first phase of the experiment.

The objective of this research is to give answers to three research questions. The research questions and the main conclusions derived are outlined below:

RQ1: *Can this application potentially contribute to the improvement of the educators' teaching style?*

In the first phase, participants carried out their short lectures without being aware of the metrics that the system took into consideration in order to provide an automated evaluation of their teaching style. Through the results of the interviews, it was observed that during the first phase the participants were concerned about their performance as they anticipated better results because they did not know which metrics are considered "good" by the system in order to acquire a good evaluation. On the other hand, during the second phase of the interviews the participants were satisfied with the results once they understood the function of the application and for this reason their performance improved. The results of the graphics' analysis showed that, indeed, the application helped in the improvement of the educators' teaching style. Concerning the metric of speech and body activity there was no statistically significant difference between the first and second phase. This is due to the fact for the body activity metric participants scores were high before the intervention, and as a result the improvement after the intervention was not statistically significant. For the speech metric there was no statistically significant difference because the participants presented difficulty to comply with the standards that were defined for word density, speed and intonation. Furthermore, the results of the questionnaire showed that the participants considered the application to be useful for improving their teaching style. Therefore, using this system, educators could be trained to use their own body language properly and effectively during lectures. According to the research of Selma et al. (2015), educators must use their body language in an effective way. Doing so, they will be able to provide a more charming and sufficient learning environment, in addition to enhancing the communication and the understanding of students (Tai et al., 2014) as well as affecting their performance and evaluation. Based on the results of the experimental evaluation, the first research question has a positive answer. The application can potentially contribute to the improvement of educators' teaching style, via the improvement of the quality of lecture.

RQ2: *Does the application provide sufficient feedback regarding the teaching style of educators?*

According to the results of the interviews and the open type questions of the questionnaire, the participants claimed that the application is useful, helpful and that it provides sufficient feedback. The questionnaires results confirm the interviews' results because there was a statistically significant difference between the first and second phases. The participants agree that the application can provide satisfactory feedback regarding the facial expressions, body activity, hand movement, facial pose, average score. Furthermore, the participants agree that the feedback provided by the application is useful for improving the quality of the lecture. In order for the system to provide better feedback, it was suggested that the application should contain further explanations that defines Right and Wrong body language practises. Furthermore, the participants mentioned that it would be preferable for the users to have the choice of which metric (or metrics) the system takes into account. Based on the results of the experimental evaluation the second research hypothesis was confirmed. The application provides satisfactory feedback on the educators' teaching style, considering facial expressions, body activity, hand movements, facial pose, facial expressions, score per frame and average score.

RQ3: *Is the use of this application feasible in actual classroom conditions?*

In the interviews, all educators claimed that they understood the functions of the application. At the end of the interviews participants were asked if they would prefer to use the application in real time or to upload a video after the end of the class and get the results after the lecture. The majority of the participants preferred the upload option rather than running the application in real time because they believed that real time operation might affect their focus during class and the interaction between educators and students. The majority of the participants stated that the application needs improvement before applying it in real classrooms. They mentioned that it would be better if there was further specific information regarding their performance without having to understand the graphics. Moreover, they would like the application to recognise their writing and their outfits and provide additional statistics regarding speech recognition. Furthermore, in real classroom conditions they mentioned that the application should be able to inform the educators with a screen alert about their performance quality (Right / Wrong) in order to avoid the reading of graphics during class and thus keep the student - educator interaction undisturbed. In real classroom conditions, the lecture could be recorded and after the end of the class the educator would receive the feedback and not in real time because their focus on teaching would be affected. Regarding the third research hypothesis, the proposed application can be used at the end of the lesson by educators for self-assessment regarding their body language and their speaking skills, but at the same time of number of desirable improvements were defined.

Although the results of the experiments proved the potential of the application in improving lecture delivery practises, further experimentation can enhance the significance of the results by dealing with the limitations of the current study. For example, in the future it is desirable to assess the impact of the application with more educators and assess the application on a full series of lectures delivered over a whole semester. However, time constraints related to the completion of the project in combination with long procedures to get permissions to run the experiments in real classes for a whole semester, did not allow the implementation of such large-scale experiments for the current study. Another limitation of the present study is the small number of annotators used in the annotation process. As this process is time-consuming, a small number of annotators was used, in line with other annotation processes reported in the literature (Sharma et al., 2019). However, in the future we plan to repeat the annotation process with more annotators for ground truth generation. Another limitation of the present study can be considered the selection of the sample of participants during the evaluation process. Due to the small, and non-representative sample, the results of this study only concern the specific educators and may not generalize to the entire population. In future research, participants will be selected using random sampling and from different regions.

4.7 Conclusions

The results of the study showed the potential of the proposed system in supporting educators to improve their teaching style during lecture delivery. Furthermore, based on feedback received by educators, the application provides satisfactory feedback on the educators' teaching style, considering facial expressions, body activity, hand movements, facial pose, facial expressions, and the overall quality score. Moreover, the results showed that educators consider the proposed application easy to use as it does not require any specialized equipment. Additionally, the participants agree that the proposed application can be used at the end of the lesson by educators for self-reflection and assessment. Educators believe that the application is very useful as it can help them improve their body language during lecture delivery, thus enhancing the overall quality of their lectures by providing an enhanced learning experience for students.

Chapter 5

Conclusions and Future Works

This dissertation presents a thorough review of the existing literature regarding the use of AI and emerging technologies in the context of smart classrooms. Based on the findings from the literature review, two case studies pertaining to the use of AI in conjunction with image analysis techniques were identified. As part of the work done for the case studies, novel image analysis applications were developed and thoroughly evaluated. In this chapter the main conclusions and plans for future work in relation to the work done during the literature survey and the two case studies, are presented.

5.1 AI in Smart Classrooms

The term "Smart Classroom" has evolved over time and nowadays reflects the technological advancements incorporated in educational spaces. The rapid advances in technology, and the need to create more efficient and creative classes that support both in-class and remote activities, have led to the integration of Artificial Intelligence and smart technologies in smart classes. As part of the study conducted, a literature review related to smart classroom technology, with an emphasis on emerging technologies such as AI-related technologies was carried out. As part of this survey key technologies related to smart classes used for effective class management that enhance the convenience of classroom environments, the use of different types of smart teaching aids during the educational process and the use of automated performance assessment technologies were presented. Apart from discussing a variety of technological accomplishments in each of the aforementioned areas, the role of AI was discussed, allowing the readers to comprehend the importance of AI in key technologies related to smart classes. Furthermore, through a SWOT analysis, the Strengths, Weaknesses, Opportunities, and Threats of adopting AI in smart classes were presented, while the future perspectives and challenges in utilizing AI-based techniques in smart classes were discussed. Through the discussion it was demonstrated that classroom management and teaching aids, like smart environments and online modes of teaching (virtual, online, remote classes) transformed the educational landscape from a traditional educator-led learning to dynamic student-centred learning environment (Li et al., 2021). This change is evident in the utilization and role of AI technologies, incorporated in the wide range of smart-class technologies. Apart from the benefits arising from the use of AI in education, a number of limitations and potential problems were identified and discussed. The main limitations identified include the costs of implementing and maintaining sophisticated technical equipment, necessary technological know-how on behalf of educators and students, as well as security and privacy issues. Moreover, although AI algorithms have inherent biases that may result in unbalanced educational outcomes, the risk of greater disconnection among students due to technology overuse is a serious problem as well. All these factors combined argue for the need to ensure a cautious and balanced AI integration in educational environments. This survey targets educators and AI professionals so that the former get informed about the potential, and limitations of AI in education, while the latter can get inspiration from the challenges and peculiarities of educational AI-based systems that can guide further developments in the area.

Since the concept of smart classes is continuously enriched through the introduction of requirements and new technologies, in the future we plan to monitor this area and produce updated surveys to reflect future developments. By monitoring the continuous developments in this area, we plan to identify needs for novel applications of AI in education, so that in the future we engage in the development of contemporary applications of AI in education. Apart from developing new applications, in the future we also plan to provide specific comparative evaluations of different technologies, so that to quantify the educational impact of such technologies and highlight the need for future improvements.

5.2 Student Action Recognition During Tele-education

Strong interaction between instructors and students during online course delivery is essential for supporting the educational experience. As part of the efforts to maximise the interaction between educators and students, a pilot application that monitors the actions of the students in online courses while protecting as much as possible students' privacy was developed. Apart from developing the student action recognition system, the aim of our work was to evaluate the system so that we determine whether the proposed application for monitoring is acceptable to the stakeholders involved in online classes and whether this application can contribute to the enhancement of the educational experience. As part of the research, the application was evaluated by 75 participants, which included students, parents, and educators, ensuring that the views of the main stakeholders in the educational process are considered. Before the intervention, an online questionnaire was completed by the participants, who then watched a video about the function of the application and/or used the actual application. After the intervention, the participants completed an online questionnaire with similar questions. The results indicate that the use of student action recognition systems is feasible in online courses and accepted by educators, students and parents. Based on the results, most participants believe that the proposed application can contribute to the enhancement of the efficiency of distance education with regard to the student active participation, concentration level, learning results, educator-student interaction, students' interest, and students' evaluation.

Several future works can be derived from this work. First and foremost, experiments with the proposed application can be conducted during online classes to examine the effect of the application on educational results. Secondly, the performance and efficiency of the suggested networks could be improved by considering different network architectures and/or using extended training datasets. Thirdly, the current action set can be extended to include more actions, and more videos can be collected for better evaluation of the performance of the network. Moreover, future efforts are directed towards rendering the application compatible with mobile and tablet devices. Last but not least, the application could integrate methods for statistical analyses for each student, such as the duration of specific actions performed by students in online lessons, so that educators are presented with a holistic view of class activity while students are presented with a self-report aiming that would allow self-assessment and improvement.

In the future, we plan to conduct a comparative evaluation of the impact of the proposed application on actual student learning outcomes. Within this context, the results of the examinations of students who will use the proposed systems will be compared with the results of a control group consisting of students who are not using the proposed applications. Significant information regarding the impact of the proposed system can be derived by this specific comparative evaluation, leading to conclusions regarding the impact of the proposed applications towards the optimization of the learning process.

5.3 Automated Lecture Style Assessment System.

The adoption of a correct teaching style can enhance the verbal communication of educators whereas a low-quality teaching style can result to lowering student’s level of interest and concentration. As an attempt to assist educators to improve their teaching style expressed by body language and speaking characteristics, a teaching style analysis system that assesses the body language of educators was developed. The aim of the work presented in this case study is to develop and evaluate an integrated system that provides automated lecture style evaluation, allowing educators to get instant feedback related to the goodness of their lecturing style. The proposed system aims to promote improvement of lecture quality, that could upgrade the overall student learning experience. The proposed application utilizes specific measurable biometric characteristics, such as facial expressions, body activity, speech rate and intonation, hand movement, and facial pose, extracted from a video showing the educator from the audience point of view. Measurable biometric features extracted during a lecture are combined to provide educators with a score reflecting lecture style quality both at frame rate and by providing lecture quality metrics for the whole lecture. The performance evaluation of the proposed system was compared with the performance of humans in the task of lecture style evaluation. Results indicate that the proposed system not only achieves similar performance to human observers, but in some cases, it outperforms them. Furthermore, an investigation into the usability of the application, and the impact of the proposed application in improving the educators’ teaching style was carried out. As part of this effort the pilot application has been assessed by educators of primary, secondary and university education. The experimental investigation involved two phases. In the first phase participants delivered a short lecture that was evaluated using the automated teaching style analysis application. After the lecture participants were informed about the operation of the application and they were presented with the feedback generated by the teaching style analysis. During the second phase participants delivered a second short lecture. By comparing the lecture style quality between the two phases, conclusions related to the impact of the application in improving teaching style were derived. Experimental results demonstrate that the application provides satisfactory feedback that supports educators in improving their teaching style. Furthermore, participants stated that it is feasible to use the application in real class conditions, and the feedback provided can be used for self-assessment, reflection and improvement regarding educator's body language and speaking skills.

In the future, we aim to introduce the Teaching Style Assessment (TSA) application in real classrooms and assess its performance over a series of lectures delivered by a large number of educators. In parallel, feedback received during the evaluation will guide further improvements to the systems. For example, we plan to improve the interface and feed visualization so that users get feedback in a user-friendly manner. Furthermore, in the future we will consider the use of additional cameras and/or wearable cameras pointing at the educator, to cover the movements of educator in class rather than using a single static camera that captures images only at a certain location. Further study is also required to make sure that the use of the TSA application in real school environments does not violate any data privacy rules of educators and students. In the future, we aim to examine the use, impact, and operation of the proposed system in other potential areas besides education. For example, the proposed teaching style evaluation methodology can be used for assessing the body language of sales personnel. By analysing non-verbal cues like gestures and tone of voice, the system can identify effective sales techniques and areas for improvement, enhancing communication and rapport-building skills. The commercial exploitation of the Teaching Style Assessment (TSA) system will also be going to be addressed in the future. As part of this effort, we have already applied for further funding that will allow the development of a proof-of-concept commercial application.

5.4 Concluding Comments

In this thesis, an experimental investigation regarding the impact and acceptance of smart systems in education is presented. This work will contribute to the advancement of AI technologies in the field of education and create new opportunities for learning and personalization of education. The use of AI-based educational tools and systems will provide students with a more engaging, interactive and personalized learning experience. This work will bring innovative solutions to the traditional education system.

Furthermore, the systems developed will provide AI-based tools that aims to strengthen the position of educators in the educational process. Currently, a significant number of educators feel threatened by the introduction of AI in education, and as a result, they are skeptical of educational AI applications. The educator-centered nature of the proposed applications can help educators to realize that AI can be beneficial to the educational system and educators, encouraging them to introduce other forms of smart AI empowered systems in their classes contributing in that way to the technological transformation of the educational system.

In conclusion, nowadays AI is getting integrated in many aspects of modern life and provides a new perspective regarding humanity's relation with technology. As AI continues to become the norm of use in our technologies, its effectiveness, and responsible implementation are key issues. More specifically, the development of AI in education meets modern requirements and represents a chance to make considerable advances. The application of AI technologies and tools in learning environments or processes is increasing in importance, as it provides the potential for educators, learners and scholars to transform future teaching for the benefit of both the stakeholders related to education, and eventually for the whole society.

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APPENDIX A

Video Capture Protocol for Student Action Recognition Database

VIDEO CAPTURE PROTOCOL

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Protocol purpose: The purpose of this study is to examine the participation of primary school students' during teleconferencing. For this purpose, students will be asked to perform specific actions related to their attendance during the online courses.

STUDENTS INFORMATION

For each student collect name , gender and age information.

STUDENTS ACTIONS

Students will be asked to perform the following specific actions :

[Time required **10 seconds** per action]

- Absent (class 1)
- Attending (class2)
- Hand Raising (class 3) [**5** second **open-hand** and **5** second **close-hand**]
- Looking Elsewhere (class 4)
- Telephone Call (class 5)
- Using Phone: Texting, playing games (class 6)
- Writing (class 7)

NOTE : Capture two set of videos (included all actions per set) for each student with different clothes and if possible different background, in each set.

DISTANCE

Students distance recommended from the monitor is between 20 and 40 inches.

EQUIPMENT

Personal Computer (PC) or Portable Personal Computer(laptop)

Computer Camera

VIDEO RESOLUTION

Does not exceed 600x600 and is not below 300x300.

SAVE DATA

Follow the steps:

Step 1 : Create two folders(two sets)for each student.

For example: ID_001a, ID_001b

Step 2: Save videos for each action in folders.

For example: ID_001a_CL_01, ID_001b_CL_01

CONTACT INFORMATION

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APPENDIX B

CNN - Architecture based image classification

Convolution Neural Network **(CNN)** constitutes a deep learning model comprised of convolution layer, non-linearity layer, pooling layer, and batch normalization. Moreover, concerning the last layers, it comprises of fully-connected, drop out, softmax and classification output layers. CNN based-image classification involves two main parts, the feature extraction of image and the classification as a means of classifying images (Figure B.1).

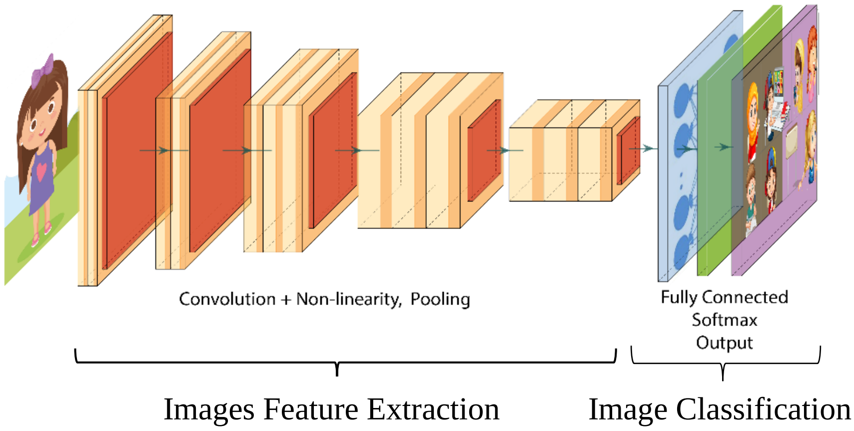


Figure B.1 : Typical architecture for CNN based-image classification.

Therefore, I will briefly provide a description concerning the main role of each layer in image classification applications.

(a) Convolution layer contains filters that detect various patterns found in image (spectrogram) like shapes, objects, edges and textures (Raghu et., 2020).

(b) Non-linearity layer constitutes the layer following the convolution layer. Non-linearity may be used to cut-off or even adjust the output generated. The popular types of non-linear activation functions are the Sigmoid, Tanh, ReLU, and Softplus (Figure B.2). Every layer has an activation function except the output layer. The activation function of Rectified Linear Units (ReLU) defined in (1) is widely used as the expression of its gradient (2) is simpler and more efficient than the other activation functions.

Rectifies Linear Units (ReLU): g(x) = max (0, x) (1)

$$\frac{d\,g\prime(x)}{dx} = \{\,1\,if \quad x \geq \;0\,;\;\; 0\,else\} \quad (2)$$

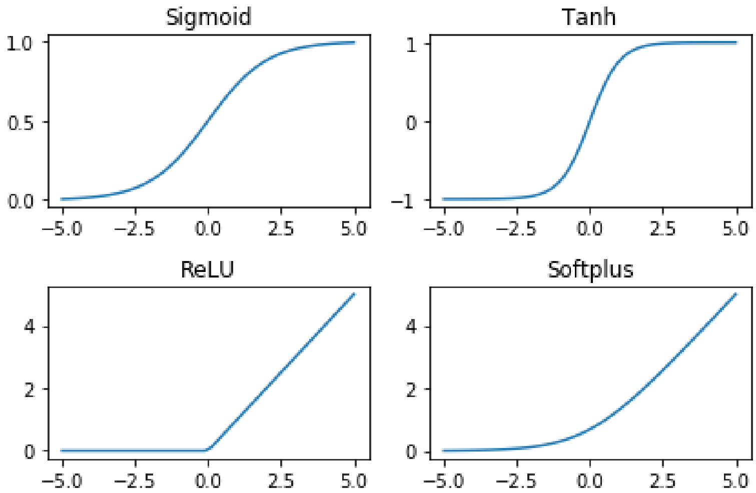


Figure B.2 : Popular types of non-linear activation functions

(c)Pooling layer is used to decreases the complexity. In the image processing, a reduction of resolution is considered. Max-pooling is regarded as the most common type among the pooling methods. It divides the image in sub-region rectangles, returning only the maximum value inside every sub-region (ALBAWI et al., 2017).

(d)Fully - connected layer (fc) is the one involving a plethora of parameters, as a means of taking plenty of time in training (V. Dumoulin and F. Visin, 2016; Kwak 2016) and uses the dropout technique as a means of eliminating the amount of nodes and connections during training. In a fc layer, every node being in the final frames of the pooling layer is connected to a vector of the first layer through the fc layer.

The CNN has an excellent performance in deep learning problems. Generally, the applications of CNN for image-based classification are ideal because of its self-feature capability of learning and its excellent results concerning classification on multi-class problems of classification (Raghu et., 2020) as in our study.

APPENDIX C

Implementation Details of the Automated Lecture Style Assessment Method

The suggested methodology does not require specialized equipment as it functions only by using each educator's personal device. It has autonomous operation and does not use Cloud. The methods were implemented using Python 3.10.10, and utilize several dedicated libraries. including librosa, numpy, pydub, and moviepy. These libraries are used for audio and video processing and analysis. Furthermore, the code uses OpenCV (computer vision library) and Mediapipe library to detect hands and faces in a video file and math module for mathematical computations. Also, our code includes the CNN and Googlenet model for facial expressions and body activity respectively.

The Mediapipe Hand Detection module was initialized with the following parameters (a) static_image_mode = False. The mode is set to dynamic; it will automatically handle the hand detection frame by frame, (b) max_num_hands=2. The maximum number of hands to detect is set to 2 and (c) min_detection_confidence=0.5. Minimum confidence value ([0.0, 1.0]) for a hand to be considered successfully detected. If a hand is detected in the current frame, the program draws landmarks on the hands and estimates the direction of hand movement.

Face detection is performed using the OpenCV and Mediapipe Face Detection module to detect faces and determine the direction a person is looking using a video file. If a face is detected in the current frame, the program draws a rectangle around the face, and determines the location of the nose tip.

There are specific parameters which are associated with facial pose estimation and hand detection. The parameters are: (a) Minimum Detection Confidence. Determines confidence level for valid hand detection, (b) Maximum Number of Hands. Limits the number of hands to be detected in a frame, (c) Hand/Face Landmark Model Selection. Chooses between different models for varied complexity, (d) Input Image Resolution. Adjusts resolution for accuracy and computational efficiency balance and (e)Aspect Ratio and Frame Rate of Input Video. Configures for optimal performance under varying video conditions.

Furthermore, this code is designed to extract audio from a video file and analyze its various characteristics such as speech intensity, speaking speed, and speaking tone. The audio characteristics are based on import necessary libraries, including librosa, numpy, pydub, and moviepy. The speech detection parameters are (a) detect_nonsilent(audio, min_silence_len=100, silence_thresh=-50). Detects non-silent chunks in the audio. The min_silence_len parameter is set to 100 milliseconds, and silence_thresh is set to -50 dBFS. It returns a list of start and end times for non-silent segments and (b) librosa.onset.onset_detect(y=y, sr=sr). Detects onset events in the audio signal, which can be interpreted as the start of spoken words. A loop through detected words, analyzing the root mean square (RMS) energy of each segment to classify it as a 'question' or 'statement'. The classification is based on the RMS energy threshold.

CNN and GoogleNet were used for the facial expressions and actions recognition respectively. For the CNN and GoogleNet, prior to the training process data augmentation was used (Shorten et al., 2019) including scaling, translation, rotation and reflection in order to increase the size of our dataset. Furthermore, transfer learning was used to train the networks. We have used a cross-entropy loss function and trained a CNN and a GoogleNet using the Adam optimizer (Kingma et al., 2014). We have used L2 regularization schemes with weight decays of 10^{-4} and 10^{-6} respectively. Regarding the training hyperparameters, for the CNN we considered a learning rate of 0.0005, a batch size of 64, and 100 epochs. Similarly, for GoogleNet we considered a learning rate of 0.0001, a batch size of 11, and 15 epochs.

APPENDIX D

Online Questionnaire for the Experimental User Evaluation of the Case Study I (Student Action Recognition during Tele-education)

Αξιολόγηση της συμμετοχής των μαθητών στα διαδικτυακά μαθήματα

Αγαπητοί εκπαιδευτικοί,

Θα σας παρακαλούσα όπως συμμετάσχετε στην έρευνα που διεξάγεται στα πλαίσια της διδακτορικής μου διατριβής με θέμα «Ο ρόλος της τεχνητής νοημοσύνης και των αναδυόμενων τεχνολογιών σε έξυπνες τάξεις». Σκοπός της παρούσας έρευνας είναι να εξετάσουμε την αποδοχή χρήσης πειραματικής εφαρμογής καταγραφής δράσεων των μαθητών/φοιτητών στα διαδικτυακά μαθήματα. Η συμμετοχή σας στην παρούσα έρευνα, είναι πολύ σημαντική, καθώς θα συμβάλετε στη διεξαγωγή της και στην επίτευξη των στόχων που έχουν τεθεί. Αναμένεται η συμμετοχή σας στην έρευνα να έχει διάρκεια περίπου 10λεπτά.
Η έρευνα είναι ανώνυμη και δεν προκύπτουν οποιοιδήποτε κίνδυνοι από την συμμετοχή σας στην παρούσα έρευνα.

Σας ευχαριστώ για την ανταπόκρισή και τη συνεργασία σας !

Με εκτίμηση,
Ελένη Α. Δημητριάδου
Διδακτορική Φοιτήτρια και Ερευνητικός Συνεργάτης
Τμήμα Πολυμέσων και Γραφικών Τεχνών, Τεχνολογικό Πανεπιστήμιο Κύπρου
CYENS Centre of Excellence

Για οποιαδήποτε περαιτέρω πληροφορία παρακαλώ επικοινωνήστε μαζί μας :
ela.dimitriadou@edu.cut.ac.cy

ΜΕΡΟΣ Ι : ΔΗΜΟΓΡΑΦΙΚΑ ΔΕΔΟΜΕΝΑ

Παρακαλώ να απαντήσετε στις πιο κάτω ερωτήσεις , οι οποίες αφορούν τα προσωπικά σας στοιχεία, επιλέγοντας στο αντίστοιχο κουτάκι για ό,τι ισχύει.

* Υποδεικνύει απαιτούμενη ερώτηση

1. *1.Χώρα :* *

Να επισημαίνεται μόνο μία έλλειψη .

- ◯ Κύπρος
- ◯ Ελλάδα
- ◯ Άλλη

2. *2.Φύλο :* *

Να επισημαίνεται μόνο μία έλλειψη.

- Άνδρας
- Γυναίκα
- Δεν επιθυμώ να απαντήσω

3. *3.Προφίλ :*

Να επισημαίνεται μόνο μία έλλειψη ανά σειρά.

	Πρωτοβάθμια	Δευτεροβάθμια	Τριτοβάθμια	Άλλο
Εκπαιδευτικός				

ΜΕΡΟΣ ΙΙ : ΤΗΛΕΚΠΑΙΔΕΥΣΗ

Η τηλε-εκπαίδευση (tele-education) ορίζεται ως η εξ' αποστάσεως εκπαίδευση στην οποία ο εκπαιδευτικός και ο μαθητής χωρίζονται από απόσταση, χρόνο ή και τα δύο. Λόγω της πανδημίας COVID-19, πολλά σχολεία σε όλο τον κόσμο έχουν χρησιμοποιήσει την τηλε-εκπαίδευση για την παράδοση μαθημάτων.Οι ακόλουθες ερωτήσεις αφορούν την εμπειρία σας όσο αφορά την τηλε-εκπαίδευση. Απαντήστε όσο πιο ειλικρινά μπορείτε.

4. *1.Προηγούμενη εμπειρία σε χρήση τεχνολογίας :* *

Να επισημαίνεται μόνο μία έλλειψη.

- Καθόλου
- Ελάχιστα
- Λίγο
- Μέτρια
- Πολύ
- Πάρα πολύ

5. *2. Εμπλοκή σε διαδικτυακά μαθήματα :* *

Να επισημαίνεται μόνο μία έλλειψη.

- Καθόλου
- Ελάχιστα
- Λίγο
- Μέτρια
- Πολύ
- Πάρα πολύ

6. *3. Σε ποιο τομέα έχετε χρησιμοποιήσει τις διαδικτυακές πλατφόρμες :* *

Να επισημαίνεται μόνο μία έλλειψη.

- Δημόσιο τομέα
- Ιδιωτικό τομέα

7. *4. Ποιες από τις πιο κάτω τεχνολογίες χρησιμοποιείτε πιο συχνά στα διαδικτυακά μαθήματα ;* *

Να επισημαίνεται μόνο μία έλλειψη.

- Microsoft Teams
- Skype
- Zoom
- Google Meetings
- Άλλο
- Κανένα
- Δεν γνωρίζω

8. *5.Ποιες συσκευές χρησιμοποιείτε στα διαδικτυακά μαθήματα ;* *

Να επισημαίνεται μόνο μία έλλειψη.

- Laptop
- Desktop Computers
- Tablet
- Smartphone
- Άλλες συσκευές
- Δεν γνωρίζω

9. *6.Πόσο συχνά χρησιμοποιείτε την κάμερα στα διαδικτυακά μαθήματα ;* *

Να επισημαίνεται μόνο μία έλλειψη.

- Καθόλου
- Ελάχιστα
- Λίγο
- Μέτρια
- Πολύ
- Πάρα πολύ

10. *7. Θεωρείτε ότι η χρήση κάμερας είναι αναγκαία στα διαδικτυακά μαθήματα ;* *

Να επισημαίνεται μόνο μία έλλειψη.

- Καθόλου
- Ελάχιστα
- Λίγο
- Μέτρια
- Πολύ
- Πάρα πολύ

11. *8.Οι ακόλουθες δηλώσεις διερευνούν την εμπειρία σας στα διαδικτυακά μαθήματα. Για κάθε δήλωση προσδιορίστε πόσο καλά σας περιγράφει επιλέγοντας το κατάλληλο πλαίσιο.* *

Σε ποιο βαθμό αντιμετωπίζετε κατά την τηλεκπαίδευση ***δυσκολίες*** *με :*

Να επισημαίνεται μόνο μία έλλειψη ανά σειρά.

	Καθόλου	Ελάχιστα	Λίγο	Μέτρια	Πολύ	Πάρα πολύ
Παρουσία μαθητών	⬭	⬭	⬭	⬭	⬭	⬭
Ενεργή συμμετοχή μαθητών	⬭	⬭	⬭	⬭	⬭	⬭
Επίπεδο συγκέντρωσης	⬭	⬭	⬭	⬭	⬭	⬭
Μαθησιακά αποτελέσματα	⬭	⬭	⬭	⬭	⬭	⬭
Έλεγχο τάξης	⬭	⬭	⬭	⬭	⬭	⬭
Αλληλεπίδραση δασκάλου-μαθητή	⬭	⬭	⬭	⬭	⬭	⬭
Ενδιαφέρον μαθητών	⬭	⬭	⬭	⬭	⬭	⬭
Αξιολόγηση μαθητών	⬭	⬭	⬭	⬭	⬭	⬭

12. *9.Είστε ευχαριστημένοι με τα διαδικτυακά μαθήματα ;* *

Να επισημαίνεται μόνο μία έλλειψη.

- Καθόλου
- Ελάχιστα
- Λίγο
- Μέτρια
- Πολύ
- Πάρα πολύ

13. *10. Θεωρείτε ότι είναι χρήσιμο να ενημερώνεστε για τις ενέργειες των μαθητών κατά τη διάρκεια των διαδικτυακών μαθημάτων ;* *

Να επισημαίνεται μόνο μία έλλειψη.

- Καθόλου
- Ελάχιστα
- Λίγο
- Μέτρια
- Πολύ
- Πάρα πολύ

14. *11. Αναφέρετε, ποιές δυσκολίες είχατε να αντιμετωπίσετε κατά την διάρκεια των διαδικτυακών μαθημάτων.*

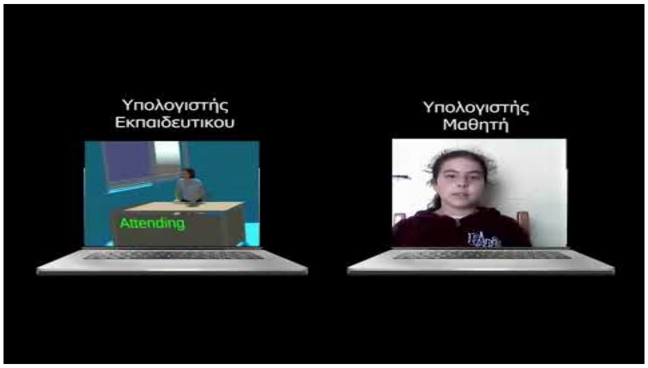
15. *12.Αναφέρετε, πως νομίζετε ότι μπορεί να επιλυθούν οι πιο πάνω δυσκολίες που έχετε αναφέρει.*

16. *13.Παρακαλώ, καταγράψτε κάποιο άλλο σχόλιο που θέλετε να αναφέρετε σχετικά με την εμπειρία σας κατά τη διάρκεια των διαδικτυακών μαθημάτων.*

ΜΕΡΟΣ ΙΙΙ : ΤΗΛΕΚΠΑΙΔΕΥΣΗ

Για να μπορέσετε να απαντήσετε στις πιο κάτω ερωτήσεις, υποθέστε ότι θα σας δοθεί μια εφαρμογή όπως αυτή που θα παρακολουθήσετε στο βίντεο, όπου στόχο θα έχει να καταγράφονται οι κινήσεις των μαθητών στα διαδικτυακά μαθήματα και ο εκπαιδευτικός θα λαμβάνει μόνο την πληροφορία ώστε να μην παραβιάζονται τα προσωπικά δεδομένα των μαθητών. Οι ακόλουθες ερωτήσεις αφορούν τις απαιτήσεις σας σχετικά με την εφαρμογή αυτή.

Σας παρακαλούμε να παρακολουθήσετε το πιο κάτω βίντεο της πειραματικής μας εφαρμογής προτού απαντήσετε τις ακόλουθες ερωτήσεις.



http://youtube.com/watch?v=oNTSoaH-3uU

17. *1.Οι ακόλουθες δηλώσεις διερευνούν τις αντιδράσεις σας σχετικά με την εφαρμογή που παρουσιάζεται στο βίντεο. Για κάθε δήλωση προσδιορίστε πόσο καλά σας περιγράφει επιλέγοντας το κατάλληλο πλαίσιο.* *

*Σε ποιο βαθμό η εφαρμογή **διευκολύνει** την τηλεκπαίδευση σχετικά με :*

Να επισημαίνεται μόνο μία έλλειψη ανά σειρά.

	Καθόλου	Ελάχιστα	Λίγο	Μέτρια	Πολύ	Πάρα πολύ
Παρουσία μαθητών	⬭	⬭	⬭	⬭	⬭	⬭
Ενεργή συμμετοχή μαθητών	⬭	⬭	⬭	⬭	⬭	⬭
Επίπεδο συγκέντρωσης	⬭	⬭	⬭	⬭	⬭	⬭
Μαθησιακά αποτελέσματα	⬭	⬭	⬭	⬭	⬭	⬭
Έλεγχο τάξης	⬭	⬭	⬭	⬭	⬭	⬭
Αλληλεπίδραση δασκάλου-μαθητή	⬭	⬭	⬭	⬭	⬭	⬭
Ενδιαφέρον μαθητών	⬭	⬭	⬭	⬭	⬭	⬭
Αξιολόγηση μαθητών	⬭	⬭	⬭	⬭	⬭	⬭

18. *2.Θεωρείτε ότι η χρήση κάμερας είναι αναγκαία στα διαδικτυακά μαθήματα ;* *

Να επισημαίνεται μόνο μία έλλειψη.

- Καθόλου
- Ελάχιστα
- Λίγο
- Μέτρια
- Πολύ
- Πάρα πολύ

19. *3.Θεωρείτε ότι είναι χρήσιμο να ενημερώνεστε για τις ενέργειες των μαθητών κατά τη διάρκεια των διαδικτυακών μαθημάτων ;* *

Να επισημαίνεται μόνο μία έλλειψη.

- Καθόλου
- Ελάχιστα
- Λίγο
- Μέτρια
- Πολύ
- Πάρα πολύ

20. *4.Θεωρείτε ότι η εφαρμογή είναι χρήσιμη ;* *

Να επισημαίνεται μόνο μία έλλειψη.

- Καθόλου
- Ελάχιστα
- Λίγο
- Μέτρια
- Πολύ
- Πάρα πολύ

21. *5. Πιστεύετε ότι η εφαρμογή επηρεάζει την ιδιωτικότητα των μαθητών ;* *

Να επισημαίνεται μόνο μία έλλειψη.

- Καθόλου
- Ελάχιστα
- Λίγο
- Μέτρια
- Πολύ
- Πάρα πολύ

22. *6.Θεωρείτε ότι είναι εφικτή η χρήση της εφαρμογής κατά τη διάρκεια των διαδικτυακών μαθημάτων ;* *

Να επισημαίνεται μόνο μία έλλειψη.

- Καθόλου
- Ελάχιστα
- Λίγο
- Μέτρια
- Πολύ
- Πάρα πολύ

23. *7.Παρακαλώ, καταγράψτε κάποιο άλλο σχόλιο που θέλετε να αναφέρετε σχετικά με την εφαρμογή που παρακολουθήσατε στο βίντεο.*

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24. Θα ήταν πολύτιμη η βοήθεια σας αν μπορούσατε να συμμετέχετε σε συνέντευξη διάρκειας περίπου 10 λεπτών, όπου θα έχετε την ευκαιρία να δοκιμάσετε την πειραματική εφαρμογή που παρακολουθήσατε στο βίντεο !

Παρακαλώ στείλτε μας email στο ela.dimitriadou@edu.cut.ac.cy *για να διευθετήσουμε τη συνέντευξη όποτε σας βολεύει.*

Σας ευχαριστώ θερμά για την συμμετοχή σας!

Αξιολόγηση της συμμετοχής των μαθητών στα διαδικτυακά μαθήματα

Αγαπητοί γονείς και κηδεμόνες,

Θα σας παρακαλούσα όπως συμμετάσχετε στην έρευνα που διεξάγεται στα πλαίσια της διδακτορικής μου διατριβής με θέμα «Ο ρόλος της τεχνητής νοημοσύνης και των αναδυόμενων τεχνολογιών σε έξυπνες τάξεις». Σκοπός της παρούσας έρευνας είναι να εξετάσουμε την αποδοχή χρήσης πειραματικής εφαρμογής καταγραφής δράσεων των μαθητών/φοιτητών στα διαδικτυακά μαθήματα. Η συμμετοχή σας στην παρούσα έρευνα, είναι πολύ σημαντική, καθώς θα συμβάλετε στη διεξαγωγή της και στην επίτευξη των στόχων που έχουν τεθεί. Αναμένεται η συμμετοχή σας στην έρευνα να έχει διάρκεια περίπου 10λεπτά.
Η έρευνα είναι ανώνυμη και δεν προκύπτουν οποιοιδήποτε κίνδυνοι από την συμμετοχή σας στην παρούσα έρευνα.
Σας ευχαριστώ για την ανταπόκρισή και τη συνεργασία σας !

Με εκτίμηση,
Ελένη Α. Δημητριάδου
Διδακτορική Φοιτήτρια και Ερευνητικός Συνεργάτης
Τμήμα Πολυμέσων και Γραφικών Τεχνών, Τεχνολογικό Πανεπιστήμιο Κύπρου
CYENS Centre of Excellence

Για οποιαδήποτε περαιτέρω πληροφορία παρακαλώ επικοινωνήστε μαζί μας :
ela.dimitriadou@edu.cut.ac.cy

ΜΕΡΟΣ Ι : ΔΗΜΟΓΡΑΦΙΚΑ ΔΕΔΟΜΕΝΑ

Παρακαλώ να απαντήσετε στις πιο κάτω ερωτήσεις , οι οποίες αφορούν τα προσωπικά σας στοιχεία, επιλέγοντας στο αντίστοιχο κουτάκι για ό,τι ισχύει.

* Υποδεικνύει απαιτούμενη ερώτηση

1. *1.Χώρα :* *

   Να επισημαίνεται μόνο μία έλλειψη.

   ◯ Κύπρος
   ◯ Ελλάδα
   ◯ Άλλη

2. *2.Φύλο :* *

Να επισημαίνεται μόνο μία έλλειψη.

- Άνδρας
- Γυναίκα
- Δεν επιθυμώ να απαντήσω

ΜΕΡΟΣ ΙΙ : ΤΗΛΕΚΠΑΙΔΕΥΣΗ

Η τηλε-εκπαίδευση (tele-education) ορίζεται ως η εξ' αποστάσεως εκπαίδευση στην οποία ο εκπαιδευτικός και ο μαθητής χωρίζονται από απόσταση, χρόνο ή και τα δύο. Λόγω της πανδημίας COVID-19, πολλά σχολεία σε όλο τον κόσμο έχουν χρησιμοποιήσει την τηλε-εκπαίδευση για την παράδοση μαθημάτων.Οι ακόλουθες ερωτήσεις αφορούν την εμπειρία σας όσο αφορά την τηλε-εκπαίδευση. Απαντήστε όσο πιο ειλικρινά μπορείτε.

3. *1.Πόσο εξοικειωμένοι είστε με τη χρήση τεχνολογίας ;* *

Να επισημαίνεται μόνο μία έλλειψη.

- Καθόλου
- Ελάχιστα
- Λίγο
- Μέτρια
- Πολύ
- Πάρα πολύ

4. *2.Εμπλοκή των παιδιών σας στα διαδικτυακά μαθήματα :* *

Να επισημαίνεται μόνο μία έλλειψη.

- Καθόλου
- Ελάχιστα
- Λίγο
- Μέτρια
- Πολύ
- Πάρα πολύ

5. *3.Σε ποιο τομέα έχουν χρησιμοποιήσει τα παιδιά σας τις διαδικτυακές πλατφόρμες ;* *

Να επισημαίνεται μόνο μία έλλειψη.

- Δημόσιο τομέα
- Ιδιωτικό τομέα

6. *4.Ποιες από τις πιο κάτω τεχνολογίες χρησιμοποιούν τα παιδιά σας πιο συχνά στα διαδικτυακά μαθήματα ;* *

Να επισημαίνεται μόνο μία έλλειψη.

- Microsoft Teams
- Skype
- Zoom
- Google Meetings
- Άλλο
- Κανένα
- Δεν γνωρίζω

7. *5.Ποιες συσκευές χρησιμοποιούν τα παιδιά σας στα διαδικτυακά μαθήματα ;* *

Να επισημαίνεται μόνο μία έλλειψη.

- Laptop
- Desktop Computers
- Tablet
- Smartphone
- Άλλες συσκευές
- Δεν γνωρίζω

8. *6.Πόσο συχνά χρησιμοποιούν τα παιδιά σας την κάμερα στα διαδικτυακά μαθήματα ;* *

Να επισημαίνεται μόνο μία έλλειψη.

- Καθόλου
- Ελάχιστα
- Λίγο
- Μέτρια
- Πολύ
- Πάρα πολύ

9. *7.Θεωρείτε ότι η χρήση κάμερας είναι αναγκαία στα διαδικτυακά μαθήματα των μαθητών ;* *

Να επισημαίνεται μόνο μία έλλειψη.

- Καθόλου
- Ελάχιστα
- Λίγο
- Μέτρια
- Πολύ
- Πάρα πολύ

10. *8.Οι ακόλουθες δηλώσεις διερευνούν την εμπειρία των παιδιών σας στα διαδικτυακά μαθήματα . Για κάθε δήλωση προσδιορίστε πόσο καλά σας περιγράφει επιλέγοντας στο κατάλληλο πλαίσιο.* *

*Σε ποιο βαθμό αντιμετωπίζουν τα παιδιά σας κατά την τηλεκπαίδευση **δυσκολίες** με :*

Να επισημαίνεται μόνο μία έλλειψη ανά σειρά.

	Καθόλου	Ελάχιστα	Λίγο	Μέτρια	Πολύ	Πάρα πολύ	Δεν γνωρίζω
Ενεργή συμμετοχή							
Επίπεδο συγκέντρωσης							
Μαθησιακά αποτελέσματα							
Αλληλεπίδραση Μαθητή-εκπαιδευτικού							

11. *9.Είστε ευχαριστημένοι με τα διαδικτυακά μαθήματα των παιδιών σας ;* *

Να επισημαίνεται μόνο μία έλλειψη.

- Καθόλου
- Ελάχιστα
- Λίγο
- Μέτρια
- Πολύ
- Πάρα πολύ

12. *10.Θεωρείτε ότι είναι χρήσιμο να ενημερώνεται ο εκπαιδευτικός για τις ενέργειες των μαθητών κατά τη διάρκεια των διαδικτυακών μαθημάτων ;* *

Να επισημαίνεται μόνο μία έλλειψη.

- Καθόλου
- Ελάχιστα
- Λίγο
- Μέτρια
- Πολύ
- Πάρα πολύ

13. *11.Τα διαδικτυακά προγράμματα εκμάθησης βοηθούν τα παιδιά σας ;* *

Να επισημαίνεται μόνο μία έλλειψη.

- Καθόλου
- Ελάχιστα
- Λίγο
- Μέτρια
- Πολύ
- Πάρα πολύ

14. *12.Τα παιδιά σας αισθάνονται ότι συμμετέχουν στα διαδικτυακά μαθήματα ;* *

Να επισημαίνεται μόνο μία έλλειψη.

- Καθόλου
- Ελάχιστα
- Λίγο
- Μέτρια
- Πολύ
- Πάρα πολύ

15. *13.Αναφέρετε, ποιές δυσκολίες έχουν να αντιμετωπίσουν τα παιδιά σας κατά την διάρκεια των διαδικτυακών μαθημάτων.*

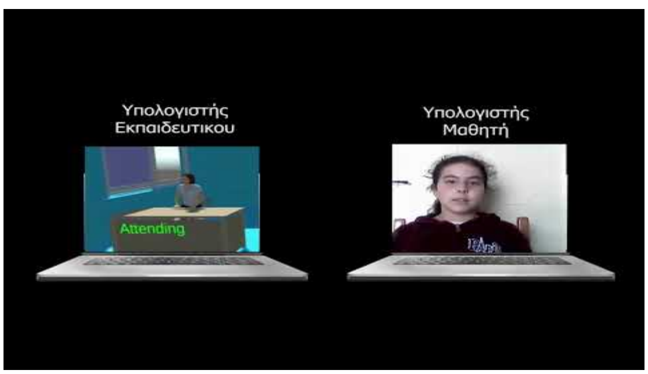
16. *14.Αναφέρετε, πως νομίζετε ότι μπορεί να επιλυθούν οι πιο πάνω δυσκολίες που έχετε αναφέρει.*

17. *15.Παρακαλώ, καταγράψτε κάποιο άλλο σχόλιο που θέλετε να αναφέρετε σχετικά με την εμπειρία των παιδιών σας κατά τη διάρκεια των διαδικτυακών μαθημάτων.*

ΜΕΡΟΣ III : ΤΗΛΕΚΠΑΙΔΕΥΣΗ

Για να μπορέσετε να απαντήσετε στις πιο κάτω ερωτήσεις, υποθέστε ότι θα σας δοθεί μια εφαρμογή όπως αυτή που θα παρακολουθήσετε στο βίντεο, όπου στόχο θα έχει να καταγράφονται οι κινήσεις των μαθητών στα διαδικτυακά μαθήματα και ο εκπαιδευτικός θα λαμβάνει μόνο την πληροφορία ώστε να μην παραβιάζονται τα προσωπικά δεδομένα των μαθητών. Οι ακόλουθες ερωτήσεις αφορούν τις απαιτήσεις σας σχετικά με την εφαρμογή αυτή.

Σας παρακαλούμε να παρακολουθήσετε το πιο κάτω βίντεο της πειραματικής μας εφαρμογής προτού απαντήσετε τις ακόλουθες ερωτήσεις.



http://youtube.com/watch?v=oNTSoaH-3uU

18. *1.Οι ακόλουθες δηλώσεις διερευνούν τις αντιδράσεις σας σχετικά με την εφαρμογή που παρουσιάζεται στο βίντεο. Για κάθε δήλωση προσδιορίστε πόσο καλά σας περιγράφει επιλέγοντας το κατάλληλο πλαίσιο.* *

Σε ποιο βαθμό η εφαρμογή ***διευκολύνει*** *την τηλεκπαίδευση των παιδιών σας σχετικά με :*

Να επισημαίνεται μόνο μία έλλειψη ανά σειρά.

	Καθόλου	Ελάχιστα	Λίγο	Μέτρια	Πολύ	Πάρα πολύ
Ενεργή συμμετοχή	◯	◯	◯	◯	◯	◯
Επίπεδο συγκέντρωσης	◯	◯	◯	◯	◯	◯
Μαθησιακά αποτελέσματα	◯	◯	◯	◯	◯	◯
Αλληλεπίδραση Μαθητή-Εκπαιδευτικού	◯	◯	◯	◯	◯	◯

19. *2.Θεωρείτε ότι η χρήση κάμερας είναι αναγκαία στα διαδικτυακά μαθήματα των μαθητών ;* *

Να επισημαίνεται μόνο μία έλλειψη.

- ◯ Καθόλου
- ◯ Ελάχιστα
- ◯ Λίγο
- ◯ Μέτρια
- ◯ Πολύ
- ◯ Πάρα πολύ

20. *3.Θεωρείτε ότι είναι χρήσιμο να ενημερώνεται ο εκπαιδευτικός για τις ενέργειες των μαθητών κατά τη διάρκεια των διαδικτυακών μαθημάτων ;* *

Να επισημαίνεται μόνο μία έλλειψη.

- Καθόλου
- Ελάχιστα
- Λίγο
- Μέτρια
- Πολύ
- Πάρα πολύ

21. *4.Η εφαρμογή θα βοηθήσει τους μαθητές στην εκμάθηση του μαθησιακού περιεχομένου μέσω τηλεδιάσκεψης ;* *

Να επισημαίνεται μόνο μία έλλειψη.

- Καθόλου
- Ελάχιστα
- Λίγο
- Μέτρια
- Πολύ
- Πάρα πολύ

22. *5.Οι μαθητές με την εφαρμογή θα αισθάνονται ότι συμμετέχουν στα διαδικτυακά μαθήματα ;* *

Να επισημαίνεται μόνο μία έλλειψη.

- Καθόλου
- Ελάχιστα
- Λίγο
- Μέτρια
- Πολύ
- Πάρα πολύ

23. *6.Θεωρείτε ότι η εφαρμογή είναι χρήσιμη για τους μαθητές ;* *

Να επισημαίνεται μόνο μία έλλειψη.

- Καθόλου
- Ελάχιστα
- Λίγο
- Μέτρια
- Πολύ
- Πάρα πολύ

24. *7. Πιστεύετε ότι η εφαρμογή επηρεάζει την ιδιωτικότητα των μαθητών ;* *

Να επισημαίνεται μόνο μία έλλειψη.

- Καθόλου
- Ελάχιστα
- Λίγο
- Μέτρια
- Πολύ
- Πάρα Πολύ

25. *8.Θεωρείτε ότι είναι εφικτή η χρήση της εφαρμογής κατά τη διάρκεια των διαδικτυακών μαθημάτων ;* *

Να επισημαίνεται μόνο μία έλλειψη.

- Καθόλου
- Ελάχιστα
- Λίγο
- Μέτρια
- Πολύ
- Πάρα πολύ

26. *9.Παρακαλώ, καταγράψτε κάποιο άλλο σχόλιο που θέλετε να αναφέρετε σχετικά με την εφαρμογή που παρακολουθήσατε στο βίντεο.*

27. Θα ήταν πολύτιμη η βοήθεια σας αν μπορούσατε να συμμετέχετε σε συνέντευξη διάρκειας περίπου 10 λεπτών, όπου θα έχετε την ευκαιρία να δοκιμάσετε την πειραματική εφαρμογή που παρακολουθήσατε στο βίντεο !

Παρακαλώ στείλτε μας email στο ela.dimitriadou@edu.cut.ac.cy *για να διευθετήσουμε τη συνέντευξη όποτε σας βολεύει.*

Σας ευχαριστώ θερμά για την συμμετοχή σας!

Αξιολόγηση της συμμετοχής των μαθητών στα διαδικτυακά μαθήματα

Αγαπητοί μαθητές/μαθήτριες και φοιτητές/φοιτήτριες,

Θα σας παρακαλούσα όπως συμμετάσχετε στην έρευνα που διεξάγεται στα πλαίσια της διδακτορικής μου διατριβής με θέμα «Ο ρόλος της τεχνητής νοημοσύνης και των αναδυόμενων τεχνολογιών σε έξυπνες τάξεις». Σκοπός της παρούσας έρευνας είναι να εξετάσουμε την αποδοχή χρήσης πειραματικής εφαρμογής καταγραφής δράσεων των μαθητών/φοιτητών στα διαδικτυακά μαθήματα. Η συμμετοχή σας στην παρούσα έρευνα, είναι πολύ σημαντική, καθώς θα συμβάλετε στη διεξαγωγή της και στην επίτευξη των στόχων που έχουν τεθεί. Αναμένεται η συμμετοχή σας στην έρευνα να έχει διάρκεια περίπου 10λεπτά.
Η έρευνα είναι ανώνυμη και δεν προκύπτουν οποιοιδήποτε κίνδυνοι από την συμμετοχή σας στην παρούσα έρευνα.

Σας ευχαριστώ για την ανταπόκριση και τη συνεργασία σας !

Με εκτίμηση,
Ελένη Α. Δημητριάδου
Διδακτορική Φοιτήτρια και Ερευνητικός Συνεργάτης
Τμήμα Πολυμέσων και Γραφικών Τεχνών, Τεχνολογικό Πανεπιστήμιο Κύπρου
CYENS Centre of Excellence

Για οποιαδήποτε περαιτέρω πληροφορία παρακαλώ επικοινωνήστε μαζί μας :
ela.dimitriadou@edu.cut.ac.cy

ΜΕΡΟΣ Ι : ΔΗΜΟΓΡΑΦΙΚΑ ΔΕΔΟΜΕΝΑ

Παρακαλώ να απαντήσετε στις πιο κάτω ερωτήσεις , οι οποίες αφορούν τα προσωπικά σας στοιχεία, επιλέγοντας στο αντίστοιχο κουτάκι για ό,τι ισχύει.

* Υποδεικνύει απαιτούμενη ερώτηση

1. *1.Χώρα :* *

Να επισημαίνεται μόνο μία έλλειψη.

- Κύπρος
- Ελλάδα
- Άλλη

2. *2.Φύλο :* *

Να επισημαίνεται μόνο μία έλλειψη.

- Άνδρας
- Γυναίκα
- Δεν επιθυμώ να απαντήσω

3. *3.Προφίλ :*

Να επισημαίνεται μόνο μία έλλειψη ανά σειρά.

	Πρωτοβάθμια	Δευτεροβάθμια	Τριτοβάθμια	Άλλο
Μαθητής				

ΜΕΡΟΣ ΙΙ : ΤΗΛΕΚΠΑΙΔΕΥΣΗ

Η τηλε-εκπαίδευση (tele-education) ορίζεται ως η εξ' αποστάσεως εκπαίδευση στην οποία ο εκπαιδευτικός και ο μαθητής χωρίζονται από απόσταση, χρόνο ή και τα δύο. Λόγω της πανδημίας COVID-19, πολλά σχολεία σε όλο τον κόσμο έχουν χρησιμοποιήσει την τηλε-εκπαίδευση για την παράδοση μαθημάτων.Οι ακόλουθες ερωτήσεις αφορούν την εμπειρία σας όσο αφορά την τηλε-εκπαίδευση. Απαντήστε όσο πιο ειλικρινά μπορείτε.

4. *1.Προηγούμενη εμπειρία σε χρήση τεχνολογίας :* *

Να επισημαίνεται μόνο μία έλλειψη.

- Καθόλου
- Ελάχιστα
- Λίγο
- Μέτρια
- Πολύ
- Πάρα πολύ

5. *2.Εμπλοκή σε διαδικτυακά μαθήματα :* *

Να επισημαίνεται μόνο μία έλλειψη.

- Καθόλου
- Ελάχιστα
- Λίγο
- Μέτρια
- Πολύ
- Πάρα πολύ

6. *3.Ποιες από τις πιο κάτω τεχνολογίες χρησιμοποιείτε πιο συχνά στα διαδικτυακά μαθήματα ;* *

Να επισημαίνεται μόνο μία έλλειψη.

- Microsoft Teams
- Skype
- Zoom
- Google Meetings
- Άλλο
- Κανένα
- Δεν γνωρίζω

7. *4.Ποιες συσκευές χρησιμοποιείτε στα διαδικτυακά μαθήματα ;* *

Να επισημαίνεται μόνο μία έλλειψη.

- Laptop
- Desktop Computers
- Tablet
- Smartphone
- Άλλες συσκευές
- Δεν γνωρίζω

8. *5. Πόσο συχνά χρησιμοποιείτε την κάμερα στα διαδικτυακά μαθήματα ;* *

Να επισημαίνεται μόνο μία έλλειψη.

- Καθόλου
- Ελάχιστα
- Λίγο
- Μέτρια
- Πολύ
- Πάρα πολύ

9. *6.Θεωρείτε ότι η χρήση κάμερας είναι αναγκαία στα διαδικτυακά μαθήματα ;* *

Να επισημαίνεται μόνο μία έλλειψη.

- Καθόλου
- Ελάχιστα
- Λίγο
- Μέτρια
- Πολύ
- Πάρα πολύ

10. *7.Οι ακόλουθες δηλώσεις διερευνούν την εμπειρία σας στα διαδικτυακά μαθήματα. Για κάθε δήλωση προσδιορίστε πόσο καλά σας περιγράφει επιλέγοντας το κατάλληλο πλαίσιο.* *

Σε ποιο βαθμό αντιμετωπίζετε κατά την τηλεκπαίδευση ***δυσκολίες*** *με :*

Να επισημαίνεται μόνο μία έλλειψη ανά σειρά.

	Καθόλου	Ελάχιστα	Λίγο	Μέτρια	Πολύ	Πάρα πολύ
Ενεργή συμμετοχή	⬭	⬭	⬭	⬭	⬭	⬭
Επίπεδο συγκέντρωσης	⬭	⬭	⬭	⬭	⬭	⬭
Μαθησιακά αποτελέσματα	⬭	⬭	⬭	⬭	⬭	⬭
Αλληλεπίδραση Δασκάλου-Μαθητή	⬭	⬭	⬭	⬭	⬭	⬭
Ενδιαφέρον	⬭	⬭	⬭	⬭	⬭	⬭
Αξιολόγηση	⬭	⬭	⬭	⬭	⬭	⬭

11. *8. Είστε ευχαριστημένοι με τα διαδικτυακά μαθήματα ;* *

Να επισημαίνεται μόνο μία έλλειψη.

- ⬭ Καθόλου
- ⬭ Ελάχιστα
- ⬭ Λίγο
- ⬭ Μέτρια
- ⬭ Πολύ
- ⬭ Πάρα πολύ

12. *9. Θεωρείτε ότι είναι χρήσιμο να ενημερώνεται ο εκπαιδευτικός για τις ενέργειες σας κατά τη διάρκεια των διαδικτυακών μαθημάτων ;* *

Να επισημαίνεται μόνο μία έλλειψη.

- Καθόλου
- Ελάχιστα
- Λίγο
- Μέτρια
- Πολύ
- Πάρα πολύ

13. *10. Αναφέρετε, ποιές δυσκολίες είχατε να αντιμετωπίσετε κατά την διάρκεια των διαδικτυακών μαθημάτων.*

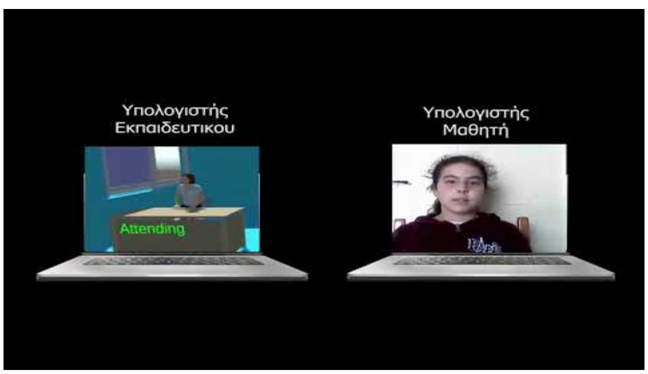
14. *11.Αναφέρετε, πως νομίζετε ότι μπορεί να επιλυθούν οι πιο πάνω δυσκολίες που έχετε αναφέρει.*

15. *12.Παρακαλώ, καταγράψτε κάποιο άλλο σχόλιο που θέλετε να αναφέρετε σχετικά με την εμπειρία σας κατά τη διάρκεια των διαδικτυακών μαθημάτων.*

ΜΕΡΟΣ ΙΙΙ : ΤΗΛΕΚΠΑΙΔΕΥΣΗ

Για να μπορέσετε να απαντήσετε στις πιο κάτω ερωτήσεις, υποθέστε ότι θα σας δοθεί μια εφαρμογή όπως αυτή που θα παρακολουθήσετε στο βίντεο, όπου στόχο θα έχει να καταγράφονται οι κινήσεις των μαθητών στα διαδικτυακά μαθήματα και ο εκπαιδευτικός θα λαμβάνει μόνο την πληροφορία ώστε να μην παραβιάζονται τα προσωπικά δεδομένα των μαθητών. Οι ακόλουθες ερωτήσεις αφορούν τις απαιτήσεις σας σχετικά με την εφαρμογή αυτή.

Σας παρακαλούμε να παρακολουθήσετε το πιο κάτω βίντεο της πειραματικής μας εφαρμογής προτού απαντήσετε τις ακόλουθες ερωτήσεις.



http://youtube.com/watch?v=oNTSoaH-3uU

16. *1.Οι ακόλουθες δηλώσεις διερευνούν τις αντιδράσεις σας σχετικά με την εφαρμογή που παρουσιάζεται στο βίντεο. Για κάθε δήλωση προσδιορίστε πόσο καλά σας περιγράφει επιλέγοντας το κατάλληλο πλαίσιο.* *

*Σε ποιο βαθμό η εφαρμογή **<u>διευκολύνει</u>** την τηλεκπαίδευση σχετικά με :*

Να επισημαίνεται μόνο μία έλλειψη ανά σειρά.

	Καθόλου	Ελάχιστα	Λίγο	Μέτρια	Πολύ	Πάρα πολύ
Ενεργή συμμετοχή	⬭	⬭	⬭	⬭	⬭	⬭
Επίπεδο συγκέντρωσης	⬭	⬭	⬭	⬭	⬭	⬭
Μαθησιακά αποτελέσματα	⬭	⬭	⬭	⬭	⬭	⬭
Αλληλεπίδραση Δασκάλου-Μαθητή	⬭	⬭	⬭	⬭	⬭	⬭
Ενδιαφέρον	⬭	⬭	⬭	⬭	⬭	⬭
Αξιολόγηση	⬭	⬭	⬭	⬭	⬭	⬭

17. *2.Θεωρείτε ότι η χρήση κάμερας είναι αναγκαία στα διαδικτυακά μαθήματα ;* *

Να επισημαίνεται μόνο μία έλλειψη.

- ⬭ Καθόλου
- ⬭ Ελάχιστα
- ⬭ Λίγο
- ⬭ Μέτρια
- ⬭ Πολύ
- ⬭ Πάρα πολύ

18. *3.Θα είστε ευχαριστημένοι αν χρησιμοποιηθεί η εφαρμογή στα διαδικτυακά σας μαθήματα ;* *

Να επισημαίνεται μόνο μία έλλειψη.

- Καθόλου
- Ελάχιστα
- Λίγο
- Μέτρια
- Πολύ
- Πάρα πολύ

19. *4.Θεωρείτε ότι είναι χρήσιμο να ενημερώνεται ο εκπαιδευτικός για τις ενέργειες σας κατά τη διάρκεια των διαδικτυακών μαθημάτων ;* *

Να επισημαίνεται μόνο μία έλλειψη.

- Καθόλου
- Ελάχιστα
- Λίγο
- Μέτρια
- Πολύ
- Πάρα πολύ

20. *5. Θεωρείτε ότι η εφαρμογή είναι χρήσιμη ;* *

Να επισημαίνεται μόνο μία έλλειψη.

- Καθόλου
- Ελάχιστα
- Λίγο
- Μέτρια
- Πολύ
- Πάρα πολύ

21. *6.Θεωρείτε ότι είναι εφικτή η χρήση της εφαρμογής κατά τη διάρκεια των διαδικτυακών μαθημάτων ;* *

Να επισημαίνεται μόνο μία έλλειψη.

- Καθόλου
- Ελάχιστα
- Λίγο
- Μέτρια
- Πολύ
- Πάρα πολύ

22. *7. Πιστεύετε ότι η εφαρμογή επηρεάζει την ιδιωτικότητα σας ;* *

Να επισημαίνεται μόνο μία έλλειψη.

- Καθόλου
- Ελάχιστα
- Λίγο
- Μέτρια
- Πολύ
- Πάρα πολύ

23. *8.Παρακαλώ, καταγράψτε κάποιο άλλο σχόλιο που θέλετε να αναφέρετε σχετικά με την εφαρμογή που παρακολουθήσατε στο βίντεο.*

24. Θα ήταν πολύτιμη η βοήθεια σας αν μπορούσατε να συμμετέχετε σε συνέντευξη διάρκειας περίπου 10 λεπτών, όπου θα έχετε την ευκαιρία να δοκιμάσετε την πειραματική εφαρμογή που παρακολουθήσατε στο βίντεο !

Παρακαλώ στείλτε μας email στο ela.dimitriadou@edu.cut.ac.cy *για να διευθετήσουμε τη συνέντευξη όποτε σας βολεύει.*

Σας ευχαριστώ θερμά για την συμμετοχή σας.

APPENDIX E

Online Questionnaire for the Experimental User Evaluation of the Case Study II (An automated lecture style assessment system)

Αυτοαξιολόγηση της γλώσσας του σώματος και ομιλίας των εκπαιδευτικών

Αγαπητοί εκπαιδευτικοί,

Στα πλαίσια της διδακτορικής μου διατριβής αναπτύξαμε ένα σύστημα το οποίο μπορούν να χρησιμοποιήσουν οι εκπαιδευτικοί για προσωπική αξιολόγηση της ποιότητας της διδασκαλίας τους σε σχέση με τις κινήσεις του σώματος και την ομιλία.

Η συμμετοχή σας στην παρούσα έρευνα, είναι πολύ σημαντική, καθώς θα συμβάλετε στη διεξαγωγή της και στην επίτευξη των στόχων που έχουν τεθεί. Αναμένεται η συμμετοχή σας στην έρευνα να έχει διάρκεια περίπου 30-35 λεπτά. Η έρευνα είναι ανώνυμη και δεν προκύπτουν οποιοιδήποτε κίνδυνοι από την συμμετοχή σας στην παρούσα έρευνα.

Σας ευχαριστώ για την ανταπόκρισή και τη συνεργασία σας !

Με εκτίμηση,
Ελένη Α. Δημητριάδου
Διδακτορική Φοιτήτρια και Ερευνητικός Συνεργάτης
Τμήμα Πολυμέσων και Γραφικών Τεχνών, Τεχνολογικό Πανεπιστήμιο Κύπρου
CYENS Centre of Excellence

Linkedin : https://www.linkedin.com/in/eleni-a-dimitriadou-8b4186250/

Google Scholar : https://scholar.google.com/citations?user=rn1kQjoAAAAJ&hl=el

Για οποιαδήποτε περαιτέρω πληροφορία παρακαλώ επικοινωνήστε μαζί μας : ela.dimitriadou@edu.cut.ac.cy

* Υποδεικνύει απαιτούμενη ερώτηση

Φόρμα συγκατάθεσης

Παρακαλώ διαβάστε το πλήρως.

1. Η τρέχουσα μελέτη θεωρείται ότι έχει ελάχιστο κίνδυνο και θα σας ζητηθεί να υποβάλετε τα σχόλιά σας σχετικά με τη προτεινόμενη εφαρμογή. *

Θα σας ζητηθεί να συμπληρώσετε ένα διαδικτυακό ερωτηματολόγιο. Η έρευνα είναι ανώνυμη, οι απαντήσεις σας θα παραμείνουν εμπιστευτικές και θα χρησιμοποιηθούν αποκλειστικά και μόνο για τους σκοπούς της παρούσας έρευνας. Να θυμάστε ότι η συμμετοχή σας είναι αποκλειστικά εθελοντική. Μπορείτε να αποσυρθείτε σε οποιοδήποτε στάδιο χωρίς οποιαδήποτε συνέπεια.

Υποβάλλοντας αυτό το ερωτηματολόγιο συναινείτε στα ακόλουθα:

Να επισημαίνεται μόνο μία έλλειψη ανά σειρά.

	Ναι	Όχι
Κατανοείτε αυτό το έντυπο συγκατάθεσης	⬭	⬭
Δίνετε τη συγκατάθεσή σας για να συμμετάσχετε σε αυτή τη μελέτη	⬭	⬭

ΜΕΡΟΣ Ι : ΔΗΜΟΓΡΑΦΙΚΑ ΔΕΔΟΜΕΝΑ *(pre-test questionnaire)*

Παρακαλώ να απαντήσετε στις πιο κάτω ερωτήσεις , οι οποίες αφορούν τα προσωπικά σας στοιχεία, επιλέγοντας στο αντίστοιχο κουτάκι για ό,τι ισχύει.

2. *1.Χώρα :* *

Να επισημαίνεται μόνο μία έλλειψη.

- Κύπρος
- Ελλάδα
- Άλλη

3. *2.Φύλο :* *

Να επισημαίνεται μόνο μία έλλειψη.

- Άνδρας
- Γυναίκα
- Δεν επιθυμώ να απαντήσω

4. *3.Προφίλ :*

Να επισημαίνεται μόνο μία έλλειψη ανά σειρά.

	Πρωτοβάθμια	Δευτεροβάθμια	Τριτοβάθμια	Άλλο
Εκπαιδευτικός				

5. *4. Ηλικία* : *

Να επισημαίνεται μόνο μία έλλειψη.

- 25-29
- 30-39
- 40-49
- 50-59
- 60 -

6. 5. *Διδακτική εμπειρία* (σε χρόνια) *:* *

7. 6. *Διδακτική ειδικότητα (πχ. φιλόλογος, μαθηματικός)* : *

8. 7. Πόσο έμπειρο θεωρείς τον εαυτό σου σε τεχνολογίες τεχνητής νοημοσύνης ; *

Να επισημαίνεται μόνο μία έλλειψη.

- Καθόλου
- Ελάχιστα
- Λίγο
- Μέτρια
- Πολύ
- Πάρα πολύ

ΜΕΡΟΣ ΙΙ : ΧΡΗΣΗ ΕΦΑΡΜΟΓΗΣ *(Phase 1 : post-test questionnaire)*

Για να μπορέσετε να απαντήσετε στις πιο κάτω ερωτήσεις, θα σας δοθεί μια εφαρμογή την οποία θα έχετε την ευκαιρία να χρησιμοποιήσετε σε πραγματικό χρόνο για αυτοαξιολόγηση της γλώσσας του σώματος και ομιλίας σας για περίπου 5-8λεπτά.

Οι ακόλουθες ερωτήσεις αφορούν τις απαιτήσεις σας σχετικά με την εφαρμογή αυτή.

9. *1.Θεωρείτε ότι η εφαρμογή είναι χρήσιμη για βελτίωση της ποιότητας της διάλεξης ;* *

Να επισημαίνεται μόνο μία έλλειψη.

- Καθόλου
- Ελάχιστα
- Λίγο
- Μέτρια
- Πολύ
- Πάρα πολύ

10. *2. Πιστεύετε ότι η εφαρμογή είναι εύκολη στη χρήση ;* *

Να επισημαίνεται μόνο μία έλλειψη.

- Καθόλου
- Ελάχιστα
- Λίγο
- Μέτρια
- Πολύ
- Πάρα πολύ

11. *3.Πιστεύετε ότι η ανατροφοδότηση που παρέχει η εφαρμογή είναι χρήσιμη για βελτίωση της ποιότητας της διάλεξης ;* *

Να επισημαίνεται μόνο μία έλλειψη.

- Καθόλου
- Ελάχιστα
- Λίγο
- Μέτρια
- Πολύ
- Πάρα πολύ

12. *4.Οι ακόλουθες δηλώσεις διερευνούν την εμπειρία σας στη χρήση της εφαρμογής. Για κάθε δήλωση προσδιορίστε πόσο καλά σας περιγράφει επιλέγοντας το κατάλληλο πλαίσιο.* *

*Σε ποιο βαθμό η εφαρμογή παρέχει **<u>ικανοποιητική ανατροφοδότηση</u>** σε σχεσή με :*

Να επισημαίνεται μόνο μία έλλειψη ανά σειρά.

	Καθόλου	Ελάχιστα	Λίγο	Μέτρια	Πολύ	Πάρα πολύ
Εκφράσεις προσώπου	◯	◯	◯	◯	◯	◯
Ενέργειες	◯	◯	◯	◯	◯	◯
Αναγνώριση ομιλίας	◯	◯	◯	◯	◯	◯
Κινήσεις χεριών	◯	◯	◯	◯	◯	◯
Κινήσεις κεφαλιού	◯	◯	◯	◯	◯	◯
Συνολικό σκορ	◯	◯	◯	◯	◯	◯

ΜΕΡΟΣ III : ΧΡΗΣΗ ΕΦΑΡΜΟΓΗΣ *(Phase 2 : post-test questionnaire)*

Για να μπορέσετε να απαντήσετε στις πιο κάτω ερωτήσεις, θα σας δοθεί η εφαρμογή που χρησιμοποιήσατε στη πρώτη φάση την οποία θα έχετε την ευκαιρία να χρησιμοποιήσετε πάλι σε πραγματικό χρόνο για αυτοαξιολόηση της γλώσσας του σώματος και ομιλίας σας για περίπου 5-8λεπτά. Η εφαρμογή μετρά συγκεκριμένα βιομετρικά χαρακτηριστικά :

Εκφράσεις προσώπου (facial expressions): Οι εκφράσεις του προσώπου αναφέρονται στις διάφορες κινήσεις και θέσεις των μυών στο πρόσωπο που μεταφέρουν συναισθηματικές καταστάσεις (πχ. λυπημένος, χαρούμενος, θυμωμένος κτλπ).

Ενέργειες εκπαιδευτικών (activity performed): Οι ενέργειες των εκπαιδευτικών αναφέρονται στις ενέργειες που εκτελούνται κατά τη διάρκεια του μαθήματος πχ. απουσιάζει από την οπτική γωνία της κάμερας, παρακολουθεί, σηκώνει το χέρι(α), γράφει, τηλεφωνεί, στέλνει μηνύματα και κοιτάζει αλλού.

Κατεύθυνση κεφαλιού (head direction): Ο όρος «κατεύθυνση κεφαλιού» αναφέρεται στον προσανατολισμό ή τη θέση του κεφαλιού σε σχέση με το υπόλοιπο σώμα (πχ. εμπρός, πίσω, δεξιά, αριστερά).

Κινήσεις χεριών (hand movements): Οι κινήσεις των χεριών αναφέρονται στις ενέργειες και χειρονομίες που πραγματοποιούνται από τα χέρια και τα δάχτυλα.

Αναγνώριση ομιλίας (speech recognition): Χαρακτηριστικά της φωνής όπως ταχύτητα ομιλίας, τόνος (δήλωση ή ερώτηση) και παύσεις κατά τη διάρκεια της ομιλίας.

Οι ακόλουθες ερωτήσεις αφορούν τις απαιτήσεις σας σχετικά με την εφαρμογή αυτή.

13. *1.Θεωρείτε ότι η εφαρμογή είναι χρήσιμη για βελτίωση της ποιότητας της διάλεξης ;* *

Να επισημαίνεται μόνο μία έλλειψη.

- Καθόλου
- Ελάχιστα
- Λίγο
- Μέτρια
- Πολύ
- Πάρα πολύ

14. *2. Πιστεύετε ότι η εφαρμογή είναι εύκολη στη χρήση ;* *

Να επισημαίνεται μόνο μία έλλειψη.

- Καθόλου
- Ελάχιστα
- Λίγο
- Μέτρια
- Πολύ
- Πάρα Πολύ

15. *3.Πιστεύετε ότι η ανατροφοδότηση που παρέχει η εφαρμογή είναι χρήσιμη για βελτίωση της ποιότητας της διάλεξης ;* *

Να επισημαίνεται μόνο μία έλλειψη.

- Καθόλου
- Ελάχιστα
- Λίγο
- Μέτρια
- Πολύ
- Πάρα πολύ

16. *4.Οι ακόλουθες δηλώσεις διερευνούν την εμπειρία σας στη χρήση της εφαρμογής. Για κάθε δήλωση προσδιορίστε πόσο καλά σας περιγράφει επιλέγοντας το κατάλληλο πλαίσιο.* *

*Σε ποιο βαθμό η εφαρμογή παρέχει **ικανοποιητική ανατροφοδότηση** σε σχεσή με :*

Να επισημαίνεται μόνο μία έλλειψη ανά σειρά.

	Καθόλου	Ελάχιστα	Λίγο	Μέτρια	Πολύ	Πάρα πολύ
Εκφράσεις προσώπου	⬭	⬭	⬭	⬭	⬭	⬭
Ενέργειες	⬭	⬭	⬭	⬭	⬭	⬭
Αναγνώριση ομιλίας	⬭	⬭	⬭	⬭	⬭	⬭
Κινήσεις χεριών	⬭	⬭	⬭	⬭	⬭	⬭
Κινήσεις κεφαλιού	⬭	⬭	⬭	⬭	⬭	⬭
Συνολικό σκορ	⬭	⬭	⬭	⬭	⬭	⬭

17. *5. Τι επιπλέον μετρικές θα θέλατε να περιλαμβάνει η εφαρμογή που χρησιμοποιήσατε;* *

____

18. *6. Αναφέρετε, ποιές δυσκολίες είχατε να αντιμετωπίσετε κατά την διάρκεια χρήσης της εφαρμογής.*

19. *7.Παρακαλώ, καταγράψτε κάποιο άλλο σχόλιο που θέλετε να αναφέρετε σχετικά με την εμπειρία σας κατά τη διάρκεια χρήσης της εφαρμογής.*

Σας ευχαριστώ θερμά για την συμμετοχή σας.

Για οποιαδήποτε περαιτέρω πληροφορία παρακαλώ επικοινωνήστε μαζί μας : ela.dimitriadou@edu.cut.ac.cy