The ethical implications of using Multimodal Learning Analytics: a framework for research and practice

By

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Declaration

I, **Haifa Abdulwahab Alwahaby**, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

Signature

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January 2025

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Abstract

A growing number of multimodal data (MMD) streams and complex artificial intelligence (AI) models are being used in learning analytics research to allow us to better understand, model and support learning, together with teaching processes. Considering MMDs' potentially more invasive, extremely granular and temporal nature compared to log files, they may present additional ethical challenges in comparison to more traditional learning activity data. The systematic review undertaken during this study revealed a dearth of ethical considerations in previous multimodal learning analytics (MMLA) literature. Consequently, this study aims to identify the ethical issues associated with the use of MMLA and propose a practical framework to assist end-users to become more aware of these issues and potentially mitigate them. To gain a better understanding of the ethical issues and how they may be mitigated, the study aims to investigate the ethical concerns associated with the use of MMLA in higher education by collecting the opinions and experiences of appropriate stakeholders. Accordingly, structured individual interviews were conducted via Microsoft Teams, a video conferencing software, due to COVID-19 restrictions. In total, 60 interviews were conducted with educational stakeholders (39 higher education students, 12 researchers, eight educators and one representative of an educational technology company). Based on the thematic coding of verbatim transcriptions, nine distinct themes were identified. In response to the themes and accompanying probing questions presented to the MMLA stakeholders, and based on the ethical guidance and recommendations identified from previous literature, a first draft of the MMLA ethical framework was prepared. Subsequently, the draft was evaluated by 27 evaluators (seven higher-education students, 13 researchers–practitioners, four teachers, one ethics expert and two policymakers) by means of structured interviews. Additionally, a group of researchers adopted the framework in their research and provided constructive feedback. Based on the thematic analysis of the interviews, the framework was continually improved for three rounds until data saturation was achieved. This resulted in the presentation of the first MMLA ethical framework, which was the principal goal of this study. This thesis delivers three key contributions: (1) a systematic review of previous MMLA literature that confirms the lack of ethical considerations in the literature; (2) an examination of the ethical issues connected with MMLA from the perspective of different stakeholders; and (3) an ethical MMLA framework for higher education. By developing the framework, this thesis aims to increase awareness of the potential ethical issues and therefore, alleviate them by promoting a more ethical design, along with the development and use of MMLA in a higher education setting.

Impact Statement

Although Multimodal Learning Analytics (MMLA) provides a significant opportunity to improve teaching and learning practice, it may also present numerous ethical concerns. As a relatively new field, MMLA can exploit the lessons learned from the ethical issues experienced by using AI in education, for instance concerns pertaining to privacy, fairness and trustworthiness. It is equally important, and possibly more crucial, to address these issues when implementing MMLA tools in real-world educational settings, given that misuse or abuse of these tools may cause students harm. Furthermore, the highly granular, temporal and synthesised nature of the multimodal data employed in MMLA systems means that the interpretation and discussion of these ethical technology dimensions are even more complex. Similarly, the systematic literature review determined that ethical considerations were rarely raised or considered by MMLA researchers (Alwahaby et al., 2022). Therefore, the purpose of this study is to fill this significant gap in the literature by investigating and identifying the ethical concerns associated with the use of MMLA in higher education. Additionally, it proposes a practical framework to support end-users with identifying and alleviating these problems.

The three main impacts of the study are as follows:

First, it provides critical empirical evidence regarding the current state of ethical considerations and discussions within the field of MMLA. It identifies a significant gap in the ethical discourse that the research intends to fill. The primary goal of this approach is to raise awareness amongst researchers in this critical area. Researchers examining the ethical issues associated with the use of MMLA can build upon the current research to explore and develop this area further, delivering more robust and informed ethical practices.

Second, the qualitative interviews conducted in this study provided beneficial information and feedback from a variety of relevant stakeholders, for instance researchers, educators and students. By incorporating different opinions, the study delivers a better understanding of ethical challenges and considerations, allowing researchers and practitioners to expand upon these findings and develop more comprehensive and inclusive approaches to implementing MMLA.

Third, this study presents the first ethical framework developed specifically with regard to MMLA (Alwahaby & Cukurova, 2024), providing a wide-ranging approach to confronting the ethical challenges related with MMLA.

- Concerning end-users, such as educators and students in higher education, the framework aids the safe and effective use of MMLA, guaranteeing that the potential risks are diminished while capitalising upon the benefits of these systems.
- Researchers and practitioners can apply the framework to proactively identify and tackle ethical dilemmas in the design, evaluation and employment of MMLA systems.
- Higher education institutions and policymakers can adapt the framework to their specific needs, enabling them to establish ethical guidelines modified to their unique settings.
- Technology companies can use the framework to develop MMLA tools that adhere to ethical principles, which, in turn, can enhance their credibility and social impact.

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Abbreviations

AI……………………………………………………………………….Artificial Intelligence

AIED……………………………………………………………………Artificial Intelligence in Education

EDA…………………………………………..……………….... Electrodermal Activity

EDM……………………………………………………………………Educational Data Mining

ERSs …………………………………………………………………..Educational Recommender Systems

GDPR……………………………………………………………………General Data Protection Regulation

LA..Learning Analytics

LAK……………………………………………………………………Learning Analytics and Knowledge

ML...Machine Learning

MMD..Multimodal Data

MMLA..Multimodal Learning Analytics

OLMs……………………………….……..……………….…..Open Learner Models

PILAR …………………………………………………………...…Pragmatic Inquiry for Learning Analytics Research

SBA ………………………………………………………….……Sensing-based analytics

SLR..Systematic Literature Review

1 Chapter One: Introduction

1.1 Rationale of the Study

My reason for conducting this research is professional in nature. My interest in sensing technology dates back to 2012, when I became interested in tracking human motion as part of the research for my master's dissertation titled: "*Interactive Installation, Exploration and Design of a Tracking Motion Installation"*. During this research I developed and produced an interactive installation to explore the concept of tracking human body movements.

After obtaining my master's I began teaching at a university. At that point, I realised that teaching students is a considerable challenge which I enjoy tremendously. However, I encountered a few difficulties related to understanding the challenges my students experienced and determining what level of support to offer them. Additionally, I have always been intrigued by the idea of using technology to uncover the hidden complexities associated with the learning process. Whilst reading I discovered the fields of learning analytics (LA) and multimodal learning analytics (MMLA), which immediately piqued my interest. Learning analytics can be defined as "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs" (Long & Siemens, 2011). MMLA is an emerging field that is concerned with identifying methods of processing learning data obtained from a variety of sources, enabling the automatic verification of beneficial information for students (Ochoa et al., 2013). The primary objective of MMLA is to accurately identify learning-related constructs, unobtrusively and in an appropriate manner by processing MMD. Consequently, this can be used to develop engaging and motivating teaching and establish systems that account for those constructs by way of a system design that improves learning (Giannakos et al., 2022).

I was particularly interested in exploring the limitless possibilities that MMLA can provide to support the learning process. Nevertheless, at that time I was most concerned about maintaining the privacy of my students. To collect data for MMLA, a variety of sensors are utilised, including cameras. Consequently, a number of ethical concerns may arise. Using MMLA while protecting students from potential harm was of interest to me. Therefore, in an attempt to address this issue I read a substantial amount of MMLA research in search of solutions offered by previous researchers. However, I was surprised to discover a gap in the discussions pertaining to the ethical issues related to MMLA. Hence, I decided to undertake this research.

1.2 Significance of the Study

The principle objective of this study is to identify and explore the ethical issues associated with the use of MMLA in higher education. Accordingly, the aim is to develop an ethical framework that will allow end-users, for instance educators and students, to exploit what MMLA offers, while preventing potential harm. Following the systematic literature review, it was determined that ethical considerations were seldom raised or considered by MMLA researchers (Alwahaby et al., 2022). Therefore, this study seeks to fill this significant gap in the literature.

1.3 Aim

The focus of this research study will be to explore the ethical implications, requirements and considerations related to using MMLA. Only a few studies have been conducted to date that explore the ethical considerations associated with using MMLA in physical spaces in the context of higher education. There is therefore a significant need for MMLA studies in these specific contexts to explore new ways of maintaining and safeguarding individuals' privacy, as well as to ensure the ethical and trustworthy collection and use of personal data. Furthermore, significant concerns pertaining to data ethics and the ethics of artificial intelligence (AI) in particular, for example transparency, accountability, fairness and bias, should also be considered within the context of MMLA.

This research therefore sets out to examine the ethical issues related to the use of MMLA, aiming to draw up an ethical MMLA framework and provide practical suggestions for the implementation of this framework.

1.4 Research Questions

1. What are specific examples of MMLA being employed in education and the related ethical concerns mentioned in the literature?
2. What are the opinions of researchers, practitioners and students on the ethical use of MMLA in higher education?
3. How can MMLA be applied in a more ethical way in higher education?

1.5 Research Background

1.5.1 Ethics, Moral Philosophy and the Fundamentals of the Ethics of Digital Technology

As an initial step towards establishing this research, it is crucial to understand the fundamental concepts of ethical and moral philosophy, as well as how the definition has evolved over time. Primarily, the development of philosophical ethics first emerged in Greece and Asia during the 6th to

4th centuries BC. At its most basic, the ancient Greek philosopher Socrates regarded ethics as having the purpose of defining what is known as “the good life”—the kind of life that is fitting for human beings, a type of life that is worth choosing among the many possibilities of human existence (Vallor, 2016). Ethics, as part of philosophy, is concerned with how we should determine what is morally right and wrong. Nonetheless, the terms “ethics” and “morals” are frequently used interchangeably; a point of distinction between them is that ethics investigates the rationale behind our moral lives, specifically through the critical examination and analysis of concepts and principles that are, or could be, used to justify our moral choices and actions (Reiss, 1999).

As Fieser (2000) explains, there are three main schools of ethics: metaethics, normative ethics (deontology, utilitarianism and virtue ethics), and applied ethics. Applied ethics combines consequential and non-consequential approaches in a particular context, for instance medical ethics (Breidbach et al., 2020; Fieser, 2000). Another example is bioethics, which is a field within applied ethics that studies ethical concerns pertaining to biology and biological systems. It is established on four universal principles: (1) autonomy, (2) nonmaleficence, (3) beneficence and (4) justice (Beauchamp & Childress, 2001). Owing to the similarities between bioethics and digital ethics, specifically regarding the ecological approach employed when interacting with new types of agents, patients and environments (Floridi, 2013), bioethics has become an important approach for many digital ethical reasoning and decision-making processes (see, for instance, Floridi and Cowls’ (2019) principles of AI).

In her book titled: ‘Technology and the Virtues: A Philosophical Guide to a Future Worth Wanting’, Vallor (2016) claimed that as long as the future remains uncertain, it remains difficult to predict the specific conditions of life that may occur in the future, which will be improved by adhering to a specific ethical principle. Hence, these ideals may cease to motivate us. In support of his argument, different historical examples were presented. For instance, in the 18th century, the German philosopher Immanuel Kant provided a single moral rule, known as the categorical imperative, which is intended to solve all ethical dilemmas. According to Kant’s proposal, a person is only asked to think about whether the principle on which he is about to act in his particular situation will be universally observed by every other individual in a similar position.

However, this is an exceptionally abstract and general rule that has a number of issues connected with its practice. In the 19th century, the British philosophers Jeremy Bentham and John Stuart Mill argued that “the good life” could be achieved simply by selecting, among the available courses of action, the one that promises the greatest happiness for all involved. However, in the midst of all the new options concerning biomedical, mechanical and computational research that are available in the modern era, it is becoming increasingly problematic to choose the path that will provide the greatest overall benefit or the least harm for all. Given the current complex and rapidly changing state of civilisation and emerging technology, making ethical decisions, those intended to achieve “the good life”, has become increasingly challenging.

Accordingly, these concerns must be addressed in the context of a particular philosophical tradition, e.g., virtue ethics. This approach views good living to be the result of the individual moral qualities and abilities possessed by all human beings, which can be actively nurtured and developed (ibid). However, Vallor (2016) also reasoned that a recent critique of virtue ethics has challenged its very foundation with regard to the moral psychology of people’s characters. Critics of this thesis draw upon familiar studies, such as the Milgram experiments in 1961, where participants were discovered to be willing to deliver apparently fatal electric shocks on the instruction of an authority figure. They also refer to the Stanford Prison Experiment in the summer of 1971, where researchers performed a prison simulation experiment in which they examined the effects of situational variables on participants’ reactions and behaviours. Within five days the “guards” had begun to abuse the “prisoners” psychologically, forcing the experiment to be immediately terminated. These notable results support the argument that moral behaviour is determined by the circumstances in which moral agents find themselves, not by the nature of their character. Virtue ethicists have been able to respond to this situational challenge, although they pointed out that by developing ‘technomoral virtues’, humans may be able to live together more effectively in the future using advances in technology.

Ethics and technology are inextricably linked by the fact that technologies encourage particular modes of thinking, acting and valuing; they introduce new possibilities for human action and exclude or deprive others of their benefits (Vallor, 2016). Cukurova noted that it is essential for educational technology researchers to “read fundamental philosophy as most ethical questions come down to philosophical discussions and frameworks that are driven by certain values” (Holmes et al., 2021, p. 14).

These considerations will be key in determining the future design of a potential MMLA framework in order to safeguard its users against any potential harm. As an example, for the reason that moral behaviour depends on the circumstances under which agents find themselves, the MMLA framework should be designed to be flexible, so as to be suitable for use in a variety of scenarios. This is in accordance with the recommendation made by Holmes et al. (2021) that when considering an ethical framework for educational technology, it is crucial to accommodate a degree of flexibility to incorporate new knowledge, new understandings and novel approaches to supporting learning and teaching, as well as science, cultural norms, values and educational systems, which may change over time.

Furthermore, our concerns as individuals in this world are not limited to which actions are morally right or wrong, but also encompass what causes an action to be morally right or wrong. To become proficient at ethical decision making, it is imperative to understand the reasoning behind our decisions. It is common for ethical codes to become established as a result of a crisis. A code of ethics is intended to prevent unethical conduct, as well as to establish a sense of community identity, answer external criticism, and, most importantly, establish moral authority for the self-regulation of behavioural ethics (Metcalf & Crawford, 2016). We need values and moral principles to manage our lives and behaviour, and the significance of these values lies in protecting each other against threats to our physical and emotional wellbeing. In keeping with Warren and Brandeis (1890), protecting an individual person and their property has been a fundamental principle in common law for centuries, but at first only direct physical interference with people or property, known as 'trespass vi et armis', qualified for redress. Traditionally, the "right to life" only protects individuals from various forms of battery, and liberty refers to freedom from actual restraint, while property rights indicate the right of every individual to possess property. Eventually, humanity has come to be acknowledged for both its spiritual nature and its intellect. Today, the right to life includes the right to good health, the right to liberty includes freedom from oppression, whilst the term "property" includes any tangible or intangible possession (ibid.).

Therefore, ethics act as practical guidance in our daily lives. Specifically, this study is interested in technology or digital ethics, which may be defined as value systems and moral principles that govern interactions with digital technology (Buytendijk, 2019). Specifically within digital technology, the focus of this research pertains to MMLA. Research and practice in MMLA require an ethical framework, because good intentions might not be sufficient to guide the design or implementation of ethical technology (Holmes et al., 2021). Understanding the difference between undertaking ethical acts and performing them ethically, recognising the risks of unintended consequences, and having an understanding of the ethical implications of pedagogy are all fundamental (ibid.) parts of ensuring that the use of educational technology, including the use of MMLA, is safe and ethical.

1.5.2 Artificial Intelligence: Ethical Concerns and Lessons to be Learned

Through the development of AI technologies, humans are now able to design systems that can simulate human intelligence and be trained to predict, decide and ultimately make judgements in a variety of contexts. However, the use of these systems has the potential to be severely detrimental, as certain predictions might be life-changing or even life-threatening. The field of AI ethics was developed in response to a growing concern regarding the ethical implications of decision making in AI. It is a nascent field, a subset of the larger field of digital ethics, but it has grown rapidly in recent years, in an attempt to resolve issues raised by the development and application of emerging technologies, for instance AI, big data analytics and blockchain technology (Kazim & Koshiyama, 2021).

Ethical AI should be adopted to protect humans from any harm that may result from the use of this technology. Throughout recent history, humanity has experienced a few adverse consequences caused by blind faith in AI, with a tendency to treat it as infallible. Correctional Offender Management Profiling for Alternative Sanctions (COMPAS) is an example of a system where AI is used in the field of law, which has robust ethical norms. Christian (2020) described how the system is commonly used in various states in the US, e.g., Florida, to make risk assessments based on an algorithm. This algorithm assigns given situations a number from 1 to 10, to help make decisions relating to defendants, including decisions concerning bail and the risk of violent behaviour. Over the course of many years, the system has been relied upon without significant questioning of its validity. However, in 2016 a group of journalists decided to examine COMPAS more carefully, using a dataset of 7,000 defendants arrested between 2013 and 2014. They asked two questions: Did the model accurately predict which defendant was the riskiest? And, was there any evidence of model prediction bias against any group? It was astounding to discover that the model was biased in terms of skin colour as well as other issues related to this factor (ibid.).

This problem is not limited to the field of law; fairness issues may also arise in other areas, such as education (the focus of this study). For example, using algorithms to predict the performance of learners may result in bias, given that algorithms that are designed and trained on a particular dataset might not be appropriate for use with a different population. A number of factors may contribute to differences between populations, including the learners' abilities, age, ethnicity, race, religion, gender and other characteristics. The implicit values of the people who train algorithms might also generate bias. Thus, so as to protect students from this sort of harm, further investigation is required on the use and trust of these predictive models in education.

An additional example of AI being employed in a different field with ethical norms, specifically healthcare, was also presented by Christian (2020), who discussed the importance of transparency in AI and presented an example of a real-life AI decision that was life-threatening. A model result with an unusual prediction was observed when training a rule-based model to predict the survival rate of pneumonia patients. It was ascertained that if the patient had a history of asthma, then the model considered the patient to be low-risk and recommended that they be treated as an outpatient. Essentially, “asthma is not only considered to be a serious risk factor for pneumonia patients, but it would put the patient in the ICU and critical care”; therefore, “this was not just wrong; it was life threateningly dangerous” (Christian, 2020, pp. 90–91).

Similar scenarios may occur in educational settings, so increased transparency and explainability, achieved by providing obvious and detailed information regarding how decisions were reached, may help to increase students’ and teachers’ trust, saving students from inaccurate predictions and also allowing teachers to question the accuracy of certain decisions. The accuracy of predictive model results and the degree of trustworthiness of predictive models are examples of ethical issues that deserve further investigation by technology designers and researchers in the context of AI in education and MMLA.

Concerning the issue of bias in MMLA, many lessons can be learned from the broader field of the ethics of big data and AI. Crawford (2013) maintains that although large datasets can provide understanding of previously intractable problems, it is essential to recognise that both data collection and decisions based on analysis are not objective; rather, they are the products of humans, who use the data to draw conclusions and define their meaning. Thus, big data analytics are also subject to hidden biases during both the collection and analysis phases, as well as during representation through visualisation. Consider, for example, the 20 million tweets generated about Hurricane Sandy, most of which originated from Manhattan due to the high proportion of smartphone owners and Twitter users in the city. To address these inequality issues in big datasets, informed by social science, it is necessary to ask the following questions: who is excluded, where are these less visible places and what happens when one lives in the shadow of big data? (ibid.). Similarly in the context of MMLA, in order to mitigate bias, questions should be asked about the data used as training data, including where the data come from, how they were gathered, whether they are representative of all users, and what cognitive biases might be being applied to their interpretation. It is also crucial to complement data sources with qualitative research.

Moreover, as noted by Crawford (2017), because AI systems are developed by private companies and manipulated by proprietary algorithms, this may also lead to AI systems exhibiting hidden biases. For example, many AI recruitment companies analyse video interviews of job candidates so that employers can compare applicants’ facial movements, vocabulary and body language with those of their top-performing employees. This technology creates a bias in hiring by selecting candidates who are similar to current employees. While AI is incredibly powerful in relation to detecting patterns, it lacks social and contextual awareness. These concerns are significant issues when an AI system decides who is offered a job or who gets out of jail, and how people live their lives. Meticulous research is necessary prior to using these systems in the most vulnerable social institutions. Consequently, the AI Now Institute has been established at New York University in collaboration with social scientists, computer scientists, lawyers, economists and engineers to examine the implications of new AI technologies (ibid.).

There are many instances of unfair systemic behaviours that have been observed in widely utilised machine learning (ML) systems. For instance, an automated hiring system may be more likely to recommend hiring personnel from certain racial, gender or age groups (Giang, 2018), while search engines might show arrest-record ads in response to queries related to African American baby names, but not for other names (Noble, 2018). Holstein et al. (2019) contend that, despite extensive ML literature focusing predominantly on algorithmic "de-biasing," future research should also support practitioners with the collection and curation of high-quality datasets to improve the fairness of downstream ML models. Additionally, most fairness auditing methods require access to individual-level demographics (e.g., race and gender), but many teams are only able to obtain this information at coarser levels of data, if at all. It will be important to explore ways of supporting fairness auditing when there is only access to coarse-grained demographic data (e.g., neighbourhood or school demographics) in the future.

Given that all of the previously mentioned ethical issues might also arise within the context of MMLA, it is important to examine them in comprehensive detail so as to address them in a potential future ethical framework for MMLA research and practice. Additionally, as is true with all emerging technologies, once these technologies are extensively adopted, they must perform reliably in a way that can be trusted by everyone, or else they may be misused, overused or underused (Floridi, 2019). In a discussion on the importance of an ethical framework for AI, Floridi (2019) argues that ethical uncertainty promotes both reckless risk-taking and excessive caution. It is therefore essential that MMLA researchers and practitioners are provided with information on the potential ethical issues associated with the use of these technologies in educational settings.

1.5.3 Multimodal Learning Analytics: Background, History and Aims

Historically, the world of education has been dominated by language as a medium of communication and thereby as a means of learning and teaching (Kress et al., 2006). However, technological advances have given students and teachers new perspectives on learning, as well as new ways to obtain feedback on teaching and learning processes by way of learning systems. Learning technology researchers have predominantly focused on collecting information on learners through log data and clickstreams generated by learning systems (Sharma & Giannakos, 2020), a field now known as learning analytics (LA). Although there are no generally accepted definitions of learning analytics, a widely cited one was developed by the 1st International Conference on Learning Analytics and Knowledge (LAK): "Learning analytics is the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs" (Long & Siemens, 2011).

However, because traditional learning is primarily occurring in actual physical classrooms and is not limited to the use of learning systems, a variety of physical learning behaviours and indicators are missing from the investigation of learning in the digital world. The rapid and recent development of technology implies that advanced sensing tools have become more affordable for researchers, offering the possibility of new in-depth understanding and perspectives, and the provision of supplementary information for traditional data. As a result of the vast amounts of data that are now available, a new area of research has emerged in recent years that is generally referred to as multimodal learning analytics (MMLA) (Blikstein & Worsley, 2016). MMLA has been an established field for roughly ten years, concentrating on exploring the potential of big data with different modalities within learning disciplines (Scherer et al., 2012).

Human activities are becoming increasingly quantifiable via a range of sensing technologies, including wearable cameras, biosensors such as skin conductivity, heartbeat, EEG and eye tracking. Specifically, data on facial expressions, eye gaze, body movements, arm pulls and emotional states provide a better understanding of user behaviour and cognitive states. Body movement comprises dynamic changes in posture, orientation and physical gestures, while arm pulls represent deliberate upper-limb actions that may signal intent, engagement or physical interaction with the environment (Blikstein, 2013). Worsley et al. (2016) maintain that MMLA incorporates three distinctive ideas: multimodal teaching and learning, MMD and computer-supported analysis. MMLA is established on the idea that teaching and learning are undertaken through a variety of modalities, using non-traditional and traditional forms of data to characterise and model student learning in complex situations (ibid.). MMD streams and complex AI modelling techniques are increasingly being applied in learning analytics research to help us to better understand, model and support teaching and learning processes (Sharma & Giannakos, 2020). Recent individual and review studies reveal that MMD can significantly improve the performance of computational models of teaching and learning behaviours (Cukurova et al., 2019; Giannakos et al., 2019).

Although MMLA may be considered a subfield of AI in Education (AIED), the key difference between AI and MMLA is that the primary focus of AI is frequently on automation. AI is concerned with developing computational models of human abilities, including speaking, walking and playing, which allows the development of intelligent systems that are capable of replicating intelligent human behaviour, such as image and speech recognition and text analysis, together with making rational decisions based on the available input data (Russell & Norvig, 2010). Specifically, a key focus of AIED is agents and tutors (Labarthe et al., 2018). In contrast to externalising and replicating human cognition, as is the case with AI, MMLA repeatedly seeks to internalise or extend human cognition using computational models based on MMD tools.

The objective of multimodal learning analytics is to design products that may or may not integrate AI technology, but which are closely coupled with humans to enhance their cognition, assist with decision making and increase their abilities (Cukurova, 2019). Therefore, MMLA is more concerned about the data itself, and identifying ways to process learning data from different modalities to automatically find beneficial information and give learners feedback (Ochoa et al., 2013). It is important to note that research on collecting, pre-processing, e.g., cleaning data, synchronising and analysing sensor data streams may be found in adjoining areas, such as human–computer interaction (HCI), ubiquitous computing, intelligent tutoring systems (ITS), educational data mining (EDM), and user modelling, adaptation and personalisation (UMAP), besides AIED. However, none of these areas specifically focus on MMD and educational settings. The primary objective of MMLA is to identify learning-related constructs accurately, unobtrusively and in an appropriate manner by processing MMD, allowing the creation of engaging and motivating pedagogies and producing systems that consider those states via a system design that improves learning (Giannakos et al., 2022).

In MMLA research, multiple data methods are employed. In both the physical and digital spaces, computational methods are used to process and investigate these MMD. Theories associated with the assessment of human behaviour are employed and contribute to LA’s ambitious goals (Cukurova et al., 2020). MMD fusion significantly increases the prediction accuracy of learning outcomes and the understanding of complex learning processes (Cukurova et al., 2019). Apart from providing more accurate predictions of learning than single observations, MMLA uses advances in ML and sensor technology to monitor factors that are reasoned to be highly relevant to learning but which are regularly overlooked due to difficulties in their dynamic measurement and interpretation (Cukurova, Giannakos et al., 2020). MMLA research primarily focuses on the challenges related to MMD collection, integration, interpretation and visualisation from digital and physical environments. The aim is to provide students and teachers with appropriate feedback to improve the learning and teaching process, irrespective of any AI implied automation concerning any of these processes.

1.5.4 The Ethics of MMLA in Education

MMD and AI techniques have been used since the 1950s e.g., McCarthy (1959), but it is only in recent years that they have been commonly used in research on teaching and learning. Despite their potential, their use in real-world practice remains limited. The recent significant increase in the use of AI techniques and fine granular MMD adds new challenges to the role of these interventions in the educational context (Cukurova et al., 2020). The use of these interventions in education has a history of bias and discrimination, including the violation of individual autonomy and rights, non-transparent and unjustifiable outcomes, infringement of learner and teacher privacy, and unjust, unsafe, unsatisfactory and unreliable outcomes for individuals (Andrejevic & Selwyn, 2020; Knox et al., 2020; Selwyn, 2020).

To be able to reap the benefits of MMD and AI in teaching and learning research and practice, there is an urgent need to create plans and tools to address the ethical issues outlined above. Considerations of potential ethical and practical issues with the application of MMD are the first steps towards potentially hypothesising suggestions for practical solutions to move forward. Therefore, this section presents a definition and discussion of relevant ethical considerations, drawing on examples from the areas of AI and AIED as well as available work from LA research (e.g., Hakami & Hernandez-Leo, 2020). Specifically, the following sections will discuss the issues of privacy, accountability, transparency, fairness/unfairness, bias, equity, equality and trustworthiness. These areas, generated by the research fields discussed above, require further consideration and contributions from the MMLA research and practice community.

Privacy: 'The Right to Privacy' by Warren and Brandeis (1890), published in the *Harvard Law Review*, is one of the most influential essays in the history of law. Frequently referred to as humans' "right to be left alone", this publication advocates a right to privacy in the United States. Conversely, a definition of privacy is lacking. A unified definition of privacy, particularly one for learning analytics environments, remains elusive (Pardo & Siemens, 2014). Recently, researchers in LA have become increasingly interested in data privacy as a way of increasing the quality and trustworthiness of LA (Scheffel et al., 2014). Data ownership, anonymisation, collection, storage, processing and sharing of data are among the privacy challenges associated with LA, although discussions of these issues are infrequently addressed in institutional and educational policies (Prinsloo & Slade, 2013). The DELICATE checklist was conceived by Drachsler and Greller (2016), with the aim of addressing several of the privacy issues arising from the use of LA technology.

Transparency and explainability: In AI, transparency refers to a process that makes all information, decisions, decision-making processes and assumptions accessible to each stakeholder, with the aim of providing them with a better understanding (Chaudhry et al., 2022). It is affected by factors such as ease of access to information and the effectiveness with which information can be used for decision-making purposes (Turilli & Floridi, 2009). Moreover, transparency also refers to the extent to which an individual can comprehend how the system works. An explainable system is one that can translate and allow the user to understand how the system operates in human terms (Robert et al., 2020). By providing simple and understandable information related to how the system arrived at a particular outcome, the user is able to question, challenge and ultimately gain more confidence in the system. Therefore, explainability might promote greater transparency. According to Robert et al. (2020), there is typically a lack of transparency in the algorithms used to make decisions. In particular, it is not always apparent which datasets or criteria the system employs to make decisions. Several reasons contribute to this, including the fact that these algorithms are typically dynamic, designed to learn and can be highly autonomous in nature. Consequently, it is not always obvious to a user when or why decision criteria change over time. Therefore, both transparency and explainability have been offered as potential solutions to increase user trust. Prior research suggests that increased transparency in AI systems may have the overall effect of improving trust rather than diminishing it, at least when paired with corresponding, meaningful options for user control (Lee & Baykal, 2017). Abdi et al. (2020) investigated the impact of complementing educational recommender systems (ERSs) with transparent justifications for their recommendations. This had a positive effect on engagement and perceived effectiveness. However, it also resulted in an increased sense of injustice among learners, as they disagreed about how their competencies were modelled.

Furthermore, another aspect of transparency is institutional transparency. Given that data privacy and policy issues have considerable influence on LA systems, a systematic approach to tackling ethical and data protection issues is essential (Hoel et al., 2017; Pardo & Siemens, 2014). For instance, as one of their most important ethical challenges, education institutions should take care to ensure that they handle institutional transparency sensitively. As discussed by Drachsler and Greller (2016), data model transparency plays a fundamental role in the adoption of educational technology. It is therefore important to provide clear and concise information concerning how data are collected, stored, processed and shared. This issue was also addressed in the nine-point DELICATE checklist for the implementation of LA.

A further issue pertaining to transparency is the transparency relating to data collection, processing, modelling and visualisation. As the tracking of learners' data presents substantial transparency concerns, people must be aware of how they are being tracked, as noted by Duval (2011). A clear explanation of the purpose of data collection might also help to address the issue of transparency in education (Drachsler & Greller, 2016). A review of eight learning analytics policies carried out by Verbert et al. (2020) revealed that participants should also have the ability to opt out of data collection at any point without affecting the process. It is vital to have transparency at every stage of the MMLA pipeline, including data collection and processing, as well as the modelling and visualisation stages. For instance, MMLA research can significantly benefit from transparent and open learner models (OLMs), which are a focal point of the LA and educational data mining (EDM) research communities. According to the results of the randomised controlled experiment conducted by Abdi et al. (2020), combining ERSs with open learner models (OLMs) can positively impact users' perceptions and engagement.

A further aspect of transparency to consider is the model's transparency. A transparent model predicting learners' collaborative problem-solving competencies from video data has been shown in recent research to be preferred by teachers and learners over high-performing but opaque models (Cukurova et al., 2020). Rather than using non-transparent deep learning and neural network approaches, these authors developed transparent decision trees that allowed teachers and learners to examine analytics predictions. The study suggested that a more comprehensive understanding of the factors influencing learning outcomes measured in analytics and avoiding "black box" approaches where possible would result in an increase in human agency and adoption (Cukurova et al., 2020). Shibani et al. (2019) echoed these conclusions, suggesting that educators should have the authority to control educational systems, which, in turn, can promote the transparency and trustworthiness of that system. As a means of guaranteeing the fully transparent development of an LA system, students must be included in the development process beyond the usual focus group approach (de Quincey et al., 2019). An LA tool can only be regarded as transparent if the processes behind its output are sufficiently evident to users to allow confident reviews and critiques (Shum et al., 2016). However, it remains essential to test these suggestions empirically with users in real-world settings.

Accountability: The concept of accountability refers to the question of who should be held morally (and legally, if necessary) responsible when unacceptable behaviour is demonstrated (Floridi, 2021). Accountability is fundamentally related to giving people autonomy of action via knowledge, empowering all stakeholders to own their data and influence how they are interpreted and shared (Porayska-Pomsta & Rajendran, 2019, p. 42). The ethics-based theory of accountability defines it as a social setting and a process of social negotiation. Rules and moral codes may be amended to adapt to the changes and needs occurring within individual stakeholder groups, as well as to changes in our understanding of our socio-economic and scientific environments. Therefore, accountability is established as a relational phenomenon, with multiple and often conflicting expectations, priorities and investments from different stakeholders, as well as temporal shifts in who is accountable, when and for what (ibid.).

The accountability dimension has also been discussed by specific LA researchers, although it has received scant attention from the MMLA community. Based on the legal requirements of the General Data Protection Regulation (GDPR), Hoel et al. (2017) developed a requirements list for LA systems, arguing that educational institutions should demonstrate their ability to protect the data of their users and prevent any breaches of the system in order to reinforce their accountability. Furthermore, Knight et al. (2017) stated that algorithmic accountability in LA is growing, requiring complex analyses of analytics devices. In their research, Gibson and Lang (2018) stressed that it is problematical to assess the quality and accountability of LA in general; therefore, the Pragmatic Inquiry for Learning Analytics Research (PILAR) method was developed to tackle a few quality and accountability issues related to LA research in general. Nevertheless, whether these general guidelines can be contextualised within MMLA research and how they can be developed to become more meaningful for the MMLA community, remain significant research questions that still need to be answered.

Fairness, unfairness and bias: The fairness of algorithm-based decision making is described by Mehrabi et al. (2022) as the absence of discrimination or favouritism directed at individuals or groups on the basis of inherent or acquired characteristics. Algorithmic fairness in education reveals the bias and discrimination caused by algorithmic systems in educational settings (Kizilcec & Lee, 2021). It focuses on how discrimination occurs in algorithmic systems and how it can be mitigated by considering three key steps in the development process: measurement (data input), model learning (algorithm), and action (presentation or use of output) (ibid.). In agreement with Kizilcec and Lee (2021), individual fairness implies that algorithmic decisions should be the same for identical pairs of individuals that are close according to the task-specific distance metric, while group-level fairness reflects the idea of distributing scarce educational resources equably among various groups of students.

The notions of fairness we choose for a particular application depend on what we and those we include in the design process consider to be the most salient (Holstein & Doroudi, 2021). Similarly, therefore, unfairness may be defined as the dominant moral attribute of social bias (Metcalf, 2019). Unfairness in an algorithm occurs when its decisions are biased in favour of one particular group of people, i.e., cases in which AI/ML systems perform differently for different groups in a manner that might be deemed undesirable (Mehrabi et al., 2022; Holstein et al., 2019).

Within the context of fairness, it is also imperative to consider and define the concept of bias. In general, bias refers to the tendency of people to stereotype events, groups or individuals (Cardwell, 1999). Several types of bias exist, including moral, legal and statistical (Danks & London, 2017). In a technical or statistical sense, however, bias denotes the gulf between a model and reality, which represents a methodological error. A statistical bias occurs when a model departs from the world it is meant to describe, often as a result of incorrect estimation of population parameters.

Statistical bias differs from social bias in that it usually does not result in social acceptance; noticeably, it is a morally neutral assessment of a model's effectiveness (ibid.). Since ML is a statistical inference tool, algorithmic bias is often referred to as statistical bias (Holmes & Porayska-Pomsta, 2023). In keeping with Baker (2023), an algorithmic bias is a situation when particular sub-groups of a population are disadvantaged by the algorithm in comparison to others. This signifies that the predictions and recommendations resulting from the algorithm can result in particular individuals being subjected to harm even when the outcomes are generally positive. The reduction of algorithmic bias in education necessitates having access to data on the demographic characteristics of students and retaining the data for an adequate period of time to determine student outcomes (ibid.). Moreover, according to researchers investigating algorithmic fairness, bias is regularly regarded as unfair discrimination, in that it represents a negative consequence of ML that unfairly discriminates against particular groups or individuals. It can also be described as the biases that are inherent in a system and its data, which might be intentional or unintentional (Cramer et al., 2018).

Conversely, Metcalf (2019) described social bias as the unfair judgement of a person or a group of people. The central question regarding social bias lies in the assessment of the unfairness of bias, which implies principled opposition to bias and an evaluation of the material consequences of widespread prejudice. Therefore, bias is a morally significant attribute of unfairness. Addressing issues of societal bias may require adjusting data collection processes or manually incorporating an understanding of the bias into the model building process (Mitchell et al., 2021).

A major source of algorithmic bias is considered to be the data introduced during the sampling, pre-processing, cleaning and labelling, or through the data collection method. Therefore, AI researchers and designers must evaluate their decisions in light of ethical considerations at each stage of the process (Holmes & Porayska-Pomsta, 2023). These processes in the ML development pipeline are the same as those included in the design and development of MMLA. Hence, ethical considerations of decisions taken at each stage should also be carefully considered in relation to MMLA settings.

Learning measurements might also be affected by participants' varied backgrounds, resulting in bias and unfairness in an educational system. Likewise, learning measurements using MMLA systems designed for a particular group may not be applicable to other groups (Milligan, 2018). When designing learning analytics systems, it is crucial to provide algorithms that are equitable to different student populations, as argued by Doroudi and Brunskill (2019). Moreover, while knowledge-tracing algorithms are thought to be equitable for some populations of students, they can still be unfair to others (e.g., preferring fast learners over slow learners). Similarly, Verbert et al. (2020) stress the importance of addressing challenges surrounding the ethical implications of predictive systems (and bias in general) in LA research. In that context, the ability to visualise the MMDs used in prediction models could aid end-users in better understanding the assumptions made by the models and detecting biases. In terms of the training of MMLA models, data variety and large-scale data collection are critical as the fairness of the systems may be affected by many factors, such as race and gender. However, it may be difficult to collect and collate data on sensitive constructs with the intention of measuring the algorithmic fairness of MMLA systems.

As summarised above, the AI and LA research communities have focused their attention on several key aspects with respect to ethics. However, in MMLA research, it remains uncertain how similar considerations should be taken into account and contextualised.

Equality and equity: Equality and equity are two concepts that are commonly linked to fairness in education (Kizilcec & Lee, 2021). As part of AIED, educational equity might be defined as narrowing achievement gaps between different groups of learners, for example, by extensively scaling up the benefits of one-to-one tutoring to a broader audience or by filling educational service gaps (Holstein & Doroudi, 2021). Innovations achieve equality in their impact if they are equally beneficial to all groups regardless of their pre-existing outcomes (constant gap). However, to attain equity, the impact of the innovation must benefit the groups with lower baseline outcomes more, thus closing pre-existing gaps (Kizilcec & Lee, 2021).

Even in cases where teams explicitly design technologies to support underserved populations, if the design process is not guided by representative voices from those populations, the resulting technologies may fail to serve the needs of those populations or may even amplify existing equity gaps (Holstein & Doroudi, 2021). There is a mounting awareness that current AI systems tend to expose and magnify social inequalities and injustice more frequently because of the sociocultural biases reflected in the data that they consume (Porayska-Pomsta & Rajendran, 2019, p. 40). This will also make those AI models unfair. These prejudices could stem from societal prejudices related to gender, race or ethnicity, for instance police records showing that young black males commit more crimes. Furthermore, these biases may be the result of the limited amount of data representing society in general, or they may be the outcome of the specific classification algorithm applied (ibid.).

AIED systems can be examined by means of four specific lenses to better understand how and why they may increase the risk of inequalities: (1) factors inherent in the overall socio-technical design, (2) the use of datasets that reflect historical inequalities, (3) factors inherent in the underlying algorithms used to drive ML and automated decision making, and (4) factors that emerge from an intricate and dynamic interaction between automated and human decision-making (Holstein & Doroudi, 2021). A significant source of inequality in AIED technologies stems from disparities with respect to access, as technology is more accessible to certain groups of learners than others (Holstein & Doroudi, 2021). Unless AIED technologies are explicitly designed with accessibility in mind, they risk accelerating learning for some groups of learners, while inhibiting it for others (Holstein & Doroudi, 2021). Supporting impartiality entails understanding learners' experiences based on three constructs: coherence, relevance and contribution (Penuel et al., 2018). Mayfield et al. (2019) recommend preventing expenditure on research that maintains inequality as opposed to closing achievement gaps amongst student populations.

Trustworthiness: According to Jain et al. (2020), in the field of AI, the term "trustworthy AI" is used to describe AI that is lawful, ethically compliant and technically robust. Basically, trustworthiness in this area is based upon the belief that AI can achieve its full potential, while trust can be established during every stage of a system's existence, from design to development through to utilisation.

The development of a trustworthy AI system needs to examine the behaviours of the system prior to interpreting its results. One of the ways to promote trust is by way of transparency (Floridi & Taddeo, 2016). According to research, increased transparency in AI systems may improve user trust rather than reduce it, at least when combined with meaningful options for user control (Lee & Baykal, 2017). Moreover, explainability is also a key factor in building and maintaining trust among users of AI systems. A transparent process must govern the operation of AI and the purpose of the AI system, whilst the decisions it produces must be understandable to all those affected, either directly or indirectly (Jain et al., 2020). Therefore, to increase user trust both transparency and explainability have been recommended (Robert et al., 2020).

It is also important to consider the role of users' expectations when examining system output, as this may indicate a bell-shaped relationship between transparency and trust. Kizilcec (2016) ascertained that violations of expectations can lead to reduced trust in peer assessments in an online course. It was also established that interface transparency moderated this effect, to such an extent that providing a degree of transparency with procedural information promoted trust. However, providing additional information concerning outcomes nullified this effect, implying that cognitive overload may negatively influence the beneficial effects of transparency (ibid.).

The importance of ethical considerations in the use of MMLA tools in education may be derived from the fact that each of the above-mentioned issues can also potentially arise when using MMLA tools in real-world educational settings, placing students at risk of harm. In addition, the highly granular, temporal and synthesised nature of the MMD used in MMLA systems signifies that the interpretation and discussion of these ethical technology dimensions is even more challenging. It is imperative to address the ethical issues in MMLA due to the fact that this field is relatively new. By doing so, researchers and practitioners in the field will become fully aware of the potential challenges before the scaled commercial implementation of MMLA. Nonetheless, at present, ethical issues related to MMLA are rarely addressed by MMLA researchers (Alwahaby et al., 2022).

Additionally, the focus of LA researchers has long been on the collection and analysis of unimodal data generated from digital learning environments, essentially using logs and keystrokes as quantitative data sources (Mangaroska & Giannakos, 2019). Therefore, most existing initiatives have fallen short of covering discussions concerning the use of sensing technology to collect MMD generated from the physical world (e.g., eye gaze, heart rate, EEGs, galvanic skin response, face recognition or body movements), while the associated data privacy and ethical concerns are only heightened when MMD are included (Worsley et al., 2021). Martinez-Maldonado, Echeverria et al. (2020) contend that in comparison with abstracted clickstream data, sensor data, such as physiology, posture, gaze and movement, have a personal dimension and unexpected information unrelated to learning tasks, for instance daily life or personal habits, might be easily revealed (Kröger, 2018). Moreover, MMD in facial recognition analysis can consist of data such as facial expressions, placing users in danger of bias because of their personal characteristics (Xu et al., 2020). Therefore, MMLA is even more susceptible to ethical issues, which this research aims to highlight.

2 Chapter Two: Literature Review

2.1 Introduction

The aim of this chapter is to identify relevant MMLA literature by conducting a systematic literature review (SLR), which focuses on addressing the research questions set out in the previous chapter. It will also review significant research related to MMLA in education, as well as the ethical issues related to the use of MMLA. This chapter comprises several sections, including a discussion of the strategy used for the literature search, the importance of MMD in education, and the ethical considerations highlighted and addressed in MMLA research. Finally, it explores the weaknesses and strengths of the existing frameworks in relevant fields such as AI and LA.

2.2 Search Strategy

To achieve the aim of this research, an SLR was conducted. Part of the resulting review has already been included in a published paper (Alwahaby et al., 2022). Subsequently, the search was updated regularly to include papers published up to February 2024.

The SLR was conducted to identify relevant literature with a focus on addressing the research questions guiding this research and searching for existing research that will be beneficial to MMLA in education and the ethical issues related to the use of MMLA. To improve the transparency of the SLR, the search was conducted according to PRISMA guidelines (Moher et al., 2009). Furthermore, to support the robustness of this research, a four-step search protocol was generated and followed. First, the protocol defined search key words and the digital libraries that needed to be explored. Second, the quality of the resulting articles was assessed and irrelevant results filtered according to the inclusion/exclusion criteria. Third, the papers that were identified in the search were analysed and coded. Fourth, the findings were reported in a review of the literature. The search comprised literature from 2010 onwards, for the reason that the fields of LA and MMLA in education have significantly progressed over the last 15 years. The search process comprised four phases which occurred in 2019, 2020, 2021 and 2024, respectively. Precisely the same protocol was followed in each phase, except for the fact that the third and fourth phases were conducted by a single researcher (the author of this thesis).

In terms of the information sources, five digital libraries were used: Scopus, Web of Science, IEEE, ACM and Google Scholar. The latter was also employed to identify relevant papers because it is considered to be the search engine that is utilised the most and it indexes the majority of digital libraries. The keywords “multimodal learning analytics” were used to undertake a search on Google Scholar. Only the top 100 results (from a total of 824) were considered following the strategy applied by similar SLRs in the field (Matcha et al., 2019; Schwendimann et al., 2017). The search focused on the use of digital sensing technology to understand the learning process. Therefore, keywords were selected based on four main concepts: data modalities, learning, tools and physical spaces. The specific keywords included the following terms (in both singular and plural forms): multimodal data, multimodal learning analytics, sensing technologies, physical spaces, gesture recognition, tangible interactions, in addition to dashboards. Terms were combined using OR, AND, and *. The final keyword searches in relation to WOS, Scopus, ACM and IEEE are presented in Appendix 1.

In the first phase (completed in December 2019), the total number of identified records was 663, with 442 remaining after removing duplications. These were subsequently screened by two reviewers with a background in learning analytics. The reviewers read the titles and abstracts to determine whether the articles were related to multimodal learning analytics in an educational context. The two researchers reviewed each of the papers separately, recommending them for inclusion or exclusion, stating applicable exclusion criteria where relevant. The reviewers were given guidelines. They discussed and agreed on what should be included or excluded, and on the interpretation of the inclusion and exclusion criteria (available in an online repository[1]).

Following the initial screening process, 298 papers were retained in the search results. After a full-text analysis, a number of papers that did not meet the inclusion criteria were excluded. For the full-text analysis, 10% of the papers (30 papers in total) were randomly selected from the included papers, and the inter-rater agreement was calculated (Cohen's Kappa = 0.73). Disagreements between the two researchers were resolved via meetings to discuss and clarify the screening criteria.

The two researchers examined papers according to the following eligibility criteria. Specifically, papers were excluded if: they were not related to MMLA; they were not related to learning and/or educational outcomes; full text was missing (extended abstracts/abstracts only, posters, demos, doctoral consortium papers etc.); they were not empirical studies (e.g., editorials, discussion and opinion papers); and they were not published in English. A final total of 71 papers were included. To incorporate papers published during the initial search and analysis period, a second search was conducted in January 2021 following the same procedure. This was carried out by the same researchers and resulted in the identification of a further 29 papers. A third search was conducted in October 2021 by a single researcher to include papers published in 2021, during which an additional 18 papers were identified. A fourth and final phase was conducted in February 2024 by a single researcher to include papers published between November 2021 and February 2024. An additional 64

[1] https://data.mendeley.com/preview/z8mwmxdbvt?a=57aa35df-2445-47a2-ba0b-9e378c1c9cf9

papers were identified during this final search. Hence, in total, 182 papers were identified during the literature search. Each of the identified papers with their inclusion and exclusion criteria can be obtained from an online repository.[1]

Next, the papers were coded according to the data modalities they utilised, the importance of MMLA in promoting the learning process, and whether or not ethical aspects had been addressed. The labelling was agreed by the two researchers. The taxonomy of modalities was adapted from a recent systematic review (Sharma & Giannakos, 2020). Based on interest in the importance of MMLA in education and the existence of an ethical discussion, a top-down approach was employed. The coding was initially performed by one researcher. Subsequently, a second researcher examined the papers again to corroborate the results. The coding process relied on explicit content rather than on interpreting the meaning behind it. Finally, the results were synthesised into a comprehensive literature review. Figure 1 below summarises the search strategy applied in this SLR.

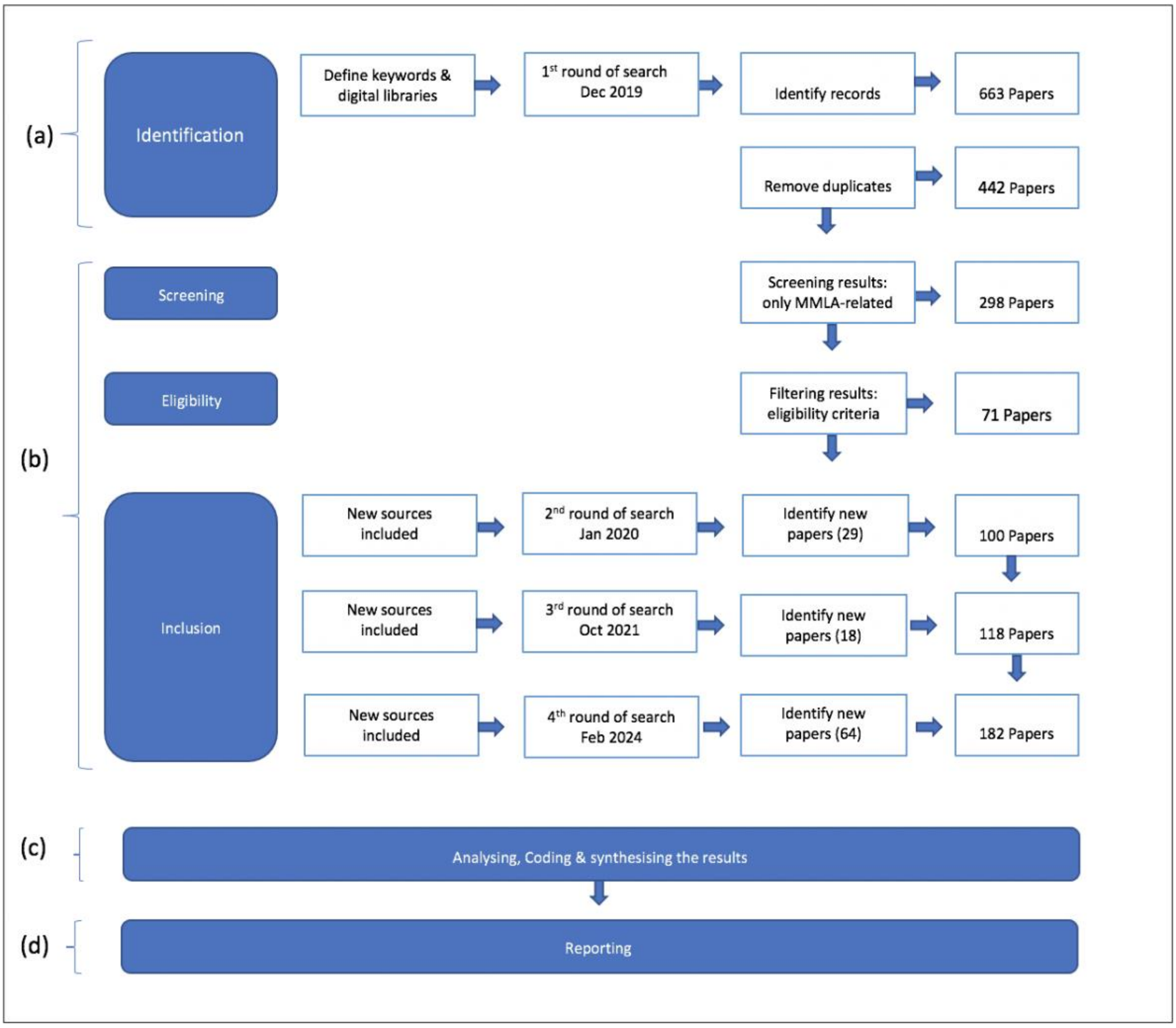


Figure 1. The methodology used in this systematic literature review

2.3 Related Work

2.3.1 The Importance of Multimodal Data in Education

Educators may encounter obstacles in identifying students' misconceptions, since it is challenging to gain access to their internal views. Therefore, researchers have been interested in collecting MMLA data as a technique for understanding and improving the learning process. Applying modern advanced sensing technology, researchers can now obtain, process, analyse and interpret MMD to augment students' learning. The following section presents an overview of the commitment that MMLA researchers have demonstrated towards improving learners' learning experiences. By examining the importance of MMLA in promoting learning processes and accelerating developments in the field, this section will provide a common understanding of the establishment of the field. Table 1 summarises studies concerning educational outcomes; Figure 2 presents the distribution of papers belonging to each educational outcome; Table 2 summarises the modalities used in the papers included, and Figure 3 presents the distribution of papers belonging to each modality category.

A review of the literature on expected educational outcomes highlights several concrete examples. The first of these is collaborative learning. Collaboration is acknowledged as one of the most valuable skills in the 21^{st} century. In addition to online collaborative learning, co-located collaboration (CC) analysis has gained increasing interest from researchers due to the advantages of using advanced sensing technologies (Praharaj et al., 2021). In this systematic review, 54 studies were identified examined collaborative learning, approximately 29% of the total number of papers (182), underlining the popularity of MMLA in collaborative learning. In a number of identified papers, audio was used as a method to assess the quality of collaborative learning (e.g., Cornide-Reyes et al., 2019; Chejara et al., 2021; Praharaj et al., 2021). In one study, a motion modality was employed to evaluate collaborative learning (Vujovic et al., 2020), while eye gaze was considered in other collaborative learning studies (Sharma, Leftheriotis et al., 2020). Gestures and postures were examined multimodally (Ezen-Can et al., 2015), while the efficacy of facial emotion recognition as a predictor of performance in a collaborative learning environment was examined by Sharma, Papavlasopoulou et al. (2021). Several papers have reported the use of location as an indicator in cooperative learning (Hsieh et al., 2010; Riquelme et al., 2020), whilst electrodermal activity (EDA) has been employed to support collaborative learning (Dindar et al., 2020).

A number of other studies have examined collaborative learning using multiple modalities (e.g., Reilly & Schneider, 2019; Cukurova et al., 2020). In addition to promoting collaborative learning, MMLAs have been extensively used to enhance other educational outcomes, including developing presentation skills (8) (e.g., Ochoa & Dominguez, 2020; Munoz et al., 2018); improving simulation-based training (15) (e.g., Martinez-Maldonado et al., 2017; Martinez-Maldonado, Echeverria, et al., 2020; Birt et al., 2019); and improving teaching practice (17) (e.g., Donnelly et al., 2016; Correa et al., 2020; Rodríguez Triana et al., 2017). Among the most important applications associated with MMLA are: predicting student knowledge in game-based learning (13) (e.g., Anderson et al., 2016; Emerson et al., 2020); supporting dancing practice (2) (Romano et al., 2019; Martinez-Maldonado et al., 2018); supporting mathematics learning (11) (e.g., Abrahamson et al., 2016; Chen et al., 2016; Oviatt et al., 2015); improving reading comprehension and writing proficiency (6) (e.g., Lai et al., 2013; Lew & Tang, 2017); supporting students' performance in coding (6) (e.g., Papavlasopoulou et al., 2018; Mangaroska et al., 2020); studying students' engagement to predict effective learning practices (8) (e.g., Ashwin & Guddeti, 2019; Emerson et al., 2020); supporting the learning of a second language (2) (Chen et al., 2016; Beardsley et al.); improving online and distance learning (6) (e.g., Deshmukh et al., 2018; Yueh et al., 2014); increasing the quality of design and learning results in hands-on engineering tasks (3) (Worsley & Blikstein, 2018; Worsley & Blikstein, 2015; Worsley et al., 2015); developing adaptive assessment (2) (Sharma et al., 2019; Sharma et al., 2020); developing student comprehension of chemistry (1) (Liu et al., 2019); increasing social interaction (2) (Yan et al., 2021; Saquib et al., 2018); debating tutoring improvement (1) (Cukurova et al., 2019); reducing the physical and mental load on elderly learners (1) (Tamura et al., 2019); supporting learners with profound intellectual and multiple learning disabilities (PMLDs) and students with special education needs (2) (Boulton et al., 2018; Chan et al., 2023); improving problem-solving skills (3) (Sinha, 2021; Mangaroska, Martinez-Maldonado et al., 2021; Mangaroska, Sharma et al., 2021.; examining the influence of emotions on learning outcomes (1) (Ahn & Harley, 2020); enhancing students' concentration (1) (Srivastava et al., 2021); predicting academic achievement (2) (Chango et al., 2019; Yan, Martinez-Maldonado, Zhao, Deppeler et al., 2022.; identifying effective learning practices (1) (Worsley, 2018); understanding students' learning trajectory (1) (Andrade, 2017); discovering relevant predictors of learning (1) (Schneider & Blikstein, 2015); boosting learning performance by way of physiological responses (8) (e.g., Liu et al., 2018; Peng & Nagao, 2021; Ciolacu & Svasta, 2021; Su et al., 2013); and predicting changes in user attention (1) (Sharma, Mangaroska et al., 2021).

Table 1. Overview of studies in terms of their educational outcomes

Educational outcomes	References
Supporting collaborative learning (54)	Cornide-Reyes et al., 2019; Riquelme et al., 2019; Noel et al., 2018; Praharaj et al., 2018; Cornide-Reyes et al., 2020; Chejara et al., 2020; Chejara et al., 2021; Praharaj et al., 2021; Vujovic et al., 2020; Sharma, Leftheriotis et al., 2020; Ezen-Can et al., 2015; Sharma, Papavlasopoulou et al., 2021; Hsieh et al., 2010; Riquelme et al., 2020; Dindar et al., 2020; Huang et al., 2019; Reilly & Schneider, 2019; Schneider, 2019; Noroozi et al., 2019; Spikol et al., 2018; Martinez-Maldonado et al., 2019; Olsen et al., 2020; Järvenoja et al., 2020; Vrzakova et al., 2020; Cukurova et al., 2020; Spikol, Ruffaldi, Landolfi et al., 2017; Spikol, Ruffaldi & Cukurova, 2017; Nakano et al., 2015; Shankar et al., 2023; Monsalves Cabello et al., 2023; Chejara et al., 2023; Zhou & Kang, 2023; Järvelä et al., 2023; Schneider & Bryant, 2024; Buseyne et al., 2023; Yan et al., 2023; Chejara et al., 2023; Ma et al., 2022; Xu et al., 2023; Fahid et al., 2023; Noël et al., 2022; Ma et al., 2022; Praharaj et al., 2022; Lewis et al., 2023; Li et al., 2023; Tang et al., 2022; Lopez et al., 2021; Miranda et al., 2022; Martinez-Maldonado et al., 2024; Feng et al., 2021; Hakami et al., 2022; Zhou et al., 2023; Vatral et al., 2022; Lin et al., 2023.
Developing presentation skills (8)	Ochoa & Dominguez, 2020; Munoz et al., 2018; Barmaki, 2015; Barmaki & Hughes, 2015; Roque et al., 2019; Ochoa et al., 2018; Vieira et al., 2021; Dominguez et al., 2021.
Improving simulation-based training (15)	Martinez-Maldonado et al., 2017; Martinez-Maldonado et al., 2018; Martinez-Maldonado et al., 2020; Birt et al., 2019; Vatral et al., 2022; Yan, Martinez-Maldonado, Zhao, Dix et al., 2022; Zhao et al., 2022; Vatral et al., 2023; Zhao et al., 2023; Martinez-Maldonado, Elliott et al., 2020; Fernandez-Nieto et al., 2021; Zhao et al., 2024; Vatral et al., 2022; Ng et al., 2022.
Improving teachers' teaching practice (17)	Donnelly et al., 2016; Martinez-Maldonado, Mangaroska et al., 2020; Correa et al., 2020; Eickholt, 2020; Prieto et al., 2018; Prieto et al., 2016; Barmaki & Hughes, 2018; Rodríguez Triana et al., 2017; Martinez-Maldonado et al., 2018; Keskinarkaus et al., 2016; Howard et al., 2019; Jensen et al., 2021; Schlotterbeck et al., 2021; Xiao et al., 2023; Huang et al., 2023; Yan, Martinez-Maldonado, Gallo Cordoba, Deppeler et al., 2022; Wang et al., 2024.
Predicting students' knowledge in game-based learning (13)	Anderson et al., 2016; Emerson et al., 2020; Larmuseau et al., 2020; Lee-Cultura Sharma, Papavlasopoulou et al., 2020; Sharma, Niforatos et al., 2020; Lee-Cultura, 2020; Martin et al., 2019; Giannakos et al., 2019; Gomes et al., 2013; Chen, 2021; Emerson et al., 2023; Henderson et al., 2021; Giannakos et al., 2021.
Supporting dancing practice (2)	Romano et al., 2019; Maldonado et al., 2018.
Supporting mathematics learning (11)	Alyuz et al., 2017; Abrahamson et al., 2016; Chen, Li et al., 2016; Oviatt et al., 2015; Oviatt & Cohen, 2013; Ochoa et al., 2013; Oviatt, 2013; Luz, 2013; Liu et al., 2019; Oviatt et al., 2021; Chen et al., 2021 .
Improve reading performance, comprehension and writing ability (6)	Lai et al., 2013; Huang et al., 2014; Lew & Tang, 2017; Hwang et al., 2011; Zheng et al., 2022; Li et al., 2024.
Supporting students' performance in coding (6)	Papavlasopoulou et al., 2018; Mangaroska et al., 2020; Sharma et al., 2021; Mangaroska, Sharma et al., 2021; Yusuf et al., 2024; Tisza et al., 2022.

Studying students' engagement to predict effective learning practices (8)	Ashwin & Guddeti, 2019; Tan et al., 2020; Emerson et al., 2020; Camacho et al., 2020; Papamitsiou et al., 2020; Vail et al., 2014; Pijeira-Díaz et al., 2018; Acosta et al., 2021.
Supporting the learning of a second language (2)	Chen et al., 2016; Beardsley et al., 2018.
Improving online / distance learning (6)	Deshmukh et al., 2018; Yueh et al., 2014; Junokas et al., 2018; Kawamura et al., 2021; Ciordas-Hertel et al., 2021; Ciordas-Hertel et al., 2022; Becerra et al., 2023.
Improving the quality of design and learning results in hands-on engineering tasks (3)	Worsley & Blikstein, 2018; Worsley & Blikstein, 2015; Worsley et al., 2015.
Enhancing adaptive assessment (2)	Sharma, Papamitsiou et al. 2020; Sharma et al., 2019.
Improving students' comprehension in Chemistry (1)	Liu et al., 2019.
Enhancing social interaction (2)	Saquib et al., 2018; Yan et al., 2021.
Discussing improving tutoring (1)	Cukurova et al., 2019.
Reducing the physical and psychological load on elderly learners (1)	Tamura et al., 2019.
Supporting students with profound intellectual and multiple learning disabilities (PMLDs) / students with special educational needs (2)	Boulton et al., 2018; Chan et al., 2023.
Improve problem-solving skills (3)	Sinha, 2021; Mangaroska, Martinez-Maldonado et al., 2021; Mangaroska, Sharma et al., 2021.
Examining the influence of emotions on learning outcomes (1)	Ahn & Harley, 2020.
Improving the attention of learners (1)	Srivastava et al., 2021.
Identify effective learning practices (1)	Worsley, 2018.
Understanding students' learning trajectory (1)	Andrade, 2017.
Discovering relevant predictors of learning (1)	Schneider & Blikstein, 2015 .
Predicting / Enhancing learning performance through physiological responses (8)	Liu et al., 2018; Peng & Nagao, 2021; Ciolacu & Svasta, 2021; Su et al., 2013; Sung et al., 2023; Alfredo et al., 2023; Ba et al., 2022; Sharma et al., 2022.
Predicting changes in user attention (1)	Sharma, Mangaroska et al., 2021.
Predicting students' academic achievement (2)	Chango et al., 2019; Yan, Martinez-Maldonado, Zhao, Deppeler et al., 2022.

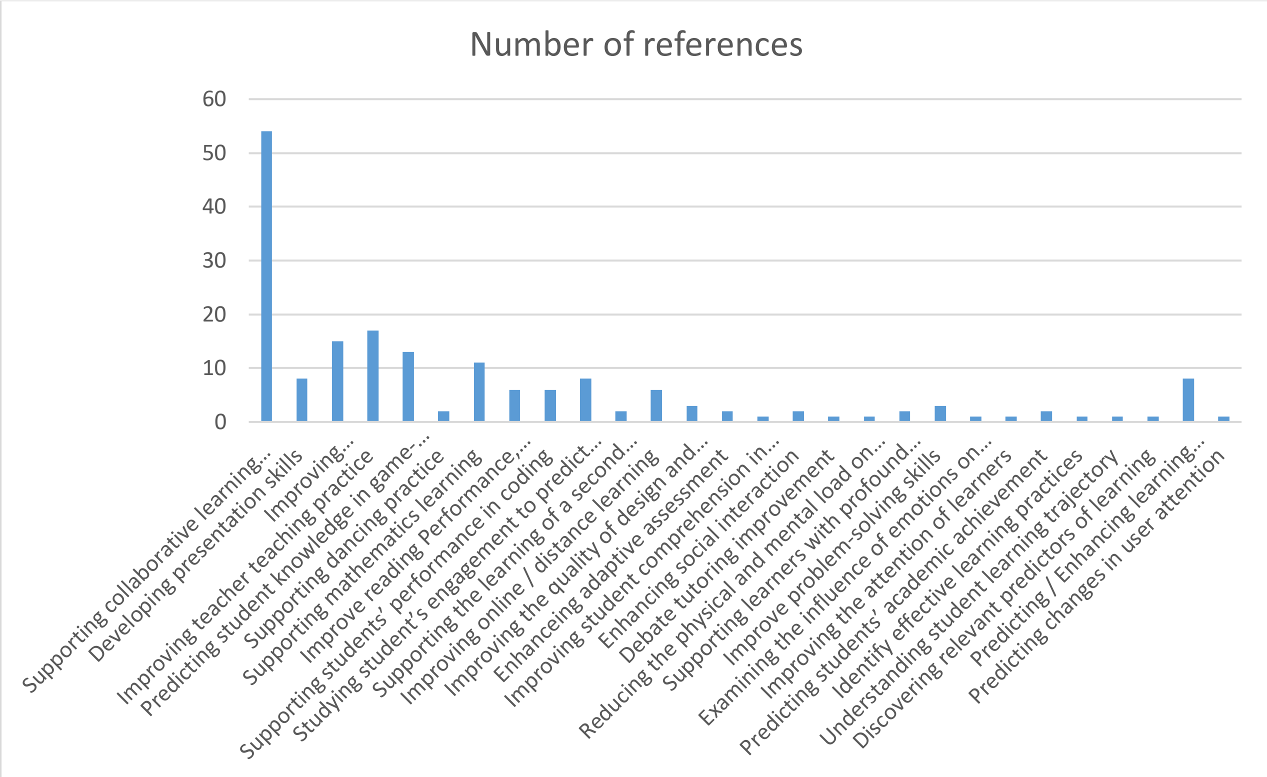


Figure 2. The distribution of papers related to each learning outcome

Table 2. Overview of studies in terms of their modality

Modality	Measurements	References
Video and audio	Presenter's pose, gaze direction, visual attention	Andrade, 2017; Boulton et al., 2018; Cornide-Reyes et al., 2019; Huang et al., 2014; Chen et al., 2016; Chen et al., 2016; Ochoa & Dominguez, 2020; Ochoa et al., 2018; Su et al., 2013; Tamura et al., 2019; Tan et al., 2020; Worsley et al., 2015; Hassan et al., 2021; Lin et al., 2023; Yusuf et al., 2024; Fahid et al., 2023; Noël et al., 2022; Lewis et al., 2023; Becerra et al., 2023; Zhou et al., 2023; Ma et al., 2022; Chen et al., 2021; Lopez et al., 2021; Dominguez et al., 2021; Vatral et al., 2022.

	Audio, characteristics of the dialogue	Anderson et al., 2016; Boulton et al., 2018; Chejara et al., 2020; Cornide-Reyes et al., 2020; Cukurova et al., 2019; Donnelly et al., 2016; Eickholt, 2020; Howard et al., 2019; Järvenoja et al., 2020; Keskinarkaus et al., 2016; Chen et al., 2016; Luz, 2013; Liu et al., 2019; Liu et al., 2018; Martinez-Maldonado et al., 2017; Martinez-Maldonado et al., 2019; Martinez-Maldonado, Elliot et al., 2020; Nakano et al., 2015; Noel et al., 2018; Ochoa & Dominguez, 2020; Ochoa et al., 2013; Ochoa et al., 2018; Olsen et al., 2020; Oviatt & Cohen, 2013; Oviatt et al., 2015; Oviatt, 2013; Praharaj et al., 2018; Prieto et al., 2018; Riquelme et al., 2019; Sharma et al., 2020; Spikol, Ruffaldi, Landolfi et al., 2017; Spikol, Ruffaldi & Cukurova, 2017; Vrzakova et al., 2020; Worsley & Blikstein, 2018; Worsley et al., 2015; Worsley, 2018; Yueh et al., 2014; Praharaj et al., 2021; Peng & Nagao, 2021; Oviatt et al., 2021; Chejara et al., 2021; Jensen et al., 2021; Schlotterbeck et al., 2021; Chen, 2021; Lin et al., 2023; Monsalves Cabello et al., 2023; Zhou & Kang, 2023; Vatral et al., 2022; Buseyne et al., 2023; Zhao et al., 2022; Vatral et al., 2023; Xu et al., 2023; Noël et al., 2022; Ma et al., 2022; Praharaj et al., 2022; Lewis et al., 2023; Chejara et al., 2023; Martinez-Maldonado et al., 2024; Vatral et al., 2022; Vatral et al., 2022; Zhao et al., 2023; Hakami et al., 2022; Huang et al., 2023; Chejara et al., 2023; Chen et al., 2021; Martinez-Maldonado et al., 2022; Lopez et al., 2021; Gong et al., 2021; Fernandez-Nieto et al., 2021; Miranda et al., 2022; Dominguez et al., 2021; Vatral et al., 2022; Ge et al., 2021.
	Facial data and emotions	Lin et al., 2023; Alyuz et al., 2017; Ashwin & Guddeti, 2019; Boulton et al., 2018; Deshmukh et al., 2018; Emerson et al., 2020; Emerson et al., 2020; Giannakos et al., 2019; Chen et al., 2016; Järvenoja et al., 2020; Keskinarkaus et al., 2016; Chen et al., 2016; Lee-Cultura, Sharma & Giannakos, 2020; Lee-Cultura, Sharma, Papavlasopoulou et al., 2020; Mangaroska et al., 2020; Martin et al., 2019; Liu et al., 2018; Papamitsiou et al., 2020; Sharma et al., 2020; Sharma, Papamitsiou et al., 2020; Vail et al., 2014; Worsley et al., 2015; Yueh et al., 2014; Peng &

		Nagao, 2021; Hassan et al., 2021; Sharma, Papavlasopoulou et al., 2021; Sinha, 2021; Kawamura et al., 2021; Srivastava et al., 2021; Lin et al., 2023; Mangaroska, Martinez-Maldonado et al., 2021; Mangaroska, Sharma et al., 2021; Xu et al., 2023; Fahid et al., 2023; Tisza et al., 2022; Henderson et al., 2021; Acosta et al., 2021; Xiao et al., 2023; Emerson et al., 2023; Gong et al., 2021; Ma et al., 2022 .
	Posture and gesture, body movement, distance, motion, position	Andrade, 2017; Ashwin & Guddeti, 2019; Correa et al., 2020; Cukurova et al., 2020; Howard et al., 2019; Keskinarkaus et al., 2016; Ochoa et al., 2013; Oviatt & Cohen, 2013; Oviatt et al., 2015; Oviatt, 2013; Spikol et al., 2018; Spikol, Ruffaldi, Landolfi et al., 2017; Spikol, Ruffaldi & Cukurova, 2017; Tamura et al., 2019; Vrzakova et al., 2020; Vujovic et al., 2020; Hassan et al., 2021; Oviatt et al., 2021; Wang et al., 2024; Vatral et al., 2022; Järvelä et al., 2023; Yusuf et al., 2024; Shoukry et al., 2022; Shankar et al., 2023; Gong et al., 2021; Miranda et al., 2022.
Eye-tracking	Students' concentration level, visual attention and behaviour	Abrahamson et al., 2016; Ahn & Harley, 2020; Emerson et al., 2020; Emerson et al., 2020; Giannakos et al., 2019; Gomes et al., 2013; Huang et al., 2019; Lee-Cultura, Sharma & Giannakos, 2020; Lee-Cultura, Sharma, Papavlasopoulou et al., 2020; Mangaroska et al., 2020; Olsen et al., 2020; Papamitsiou et al., 2020; Prieto et al., 2018; Reilly & Schneider, 2019; Schneider, 2019; Sharma et al., 2019; Sharma, Papamitsiou et al., 2020; Tamura et al., 2019; Mangaroska et al., 2021; Sharma, Papavlasopoulou, et al., 2021; Mangaroska et al., 2021 Srivastava et al., 2021; Mangaroska et al., 2021; Acosta et al., 2021; Zheng et al., 2022; Giannakos et al., 2021; Xiao et al., 2023; Li et al., 2024; Ng et al., 2022; Emerson et al., 2023.
	Learners' gaze in off-screen activity	Nakano et al., 2015; Papavlasopoulou et al., 2018; Prieto et al., 2016; Sharma, Leftheriotis et al., 2020; Vatral et al., 2022; Mangaroska, Sharma et al., 2021; Vatral et al., 2023; Schneider & Bryant, 2024.

Skin sensing	Students' physiological data, arousal and EDA	Dindar et al., 2020; Giannakos et al., 2019; Hwang et al., 2011; Chen et al., 2016; Järvenoja et al., 2020; Huang et al., 2019; Lee-Cultura, Sharma & Giannakos, 2020; Lee-Cultura, Sharma Papavlasopoulou et al., 2020; Lew & Tang, 2017; Liu et al., 2018; Mangaroska et al., 2020; Martinez-Maldonado et al., 2018; Martinez-Maldonado, Echeverria et al., 2020; Martinez-Maldonado, Elliott et al., 2020; Noroozi et al., 2019; Papamitsiou et al., 2020; Pijeira-Díaz et al., 2018; Reilly & Schneider, 2019; Schneider, 2019; Sharma et al., 2020; Tamura et al., 2019; Worsley & Blikstein, 2015; Worsley & Blikstein, 2018; Worsley et al., 2015; Peng & Nagao, 2021; Ciolacu & Svasta, 2021; Kawamura et al., 2021; Mangaroska, Sharma et al., 2021; Järvelä et al., 2023; Mangaroska, Martinez-Maldonado et al., 2021; Sung et al., 2023; Nguyen et al., 2023; Tisza et al., 2022; Alfredo et al., 2023; Ba et al., 2022; Sharma et al., 2022; Martinez-Maldonado et al., 2024; Chan et al., 2023; Giannakos et al., 2021; Becerra et al., 2023; Schneider & Bryant, 2024; Zhao et al., 2023; Martinez-Maldonado et al., 2022; Fernandez-Nieto et al., 2021; Ge et al., 2021.
	Students' cognitive load	Larmuseau et al., 2020; Sharma et al., 2020;.
In-depth camera (a type of camera used to capture three-dimensional (3D) spatial information in relation to a learner's physical movements)	Posture and gesture	Barmaki & Hughes, 2015; Barmaki & Hughes, 2018; Barmaki, 2015; Boulton et al., 2018; Emerson et al., 2020; Ezen-Can et al., 2015; Huang et al., 2019; Junokas et al., 2018; Lee-Cultura, Sharma & Giannakos, 2020; Lee-Cultura, Sharma, Papavlasopoulou et al., 2020; Martinez-Maldonado et al., 2017; Martinez-Maldonado et al., 2019; Munoz et al., 2018; Romano et al., 2019; Roque et al., 2019; Schneider & Blikstein, 2015; Schneider, 2019; Spikol et al., 2018; Vail et al., 2014; Worsley & Blikstein, 2015; Worsley & Blikstein, 2018; Worsley et al., 2015; Worsley, 2018; Vieira et al., 2021; Srivastava et al., 2021; Acosta et al., 2021; Giannakos et al., 2021; Schneider & Bryant, 2024.

Location sensing	Location, position, duration and movement	Camacho et al., 2020; Eickholt, 2020; Hsieh et al., 2010; Liu et al., 2018; Martinez-Maldonado et al., 2018; Martinez-Maldonado, Echeverria et al., 2020; Martinez-Maldonado, Elliott et al., 2020; Martinez-Maldonado, Mangaroska et al., 2020 ; Prieto et al., 2016; Prieto et al., 2018; Reilly & Schneider, 2019; Riquelme et al., 2020; Saquib et al., 2018; Yan et al., 2021; Zhao et al., 2022; Martinez-Maldonado et al., 2022; Li et al., 2023; Martinez-Maldonado et al., 2024; Zhao et al., 2023; Yan et al., 2023; Ciordas-Hertel et al., 2021; Fernandez-Nieto et al., 2021. Yan, Martinez-Maldonado, Zhao, Deppeler et al., 2022; Yan, Martinez-Maldonado, Zhao, Dix et al., 2022; Yan, Martinez-Maldonado, Gallo Cordoba, Deppeler et al., 2022.
Pressure sensing	Sitting position	Hwang et al., 2011; Su et al., 2013; Kawamura et al., 2021.
EEG sensor	EEG data, brain activity	Beardsley et al., 2018; Giannakos et al., 2019; Papamitsiou et al., 2020; Prieto et al., 2016; Sharma et al., 2019; Sharma, Papamitsiou et al., 2020; Tamura et al., 2019; Sharma, Papavlasopoulou et al., 2021; Mangaroska, Martinez-Maldonado et al., 2021; Mangaroska, Sharma et al., (2021); Xiao et al., 2023; Tang et al., 2022; Feng et al., 2021.

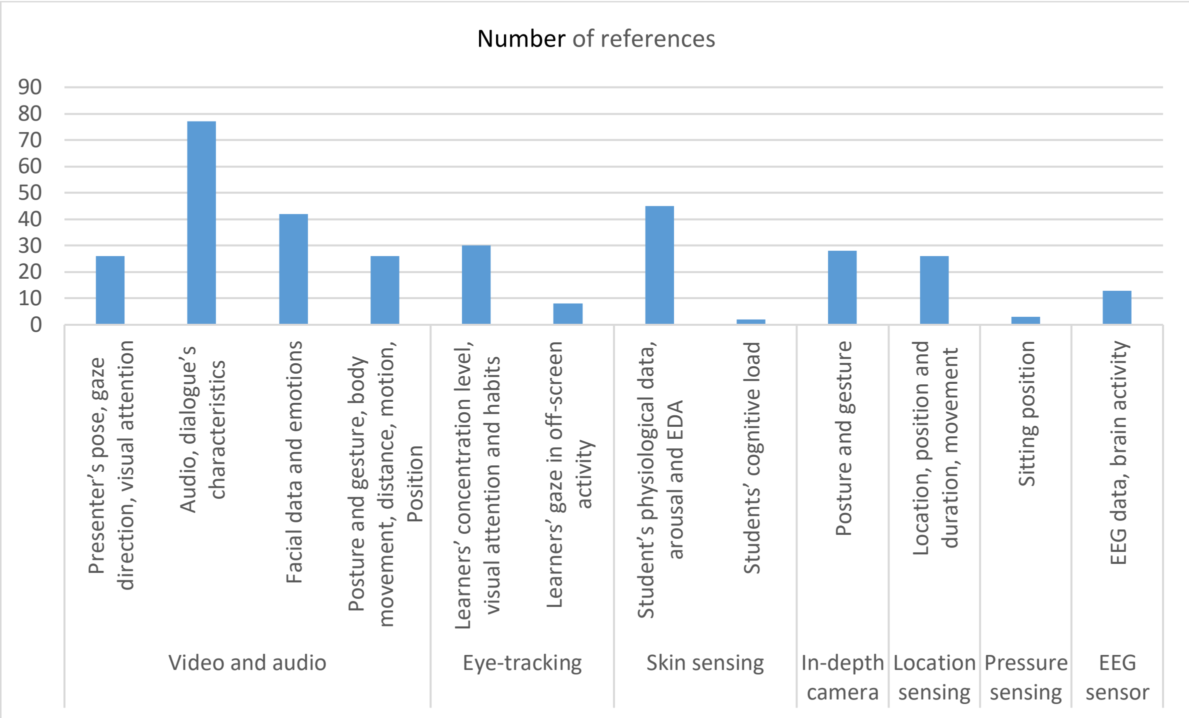


Figure 3. The distribution of papers belonging to each modality

2.3.2 Ethical Considerations in MMLA Research Highlighted and Addressed

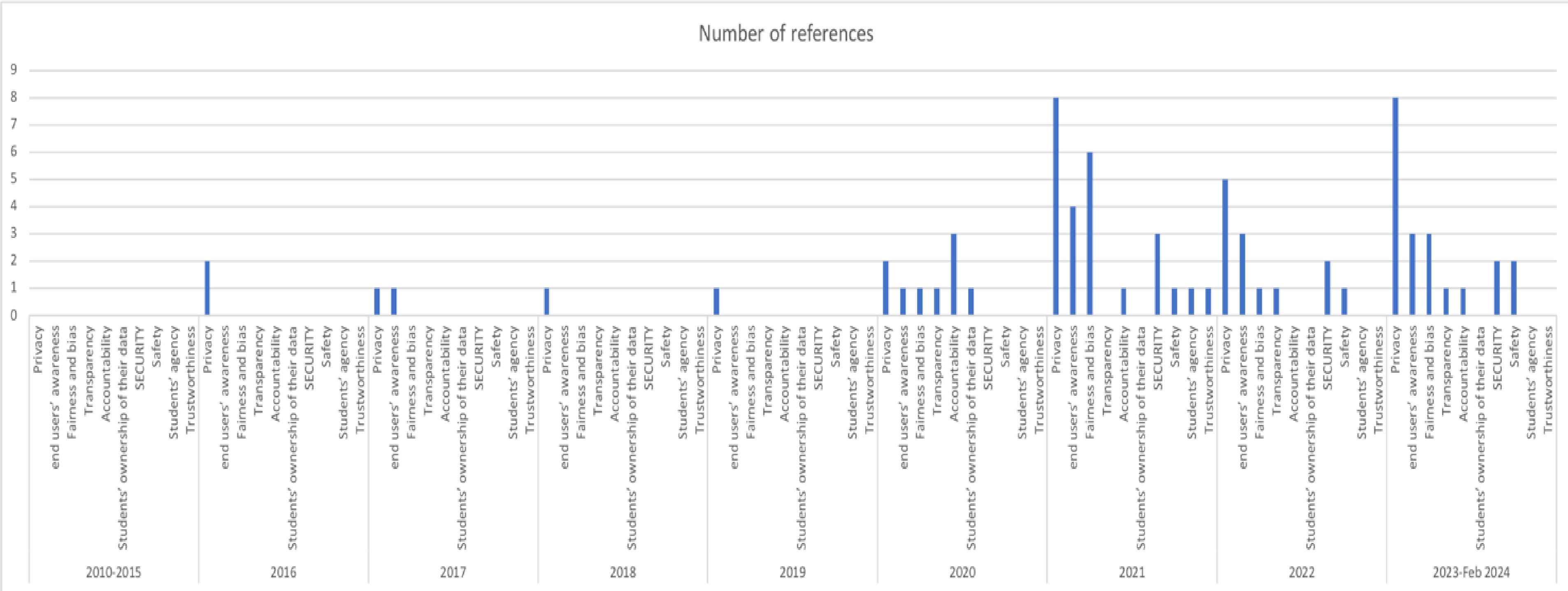
This section will address the second part of the first research question, focusing on the extent of the ethical discussion within the identified papers concerning the possible issues that might emerge with the use of MMLA tools in education. Figure 4 presents the ethical considerations highlighted in the MMLA papers. In the systematic review, 42 papers were identified that dealt with these issues. However, most of the MMLA studies reviewed primarily focused on MMLA ethics in terms of *privacy and data anonymisation*.

Privacy: Several attempts have been made to minimise privacy concerns. For example, Keskinarkaus et al. (2016) recommend processing video and audio recordings anonymously, allowing them to be shared and used during group discussions while maintaining student privacy. However, their paper did not address the potential consequences of these decisions. To analyse the cooperation of small groups, Martinez-Maldonado et al. (2019) asserted that strategies for gaining consent for recording should be established in order to account for issues relating to confidentiality and ethics. Similarly, Rodriguez Triana et al. (2017) expressed concerns pertaining to privacy and user traceability, noting that the GDPR regulations may ultimately result in technologies producing only anonymous data. Martinez-Maldonado et al. (2018) suggested that the ethical issues associated with the use of MMLA should be further explored. According to Martinez-Maldonado et al. (2017), to develop sustainable strategies to address consent, privacy and data management issues without extending classroom time, it is imperative to discuss consent, privacy and data management issues during the implementation of learning analytics technology in genuine educational settings.

A suggestion put forward by Noel et al. (2018) was to include an identification code in the survey to identify both the team number and microphone used by participants. Hassan et al. (2021) state that the collection of MMLA data can be challenging owing to concerns about privacy. For instance, students' audio and video streams can be acquired using built-in webcams and microphones on their computers. However, students may not feel comfortable with knowing that their data may be stored and processed externally. Jensen et al. (2021) maintain that teachers' autonomy to record their own data as well as security concerns could influence the collection of data. Furthermore, Dominguez et al. (2021) recommended that future versions of their data collection system should include privacy features, such as a 'delete/forget' button and the tokenisation of sensitive information. Additionally, Zhao et al. (2024) assert that even consensual audio, spatial and video recordings of students may raise ethical concerns, particularly with regard to privacy issues. These concerns include the unauthorised and accidental recording of sensitive data, along with the unsecured storage of recorded data. To prevent these problems, the paper recommends that consent be obtained from fully informed participants and that personal identifying information be removed from the collected data. It also recommends that data recorded outside of the consent period be filtered out and that data access be strictly controlled. In their article, Martinez-Maldonado, Echeverria et al. (2020) discussed the issues related to personal information, data sharing and de-identification, whereas Martinez-Maldonado, Mangaroska et al. (2020) briefly discussed the issues surrounding privacy and ethics. Despite the numerous suggestions and concerns raised by several papers, no actions have been taken.

While papers cited and discussed in the previous paragraphs have only raised privacy concerns and made recommendations, other papers have sought to take legitimate action to mitigate these privacy concerns. For example, Donnelly et al. (2016) used audio data rather than video data to reduce privacy concerns. Nevertheless, the paper did not discuss any privacy concerns associated with the use of video data, for instance the possibility that students are more likely to be identified in videos than in audio recordings. Similarly, Correa et al. (2020) noted that their data was an OpenPose output of students' skeletons without any identifying information, hence privacy would not be compromised. Furthermore, Zhao et al. (2022) speculated that wearable devices may raise privacy concerns. This resulted in the removal of data from spatial and audio datasets that could identify individual students. Participants' privacy was also protected by non-verbal features in this study. Equally, Liu et al. (2019) maintained that student IDs were anonymous and stored on an external hard drive, although the paper did not explain whether or not two-level anonymisation was employed. To guarantee privacy in the study conducted by Yan et al. (2022), the data were anonymised to protect individual identities. Likewise, the focus on group-level analysis eliminated any individual elements from future debriefings. Moreover, Zhao et al. (2023) identified privacy issues as a significant ethical concern in their study, since audio recordings were made during the simulation. Consequently, with the aim of minimising ethical concerns, all identifying information was removed from their dataset. Only colours were used to differentiate students, whilst access was strictly controlled to prevent any unintended misuse.

Figure 4. The presence of ethical considerations in MMLA papers



As discussed in the previous section and as illustrated in Figure 4, the articles retrieved during the first search for papers published between 2010 and 2019 only briefly addressed ethical issues, such as consent, data management and ethical clearance. Nonetheless, the ethical implications connected with MMLA in education were increasingly explored in the literature available between 2020 and 2024. In recent years, researchers have extended their focus on privacy issues to address other important ethical issues associated with MMLA, such as transparency, accountability and fairness. For instance:

Accountability**:** Regarding accountability, Martinez-Maldonado et al. (2020) questioned the effect of sharing instructional positioning data with other stakeholders in relation to teachers' accountability. However, the paper did not provide a detailed discussion concerning this issue or provide alternative solutions for sharing teachers' data without impacting their accountability. Nonetheless, the article did discuss other ethical concerns, for example data privacy, ethics and pervasive surveillance. Similarly, Martinez-Maldonado et al. (2020) raised questions about accountability and who should have access to the collected data. They queried whether the data should be available to teachers, students and coordinators, whether these data could be employed to assess student performance and how students' privacy could be protected. Teachers should be able to use the results of this study to formulate strategies to overcome privacy issues that surpass simply addressing them in the classroom. However, the need for further discussion remains.

Informed consent forms*:* Research has also begun to address broader ethical issues, for instance informed consent forms and student awareness. Mangaroska, Sharma et al. (2021) documented that in addition to the explanation contained in their consent sheet, students were introduced briefly to the experimental setup upon arrival at the lab, in accordance with ethical guidelines issued by the Department of Health. The introduction comprised several ethical principles, including: (1) the fact that participation was voluntary and students could opt out at any time of the experiment; (2) the use of the sensors would not result in physical or psychological harm; (3) the participants' privacy would be protected; and (4) their data would be anonymised prior to analysis. Similarly, Chejara et al. (2021) provided participants with information regarding their study and obtained written consent prior to collecting data. Furthermore, Zhou et al. (2023) obtained individual consent from students prior to the commencement of the study. There was no correlation between participation in the module and the summative assessment, and students were able to opt out of the study at any time.

In the study completed by Yusuf et al. (2024), participants were provided with information regarding video recording in an information sheet that was distributed prior to the intervention and displayed on each of the intervention days. The participants were informed that their participation was voluntary and that they could opt out at any time and ask for their video data to be deleted. Participants' privacy was safeguarded by storing their video files on an encrypted hard drive and using their video data for research purposes only. Moreover, informed consent was concisely discussed by Tisza et al. (2022), who collected physiological data and facial videos from children. The children and their parents were notified about the study beforehand and informed consent was obtained accordingly. The consent form included information on the study's purpose, procedures, potential risks and benefits, data handling and confidentiality, including the participants' right to withdraw from the study. Furthermore, prior to beginning their study, Ciordas-Hertel et al. (2021), informed participants in writing about the procedure and its purpose. The collection of data and their subsequent use were also explained. While emphasis was placed on increasing student awareness, Beardsley et al. (2020) ascertained that increasing students' awareness may have a negative impact on their participation. In their article, they introduced an informed consent understanding test as a method of educating students and teachers about the MMD collected during their participation in MMLA systems. Conversely, it was determined that improving students' understanding of consent forms resulted in fewer enrolments. Accordingly, the paper proposes that further effort is necessary to overcome this problem.

Security: More recently, there has been increasing interest in the security issues associated with MMLA and the methods available to mitigate them. As an example, Ciordas-Hertel et al. (2021) developed a prototype of a wearable device to identify the factors that affect learning in the classroom while maintaining the security and privacy of the classroom. Participants were assigned pseudonyms at the beginning of the prototype study with the aim of ensuring data protection. Thus, the participants' data could not be directly linked to their identities. Furthermore, only technical identifiers were collected. As part of the user-side application, re-identifiable sensor data was hashed with a secret salt, this procedure, also known as salting, comprises adding a random string of characters to a password ahead of hashing it, which prevented cloud services, such as Google, from being able to analyse the data. Appropriately, a direct connection was established between the smartwatch and smartphone, with the aim of tackling both performance concerns and other issues. Communication between the server-side and user-side applications was encrypted to ensure data security. Additionally, specific precautions were taken in Ciordas-Hertel et al. (2022) to protect data and privacy, given that their research methods might record sensitive information. The students were verified separately to guarantee accurate and individual data attribution. Data connections to the server were encrypted and students could only see their own data. Furthermore, pseudonyms were assigned exclusively to the recorded data, preventing re-identification in the event of a data breach. Data was hashed to reduce detail, so as to reduce the collected data. Prior to the commencement of the study, the students were provided with an explanation and presented with alternative options in terms of data collection.

In the article published by Li et al. (2023), informed written consent was obtained from students and teachers prior to the collection of any data. Video footage was only recorded with the agreement of all of the students, who consented to their data being collected and used for future research. Students' facial identities were concealed by black boxes to protect their identities in publicly shared research material. This approach not only protected the students' anonymity in real-time video footage, but it could also be used to maintain their privacy in any content disseminated in the public domain. Indoor positioning trace data was also protected by de-identified tracker labels. This particular paper recommended that researchers and practitioners should consider the possible impact of video surveillance on students' learning behaviour. Conversely, the authors reasoned that this issue was less relevant to their study given that video streaming was already available in the debriefing room, allowing students to observe clinical simulations. Nevertheless, they recommended that researchers consider and implement appropriate measures for future studies conducted in settings where video devices are utilised. It should be noted that other papers have also provided recommendations, including that by Yan et al. (2023). As students' demographics are essential for analysis, future studies that incorporate similar approaches and generate more personalised information must consider privacy and data security issues. Additionally, if researchers wish to make socio-spatial insights available to educational stakeholders, they must keep in mind the possibility that labelling can negatively affect students' self-esteem and teachers' decision-making processes.

A number of ethical issues have arisen as a result of the data-driven technical and methodological information specified by Yan, Martinez-Maldonado, Zhao, Deppeler et al. (2022). It was reasoned that although additional tracking devices heightened the collection of indoor positioning tracking data to identify teachers' spatial pedagogical approaches in large, complex learning spaces, they also raised privacy and security concerns. To reduce these problems, data anonymisation was implemented to protect individual students' privacy by way of removing all personally identifiable information from the dataset. Despite the anonymisation of the teachers' identities in this study, if visual interfaces are developed in the future to enable training and reflection, these teachers might still be identifiable. Thus, school administrators are required to safeguard the security of data. This paper concludes that this sort of data should not be used to assess teacher performance. Equally, Yan et al. (2021) raised privacy concerns related to sensing technologies. The authors implemented data security procedures to ensure that data was protected (students' names were concealed) and that they strictly limited data use to research purposes within their own research.

Fairness and bias**:** Recently, researchers have highlighted the issues of fairness and bias**.** For instance, to avoid the potential for bias in the detection of facial action units, research undertaken by Sinha (2021) indicates that the placement of the camera should be tested first on a small number of students. Algorithm bias issues were highlighted in this study. Likewise, despite the fact that the facial action unit recognition algorithms had already been trained on a population with a variety of demographic characteristics, such as age, gender and ethnicity, the analysis of automated data can still be biased. The article by Chejara et al. (2021) comprehensively discusses the generalisability level of a group**,** which is defined as the extent to which an ML model performs the same way regardless of differences such as gender, age or ethnicity. The distribution of learning labels in groups must be equal in order to achieve a high level of group generalisability. MMLA researchers, however, regularly encounter datasets with unequal data distributions across groups. Therefore, the evaluation framework presented in the article proposed using resampling techniques to overcome model bias. Acosta et al. (2021) emphasise algorithmic fairness as a key component of the development of multimodal ML models. As a method of identifying and mitigating encoded bias, slicing analysis of multimodal models of visitor visuality (the visual attention patterns exhibited by visitors) was proposed by separating results according to specific attributes, for instance gender, so as to determine whether the model performed objectively within different user populations. According to the authors, multimodal random forest models are capable of accurately predicting visitor visual attention, but they may be biased towards women. By reweighting multimodal attention models, researchers ascertained that they can reduce bias whilst only marginally affecting prediction accuracy. The results of the study also established that the effectiveness of debiasing methods varied, depending on the specific combination of ML techniques and modalities applied.

In their research, Yan et al. (2021) asserted that future research should address ethical considerations, for example the risk that incomplete data may result in decisions based on incomplete information. Similarly, Yan, Martinez-Maldonado, Gallo Cordoba, Deppeler et al. (2022) insisted that teachers should be provided with actionable insights derived from explanatory models when communicating the results of ML algorithms, allowing them to understand why a particular student may be considered to be making minimal progress. It is imperative that teachers are educated about implicit bias. The authors also argued that collecting additional demographic information, including students' socioeconomic status, could contribute to a greater understanding of the predictive results. However, ethical considerations and increased data needs must be delicately balanced. It should also be mentioned that Li et al. (2023) claimed that eye-tracking data collection and modelling techniques are less noticeable than those utilised in traditional learning methods, such as handwriting and touch gestures. Due to the fact that eye tracking uses sensors and data collection mechanisms that are typically subtle, passive or embedded in the environment, students might not be mindful of their gaze being recorded or analysed. Accordingly, eye-tracking data collection and modelling techniques may present more ethical challenges, including transparency, accountability, privacy, fairness and bias, as discussed in the previous literature.

Data misuse**:** An additional concern identified in the reviewed articles was the potential for data misuse, such as labelling, discrimination and the scoring of students based on the results of MMLA. As Yan et al. (2021) assert, future research should address ethical considerations, for instance discrimination, which can have a negative effect on both students' self-esteem and teachers' expectations, as well as the potential problems that may result from labelling socially isolated students. Consequently, it was recommended that teachers receive training on handling this information ethically and securely, and that school management refrain from using it as a tool to assess student performance or to evaluate teachers. Additionally, Yan, Martinez-Maldonado, Gallo Cordoba, Deppeler et al. (2022) discussed the risks associated with the use of predictive learning analytics to label students. According to the paper, previous literature has recommended that labels for students should not be universal but rather subject-specific in order to facilitate teacher-led instruction. Using subject-specific labelling enables teachers to interpret student performance, provide appropriate guidance and intervene when necessary, as opposed to exclusively depending on algorithms.

Apart from planning an intervention, teachers may also consider more appropriate approaches to promote social interaction or inclusion. In their research, Alfredo et al. (2023) mentioned that certain teachers expressed concern regarding the unintended misuse of the data collected to estimate stress and make decisions based on that data. Accordingly, it was proposed that these data be collected and used only in educational contexts where the specific intention is to help students go through stressful situations, reflect upon those experiences, and subsequently develop coping strategies**.** Additionally, the authors discouraged the use of stress modelling and visualisation in the monitoring of student performance or exam results. Yan, Martinez-Maldonado, Zhao, Dix et al. (2022) discussed the ethical issues associated with analytics-based assessments, principally when students are unaware that they are being assessed. Therefore, it is recommended that students should be informed of the potential uses of their data, including how their trace data may be exploited for assessment purposes, in addition to how they can access and control their data.

Unintended surveillance*:* This was also identified as an emerging ethical issue associated with the use of MMLA. The study by Zhao et al. (2023) highlighted unintended surveillance as a significant ethical concern. In a similar vein, Sinha (2021) recommended that future research should consider the possibility of unintended surveillance when various data sources are used, because positioning data alone cannot be relied upon for confidence in the final results. To reduce students' discomfort over being observed, Sinha (2021) informed them that the results would not be considered as part of their formal evaluation. Simply put, although the position tracker used in Yan, Martinez-Maldonado, Zhao, Dix et al. (2022) did not place intrusive restrictions on students, its presence may have caused them to feel as if they were being observed in conjunction with their teachers' observations. The use of sensor-based learning analytics should therefore be preceded by informed consent. In spite of the fact that this paper raised a significant issue related to surveillance, it failed to provide a detailed analysis. Moreover, Martinez-Maldonado et al. (2022), reported that as their data were collected using position tracking sensors, no fine-grained, individually identifiable information was collected. These types of data may be collected by means of video-based approaches and wearable devices, for example microphones, cameras or mobile eye-tracking devices, which are intended for surveillance purposes and therefore raise additional privacy concerns. Conversely, according to the authors, it is important to acknowledge a number of additional ethical and practical concerns when using real-life positional traces collected from students and teachers. In the first instance, interpretation and analysis of the data may be an issue. Teachers were key players in the interpretation and evaluation of the MMD in this study, thus preserving human agency. It was also therefore possible for interpretations to be biased in favour of certain types of evidence or to be influenced by particular learning models. Equally, small sample sizes may have the potential to be over-interpreted owing to the inconclusive nature of results. In light of these issues, it is believed that training can play a fundamental role in enabling accurate interpretation of automated metrics. Equally, when making judgements regarding human qualities, positioning data should be considered in conjunction with other sources of evidence. It is essential that unintended consequences are avoided, such as the misuse of data as an assessment tool. Consequently, the paper published by Martinez-Maldonado et al. (2022) suggests that the comparison of teachers' data should be restricted to providing feedback and professional development to teachers.

Student agency: This was seldom deliberated in the reviewed papers. As part of empowering student agency, the web interface designed by Ciordas-Hertel et al. (2021) permitted participants to download and delete all of their data. Considering the challenge of implementing the subsequent data entry corrections as part of an automated feature, participants could erase the data associated with individual sessions. In this way, they were able to exercise their right to rectify both simply and autonomously. However, the researchers misplaced a substantial amount of data in the process. Additionally, the right to rectify was automated, preventing researchers from exporting participants' data before any conflict or misunderstanding had been resolved and before the participants had consented to the use of their data. Despite addressing significant ethical issues, their attempt to assert student agency might be perceived as data ownership rather than agency.

In recent years, MMLA researchers have demonstrated greater interest in understanding student welfare and understanding the use of MMLA tools. Mangaroska, Martinez-Maldonado et al. (2021) introduced ten components of designing ethical and effective innovations, conducting interviews with 40 computer science students to explore their perceptions of the educational and ethical challenges associated with MMD. Various ethical questions were raised as part of the interviews, including students' emotional state while wearing sensing technology, who should have access to the data, and whether they were willing to share their own data, and if so, with whom. The results revealed that while none of the students expressed irritation with a wristband sensor, most expressed apprehension about wearing an EEG cap. Moreover, whilst most students exhibited a positive attitude towards sharing their data if they were securely anonymised, a number expressed concerns regarding power dynamics, and others were uncomfortable with sharing their data.

A few important ethical considerations were raised by the students, including the use of sensor data to assess their performance, handling each data modality differently, data-profiting, external factors influencing their well-being, and the misuse of data. The paper recommended robust privacy protection, underlining that, due to the nature of MMLA data, particular information will not be related to the learning activity. The development of an MMLA framework was also suggested to manage the impact of surveillance, power relations and students' identities. Although this article attempted to tackle ethical issues from the perspective of the student, the interviews only covered a limited number of ethical concerns, predominantly focusing on students' privacy and their opinions on wearable sensors. Additionally, the issues raised relied exclusively on the perceptions of students. Hence, it remains vital to address ethical issues from the perspective of various other stakeholders.

Zhou et al. (2023) addressed concerns regarding the invasiveness of gaze detection technologies in educational settings. To automatically detect students' gaze behaviours, they proposed an alternative method that employed a single RGB camera and pre-trained computer vision models. Owing to ethical concerns, they avoided using facial recognition in their eye- tracking approach and as an alternative used head tracking in conjunction with a spatiotemporal model to estimate where students were looking. Although this method is considered less intrusive, the authors acknowledged that it is subject to limitations, principally in terms of accuracy. They also accentuated that it needed to be improved further without compromising ethical or privacy standards.

Martinez-Maldonado et al. (2024) acknowledge that three years of human-centred MMLA fieldwork conducted by 399 nursing students and 17 educators delivered several ethical lessons. First, it was reported that although students were comfortable with wearing sensors, teachers needed to be aware of potential distractions and the possibility that some students may well feel apprehensive about being observed. Second, if the purpose of the study is visibly communicated, students are more likely to be willing to participate in a complex MMD collection study. Third, multimodal sensor data may be incomplete and biased. Therefore, it is necessary to implement mechanisms so as to safeguard the trustworthiness of MMLA systems and to accommodate incomplete data. Fourth, students might find it challenging to comprehend the nature of a complex MMLA study. Thus, providing too many technical details about sensors and analytics does not guarantee increased clarity. Conversely, it may be helpful to explain the complexity of the use of MMLA to students in person, with the intention of encouraging informed consent. The fifth and final observation was that students were willing to share their MMD with others, provided that their privacy was protected and the use of their data was limited to supporting learning. While most students considered their multimodal data to be only of personal benefit, some understood that sharing it with their peers and teachers could aid in improving learning activities. Furthermore, Martinez-Maldonado, Echeverria et al. (2020) claimed that the analysis in their research considered ethical concerns, for instance human accountability, algorithmic transparency and manipulability, risks from bias and errors, and data privacy concerns. However, their study did not mention how these issues were mitigated.

A number of researchers have focused on the development of an ethical framework for MMLA. Giannakos et al. (2021) recognised that the use of sensing-based analytics is likely to generate significant concerns among stakeholders, including transparency, accountability, fairness and bias. For sensing-based analytics to be effective in learning research and practice, the paper stressed that frameworks and tools must be developed to ensure that data are not misused and that transparency and trustworthiness in sensing-based analytics aided learning systems. Therefore, it is imperative to consider methods that maintain privacy, as well as transparency and accountability. It is important to mention here that the reasons for the development of the MMLA framework have recently been published (Mangaroska, Martinez-Maldonado, et al., 2021).

The results presented above clearly reveal a lack of detailed discussion on the ethical issues associated with the use of MMLA in education. Although 42 papers were identified via the SLR that briefly discussed potential concerns pertaining to the use of MMLA in education, most of the discussion was limited to data privacy, consent forms and university ethical regulations. Hence, they did not cover most of the aspects that were reviewed and described in the previous chapter. Additionally, despite increased concern from MMLA researchers about addressing several of these issues, e.g., transparency, accountability and fairness, there remains a lack of comprehensive consideration of the ethical issues that might result from using invasive sensing technology, such as EEG, skin sensors and eye-tracking technology. Detailed recommendations for solutions to mitigate these ethical issues are also missing from the literature. Alternatively, possible concerns are highlighted, with suggestions that future research should concentrate on the ethical implications of MMLA. Likewise, there have also been demands for the development of an MMLA framework (Mangaroska, Martinez-Maldonado et al., 2021). It has also been stressed that frameworks and tools must be developed to guarantee that data are not misused and to guarantee transparency and credibility in sensing-based analytics support learning systems (Giannakos et al., 2021).

Table 3. Ethical concerns and recommendations in the MMLA literature (2020–2024)

References	Ethical Concerns
Martinez-Maldonado, Echeverria et al. (2020)	Human accountability, algorithmic transparency and manipulation, errors, bias and data privacy concerns were considered. Privacy, ownership, sharing and de-identification issues were also discussed.
Martinez-Maldonado, Mangaroska et al. (2020)	Discussions on privacy, ethics and surveillance. Additionally, teachers' accountability was questioned when positioning data were shared with other stakeholders.
Correa et al. (2020)	Uploading skeletons of students without their faces or other identifiable information will not violate the privacy of children, although the children are being recorded.
Martinez-Maldonado, Elliott et al. (2020)	Data access, use, sharing and questions regarding availability allow teachers to predict any privacy concerns.
Hassan et al. (2021)	Briefly discussed privacy concerns regarding data collection from the MMLA.

Jensen et al. (2021)	Data collection could be impacted by security and privacy concerns, as well as the autonomy of teachers to record their own data.
Yan et al. (2021)	Future research should assess the potential risk of making decisions with incomplete data. MMLA data should not be used to evaluate students and teachers.
Li et al. (2023)	Previous literature noted that eye-tracking methods may present more ethical challenges, including transparency, accountability, privacy and fairness.
References	Ethical Recommendations
Mangaroska, Sharma et al. (2021)	Besides the consent form, the experiment was briefly explained to the students. Additionally, the first 30 seconds of each data stream, except for facial expression, was normalised to avoid physiological bias.
Beardsley et al. (2020)	Informed consent comprehension tests were used to raise the awareness of students and teachers in relation to the MMD collected via the MMLA system.
Sinha (2021)	To prevent bias in the detection of facial action units, the placement of the camera was tested on a group of students. Participants' discomfort was reduced by not considering the results as a formal evaluation.
Chejara et al. (2021)	The use of resampling techniques to overcome models biased towards some groups was recommended to make learning labels more equitable across groups.
Mangaroska, Martinez-Maldonado et al. (2021)	Ten dimensions for designing ethical and effective innovation were proposed, including the avoidance of using sensor data to measure performance, along with treating data differently and ensuring more robust protection of privacy. MMLA frameworks were proposed to organise surveillance, power relations and learner identity.
Ciordas-Hertel et al. (2021)	The web interface allowed data to be downloaded and deleted. The prototype study only collected technical identifiers and assigned pseudonyms. Re-identifiable sensor

	data were hashed with a salt. Data security was ensured by encryption on both sides.
Yan, Martinez-Maldonado, Zhoa, Dix et al. (2022)	Prior to using sensor-based learning analytics, students should be informed of the potential uses of their data to address the surveillance concern. Data were anonymised to protect individual identities. The debriefings focused on group analysis, eliminating individual elements.
Yan et al. (2023)	Researchers should consider privacy and data security implications when applying their approaches. To provide educational stakeholders with socio-spatial understanding, researchers should consider how labelling might negatively affect students' self-esteem and teachers' decision making.
Zhao et al. (2023)	The identifying information in the dataset was removed and colours were used to distinguish students. Access was strictly controlled.
Ciordas-Hertel et al. (2022)	Individually verified students. The server connections were encrypted and students could only view their own data. A pseudonym was assigned to the recorded data and the data were hashed. Students received a detailed explanation of the study.
Yan, Martinez-Maldonado, Zhao, Deppeler et al. (2022)	Data anonymisation was implemented and school management had to ensure their security. Data should not be used to evaluate teachers.
Alfredo et al. (2023)	Limiting the collection and use of student data to estimate stress. Students' performance and exam results should not be monitored using stress modelling or visualisation.
Li et al. (2023)	Written consent was obtained from both students and teachers. Black boxes masked students' faces and indoor positioning data was de-identified. It was recommended that practitioners and researchers should consider how video surveillance affects learning.
Dominguez et al. (2021)	A "delete/forget" button and tokenisation of sensitive information should be added to future versions of the system.

Giannakos et al. (2021)	In sensing-based analytics, enabled learning systems, frameworks and tools must be developed to protect data and ensure transparency and trustworthiness. Transparency and accountability processes as well as privacy-preserving measures are necessary.
Zhao et al. (2024)	Data collection must be consent-based, personal identifying information must be removed, data must be filtered out after the consented period and access to data must be strictly controlled
Zhou et al. (2023)	Student consent was obtained prior to the study. Participation in the module did not affect the summative assessment. Students could opt out of the study at any time.
Yusuf et al. (2024)	Information sheets were obtained prior to the intervention and displayed during the intervention day. Any participant could opt out and delete their video data at any time. Participants' privacy was protected by using encrypted hard drives and by only using video data for research.
Mangaroska, Sharma et al. (2021)	Following guidelines provided by the Department of Health, students were informed of the experiment upon entering the lab.
Tisza et al. (2022)	Informed consent was obtained from children and their parents before the study began. A consent form explained the study's purpose, procedures, potential risks and benefits, data handling, confidentiality and withdrawal options.
Martinez-Maldonado et al. (2024)	The study established that students did not feel uncomfortable wearing sensors, although teachers might worry about the sensors distracting students. A clear explanation of the study's purpose, as well as explaining the complications connected with using MMLA, might encourage students' participation. Trustworthiness of MMLA systems must be guaranteed. As long as privacy was protected and data were used to support learning, data sharing was acceptable.

Martinez-Maldonado et al. (2022)	It is believed that teacher training can contribute to accurate interpretation of automated metrics. Positioning data should be considered alongside other sources of evidence. Teacher data should be used only for feedback and professional development.
Acosta et al. (2021)	Visitor attention-based ML models were built with algorithmic fairness in mind.

2.3.3 Existing Ethical Principles, Guidelines, Checklists, Frameworks and Initiatives from the Boundaries between Artificial Intelligence (AI), Artificial Intelligence in Education (AIED), Open Learner Models (OLMs), and Learning Analytics (LA)

This section presents a discussion of existing ethical principles, guidelines, checklists, frameworks and initiatives from the boundaries between AI, AIED, OLMs and LA. In particular, this discussion should act as a foundation and starting point for establishing an ethical framework for MMLA. Existing ethical AI and ethical AIED research has ranged from offering general guidelines (Morley et al., 2019) to developing specific checklists (Zook et al., 2017). The Institute for Ethical AI in Education (2021) developed an ethical framework for AI in Education in collaboration with over 200 experts through interviews, roundtables and the Global Summit on the Ethics of AI in Education. This framework provides educators with a detailed checklist and criteria for evaluating AI-powered edtech solutions. By utilising the framework, leaders and practitioners are able to plan, procure and apply AI on behalf of learners. As part of the framework, a number of ethical issues have been addressed, including equity, privacy, transparency and accountability.

In terms of initiatives designed to develop ethical principles for the adoption of socially beneficial AI, the focus in this section will be on the initiatives with the highest profile. The first of these is the Asilomar Principles, which were developed by means of consultation with conference attendees at the Asilomar Conference in January 2017 with support from the Future of Life Institute. A set of 23 guidelines is separated into three groups: research, ethics and values, together with long-term issues. Specifically, the 13 principles in the ethics and values section, including privacy, transparency and responsibility, can be learnt from and modified for the design of a future ethical MMLA framework.

The second initiative is the Montreal Declaration (2017), for the responsible development of AI, issued at the conclusion of the Forum on the Socially Responsible Development of Artificial Intelligence in November 2017. As its primary objective, this declaration aims to identify the principles and values of digital technology and AI related to promoting the basic interests of people and groups. The ten principles outlined by the Montreal Declaration may act as a practical guide for developing a future MMLA framework. Among the principles that should be considered for MMLA are the principles of privacy and intimacy, which address such issues as data confidentiality and the anonymity of personal profiles, providing a useful context from which to explore privacy issues more extensively. Moreover, the principle of democratic participation is consistent with numerous important ethical issues, for example the fact that decisions made by AI systems should be communicated in an understandable way to their users, as well as the continuity of accountability emphasised throughout this sub-guideline. Other important concepts, such as equity, diversity, inclusion and responsibility, are discussed in this guideline, all of which are relevant and valuable for inclusion in a future MMLA framework.

The third initiative is the Partnership on AI (2018), a multi-stakeholder organisation consisting of academics, researchers, civil society organisations and companies developing and employing AI technology, besides other stakeholders. Their eight tenets represent important factors to consider when developing MMLA frameworks, such as the understandability and interpretability of systems.

The fourth initiative promoting socially beneficial AI is the General Principles of Ethically Aligned Design: Prioritising Human Well-being with Autonomous and Intelligent Systems, along with developing an appropriate strategy to ensure that each of these risks is prevented. There were more than 250 contributors to these principles, which were published in December 2017. These included leaders from academia, industry, civil society, policy and government in the related technical and humanistic disciplines. Among the general principles were important recommendations relating to the ethical development and design of autonomous and intelligent systems, which should be considered when developing future MMLA frameworks. For example, the effectiveness dimension underlines the significance of providing evidence of AI's effectiveness as well as its value and suitability for its intended purposes. Likewise, the transparency element highlights the need for AI decisions to be transparent to a broad range of stakeholders, whereas the accountability dimension emphasises the need for AI to be created and operated in such a way that transparently explains the rationale behind its decisions. Each of these criteria is of the utmost importance in ensuring the ethical use of MMLA and their inclusion in a future framework for MMLA is recommended (IEEE Initiative on Ethics of Autonomous and Intelligent Systems, 2017).

The fifth initiative is referred to as EGE. In March 2018, the European Commission's European Group on Ethics in Science and New Technologies published a statement on AI, robotics and "autonomous" systems. It outlines a set of fundamental principles and democratic prerequisites, such as justice, equity and solidarity, which articulate the need for equal access to the benefits connected with AI, together with highlighting related issues, such as discriminatory biases in datasets used for training and running AI systems. An additional notable aspect discussed in the guidelines relates to the rule of law and accountability, which is concerned with avoiding the risks associated with AI systems. Furthermore, data protection and privacy are also important considerations that address the right to the protection of personal information and the right to privacy, both in the physical world and online. Considering the focus of these guidelines on "autonomous" systems, it is vital to contextualise them within the context of MMLA (European Commission et al., 2018).

The sixth initiative comprises AIUK's five overarching principles concerning AI code, available in the report of the Artificial Intelligence Committee of the House of Lords entitled: 'AI in the UK: Ready, willing and able?'. In the report, emphasis is placed on operationalising data ethics and incorporating ethical principles into the development and implementation of AI systems, including issues relating to the access and control of data, which are discussed in great detail with respect to open data. Furthermore, another key principle stresses the importance of intelligible AI systems being a fundamental requirement if AI is to become an integral and trusted tool. These dimensions must be taken into account in any future MMLA framework (House of Lords, 2018).

Floridi and Cowls (2019) conducted a comparative analysis to meticulously examine the six major initiatives described above related to promoting socially beneficial AI. There is a close relationship between bioethics and digital ethics. Specifically, an ecological approach is applied when interacting with new types of agents, patients and environments (Floridi, 2013). The sets of principles were compared with the four core principles commonly used in bioethics: beneficence, non-maleficence, autonomy and justice. Based on this comparative analysis, explicability was included as a new principle, aiming to enable the other principles via intelligibility (how it works) and accountability (who accepts responsibility for it). Several overlaps were observed between these principles, but these five principles were identified as an overarching framework for ethical AI (Floridi & Cowls, 2019). The adoption of all of these principles is considered essential to verify that AI is designed and deployed in a reliable, trustworthy, ethical and responsible way, although there is an absence of guidelines that describe how these principles may be applied in specific case studies and applications (Holmes & Porayska-Pomsta, 2023).

Moreover, during AI4People's first year of activity, Floridi et al. (2018) presented their "AI4People's Ethical Framework for a Good AI Society: Opportunities, Risks, Principles and Recommendations" to the European Parliament. The magnitude of these recommendations acted as an inspiration to the European Commission and influenced the development of the seven Key Requirements for Trustworthy AI that it presented in April 2019.

In April 2019, the EU Commission published its Ethics Guidelines for Trustworthy AI, which were developed by a high-level expert group (HLEG). The guidelines contain three principal components which should be met throughout the entire life cycle of an AI system: it should be lawful, ethical and robust (European Commission. Directorate General for Communications Networks, Content and Technology, & High Level Expert Group on Artificial Intelligence, 2019). Floridi (2019) notes that the guidelines have been criticised for being too ineffective and general, too similar to many other initiatives and for having barely any impact in general. However, Floridi (2019) has also argued that the principles and clarifications are robust, as they are based on social expectations in accordance with the current debate on the ethics of AI and are aligned with EU law. It is apparent that the guidelines do not provide any details on how they should be enforced, but even though they are hardly original or innovative, they do represent the closest thing to an EU standard regarding the ethics of AI.

While it is acknowledged that previous AI principles are beneficial as general guidelines, further discussions on the detailed contextualisation of these principles into education settings or the use of MMD are still absent. However, one particular framework is worth mentioning here, namely the SMILI framework, which is particularly focused on AI in Education. The SMILI framework was developed to provide researchers with a systematic method for describing, comparing and critiquing Open Learning Models (OLMs). These models enable all stakeholders in the educational process (learners, teachers, peers, etc.), to view the content of the learner models of intelligent tutoring systems or other advanced learning environments in a human-understandable manner (Bull & Kay, 2016). The particular relevance of OLMs for this research is that transparent OLMs have been central within the LA and EDM communities, substantially benefitting MMLA research. The use of OLMs can have a significant impact on users' understanding and consequently their trust, which are important ethical considerations when designing MMLA frameworks. Nonetheless, the SMILI framework lacks any specific ethical orientation apart from its emphasis on the value of transparency. While other ethical concepts are mentioned, they are discussed in the context of user experience and evaluation rather than in relation to ethical considerations per se (ibid.)

In terms of the field of LA and its relevance to MMLA, Prinsloo and Slade (2013) presented a framework comprising six principles for higher education institutions: (1) learning analytics should be employed as a tool to understand students and the learning process, and not as a measuring tool; (2) students should be involved as active agents; (3) student data and personal identity must only be stored for a specific time agreed upon in advance; (4) as learning is not linear, process learning analytics are insufficient to understand how and why students succeed; (5) institutions must be transparent about why the data are being collected, who should have access to the collected data and what measures have been taken to protect students' privacy; and (6) learning analytics generates huge amounts of data, and higher education should treat this data sustainably and ethically. However, even though this framework is an excellent starting point for ethical learning analytics, it has limitations in terms of its use for MMLA research. First, as the framework has been developed specifically for learning analytics, it lacks any consideration of MMD collected in the real world. This point requires additional consideration, given that collection techniques used in MMLA (e.g., face recognition systems) and MMD (e.g., EEG) are invasive compared to the traditional log and keystroke data used in learning analytics. Second, the framework does not address issues such as transparency, accountability and fairness related to predictive models or datasets. Finally, the framework appears too broad to be employed by MMLA practitioners, developers and researchers.

Therefore, a checklist or guidance document might be more feasible and beneficial. For instance, Drachsler and Greller (2016) provided DELICATE, an eight-point ethical considerations checklist in which they exploited the experience of a large-scale EU project. The checklist provides a quick and easy tool to assess any privacy issues that might appear as a result of the use of learning analytics. However, given that the checklist focuses predominantly on data privacy issues, including data collection, storing, anonymisation and transparency in data collection, it still cannot be used to assess other ethical concerns, such as transparency, accountability and fairness. The DELICATE checklist was evaluated by Kitto and Knight (2019), who argue for practical ethics in building solutions for LA. Hakami and Hernández-Leo (2020) recently provided a far-reaching overview of ethical considerations in the field, including fairness, accountability, transparency and human well-being. Nevertheless, even though this paper provides an excellent and in-depth discussion of these concerns, it does not consider real-world MMD.

Johanes and Thille (2019) conducted interviews with technical infrastructure designers in higher education, focusing primarily on three themes, including ethics. Their findings could inform educational stakeholders, including researchers, policymakers and infrastructure designers, to better understand the building process and experience. The EU's GDPR has also provided researchers with a general guideline for research that includes human factors. In addition, Beardsley et al. (2020)

discussed the role and the potential limitations of existing written consent forms, for example, participant comprehension. However, the effectiveness of general guidelines is limited in the context of the behaviour of technology professionals (McNamara et al., 2018); AI practitioners and researchers have become frustrated by the highly abstract principles associated with AI ethics, specifically for 'everyday practice at work' (Calvo & Peters, 2019). Hence, general guidelines should be further contextualised to meet the specific needs of particular research areas.

2.4 Chapter Summary

The literature review indicates that MMLA researchers rarely address ethical considerations. Therefore, this research will endeavour to fill this significant gap by addressing the ethical issues associated with the use of MMLA in higher education, and it will aim to mitigate these issues through the design of an MMLA ethics framework that focuses on broader definitions of ethics than mere considerations of privacy. Existing ethical frameworks will be adopted and extended to be more in keeping with the specific needs of MMLA research. In terms of an ethical dimensions framework, the ACM's FAccT guidance, which includes fairness, accountability and transparency, will be adopted and extended to also include privacy and bias, as these issues are frequently raised by learning analytics researchers.

3 Chapter Three: Methodology

3.1 Introduction and Methodology Design

This chapter aims to describe the process by which the research was designed to meet the research objectives, as well as how the data resulting from these methods were analysed. The chapter includes several sections, each describing a particular aspect of the study methodology, including justification for its adoption, the sampling approach, study participants, data collection, data analysis and finally, key considerations for the study.

The data gathering techniques used in this research are based on multiple factors related to the research goal. It is important to set a specific goal in order to identify the most efficient data gathering method; identifying the correct research method shapes and is shaped by the research questions (Punch, 2013). Thus, the research questions were addressed with the use of appropriate methodologies to meet the specific requirements of each question, as explained below in Table 4.

Table 4. The research method and data source for each research question

Research questions	Research Method	Data Source
1. What are specific examples of MMLA being employed in education and the related ethical concerns mentioned in the literature?	Systematic literature review (SLR) between 2010 and 2024 with the search updated continually.	182 papers identified from Scopus, Web of Science, IEEE, ACM, Google Scholar.

2. What are the opinions of researchers, practitioners and students on the ethical use of MMLA in higher education? 3. How can MMLA be applied in a more ethical way in higher education?	Qualitative research method (interviews).	Main data collection (60 participants including 12 researchers/practitioners, eight educators, 39 students at higher education institutions and one educational technology company). Framework evaluation: (27 participants including seven students, 13 researcher/practitioners, four teachers, one ethics expert and two policymakers). Framework evaluation after adoption: (four researcher/practitioners adopted the framework. One researcher was interviewed on behalf of the remainder of the group).

The first research question was addressed using an SLR. Part of the results of this review have already been published in a separate paper (Alwahaby et al., 2022). The search has since been updated to include papers published from 2021 until 2024. The SLR was conducted to identify relevant literature, focusing on finding the most promising advantages of applying MMLA in education and investigating the ethical considerations associated with its use. An overview of the SLR methodology was given previously in section 2.2. Given that the aims of the second and third research questions are to gain a comprehensive understanding of opinions regarding the use of MMLA in higher education, as well as potential measures to mitigate any negative consequences of MMLA use, a qualitative approach was adopted for these parts of the study to gather relevant data. This part of the research used interviews, as outlined below.

3.2 Justification for Using Qualitative Research Methods

This study employs a qualitative approach. For many years, qualitative approaches have been used in research involving human life in a variety of disciplines, including education (Denzin & Lincoln, 2011). In light of the fact that the study's research questions were designed to gain a better understanding of participants' perceptions of how MMLA might be applied in higher education and how this knowledge could be used to develop an ethical MMLA application framework, qualitative enquiry methods were chosen as the most appropriate. As Creswell (2018) notes, a qualitative approach seeks to understand what individuals and groups attribute to social or human issues. Equally, because MMLA is an emerging technology and a new topic, the variables to be examined in terms of its ethical applications are not fully known, therefore a qualitative approach is necessary (Creswell, 2018).

It should also be noted that qualitative research involves examining descriptions and meanings that cannot always be quantitatively represented. The overall purpose of the work is not necessarily to be able to provide generalisable findings, but rather to deliver detailed information regarding a small number of individuals or cases through direct quotations, detailed descriptions of situations, events, interactions and observed behaviours. This is consistent with the main objective of this study (Labuschagne, 2015).

3.3 Sampling

This study aimed to gather in-depth opinions from a range of stakeholders. Accordingly, the sample of participants included researchers/practitioners, educators, students at higher education institutions, in addition to an educational technology company.

A convenience sampling approach was employed to recruit educators and students from higher education institutions. This non-probability sampling method comprised selecting participants based on their accessibility and availability at the time of the study (Etikan, 2016). Educators and students were invited to participate in the study via a variety of platforms, such as Moodle, emails and WhatsApp groups. Accordingly, eight educators and 39 students agreed to participate in the interviews. The student participants included nine males and 30 females aged 25 to 60. They originated from a variety of ethnic and cultural backgrounds, for instance Asian, Black, White and Arab. They included master's and PhD students from diverse backgrounds and with a wide range of experience. Among the 39 students, seven were recruited from a module that used and collected MMD in practice, with the intention of supporting student learning. Consequently, these students had first-hand experience of MMLA.

Concerning the researchers/practitioners, a purposive sampling method was employed to recruit the participants. The participants were selected based on their research experience and teaching within the field of MMLA. Hence, an initial list comprising 60 researchers was prepared prior to commencing the data collection phase, with the aim of inviting them to contribute to the study. These researchers were chosen on the basis of their own publications in the field of LA and MMLA, and their details were obtained from relevant events, for instance conferences pertaining to Learning Analytics and Knowledge (LAK). The list included each participant's name, occupation, relevant publications and contact information. (The full list has been omitted from this document to protect the confidentiality of the participants.). Potential participants were invited to the study by email, which included a description of the research, its aims and objectives, in addition to what would be expected from them as a participant. A total of 60 researchers/practitioners were invited to participate in the study. A final total of 12 agreed to participate. Nonprobability purposive sampling has several limitations related to subjectivity in choosing the sample. Therefore, it is not likely to result in a representative sample (Etikan, 2016). Nonetheless, due to the nature and aims of this study, purposive sampling was deemed to be the most convenient and efficient way to obtain a range of relevant in-depth responses from people with prior experience of MMLA or ethics.

In total, the main data collection for this study involved 60 participants. Their detailed descriptions are presented in Tables 5, 6, 7 and 8 below. A sample of 60 participants may be considered small for certain methodologies, but for in-depth qualitative interviews it is a relatively large sample size. Essentially, the recruitment of new participants ceased only once the data had reached saturation in terms of the insights and themes emerging, as well as the recurrence of specific observed themes.

For the purpose of gaining further information from different stakeholders, an MMLA technology company was also approached. For the evaluation process, 27 evaluators were recruited, including seven students, 13 researcher/practitioners, four teachers, one ethics expert and two policymakers. Table 9 provides an overview of the interviewees. Moreover, following the framework development a team of four MMLA researchers adopted the framework in their experiment. Table 10 provides an overview of the researchers.

Table 5. The four groups of people interviewed as part of the study's main data collection

Group	Number of Candidates	Gender	Qualifi-cation	Background and experience
Researchers/ practitioners	N = 12	Males = 9 Females = 3	PhD	Experience in research and teaching within the field of MMLA/LA.
Teachers	N = 8	Males = 2 Females = 6	MA-MSc/ PhD	Master's and doctorate holders who were teachers in higher education, with a range of backgrounds and experience.

Students	N = 39	Males = 9 Females = 30	MA-MSc/ PhD	Master's and doctoral students with a wide range of backgrounds and experience - 7 out of 39 had experience of MMLA
MMLA technology company	N = 1	Male = 1	PhD	Experience in developing MMLA systems.

Table 6. Students interviewed as part of the study's main data collection

Student ID	Qualification	Educational background	Gender	Age group
S01	Master's student	Education and technology	Male	25–30
S02	Master's student	Interior design	Female	25–30
S03	PhD student	Education	Female	35–40
S04	Master's student	Education and technology	Female	30–35
S05	PhD student	MMLA	Female	25–30
S06	Master's student	Education and technology	Female	31–35
S07	PhD student	MMLA	Male	25–30
S08	Master's student	Education and technology	Female	31–35
S09	PhD student	Software engineering	Female	31–35
S10	PhD student	MMLA	Male	36–40
S11	PhD student	Clinical pathology	Female	36–40
S12	PhD student	Information science	Female	36–40
S13	PhD student	Learning and leadership	Female	31–35
S14	Master's student	Environmental and energy policy	Female	31–35
S15	Master's student	Environmental and energy policy	Male	31–35
S16	Master's student	Bio-integrated design	Female	25–30
S17	PhD student	Education	Female	31–35
S18	PhD student	Oral surgery	Female	31–35
S19	Master's student	Electrical engineering	Female	31–35
S20	PhD student	Pharmacy	Female	36–40
S21	Master's student	English language teaching	Female	25–30
S22	Master's student	Education and technology	Female	31–35
S23	Master's student	Learning and leadership	Female	25–30
S24	PhD student	Medical imaging	Female	36–40
S25	Master's student	Design engineering	Female	25–30
S26	PhD student	Medicinal chemistry	Female	36–40
S27	Master's student	Education and technology	Male	25–30
S28	PhD student	Law	Female	36–40
S29	PhD student	Phytochemistry	Female	25–30
S30	PhD student	Technology and learning design	Male	36–40

S31	PhD student	Psychology of human development	Female	31–35
S32	Master’s student	Education and technology	Female	41–45
S33	PhD student	Education and technology	Female	36–40
S34	PhD student	English language teaching	Female	31–35
S35	Master’s student	Social research	Male	50–55
S36	Master’s student	Education and technology	Female	46–50
S37	PhD student	Maths education	Male	31–35
S38	PhD student	Linguistics and education	Female	46–50
S39	PhD student	Linguistics and education	Male	31–35

Table 7. The researchers/practitioners interviewed as part of the study’s main data collection

Participant ID	Qualification	Occupation	Formal training and educational background	Years of experience and familiarity with MMLA
R01	PhD	Research scientist	Computer science and learning technology	3
R02	PhD	Postdoctoral researcher	Information technologies and technology-enhanced learning	8
R03	PhD	Professor	Computer science	7
R04	PhD	Postdoctoral researcher	Computer science, artificial intelligence and educational technologies	5
R05	PhD	Associate professor	Philosophy of education and computer science	7
R06	PhD	Professor	Computer engineering	5
R07	PhD	Associate lecturer	Media design and animation	1
R08	PhD	Associate professor	Computer science and modelling	5
R09	PhD	Assistant professor	Computer science	2
R10	PhD	Associate professor	Education and technology	7
R11	PhD	Professor	LA and MMLA	5
R12	PhD	Professor	Computer science and technology enhanced learning	8

Table 8. Teachers interviewed as part of the study’s main data collection

Participant ID	Qualification	Occupation	Formal training and educational background	Years of experience
T01	PhD	Associate professor	Medical education	13
T02	Master’s	Lecturer	Health informatics	2
T03	PhD	Assistant professor	Applied medical sciences	10
T04	Master’s	Lecturer	Clinical nutrition	2
T05	Master’s	Lecturer	Music and history of education	15
T06	Master’s	Lecturer	Instructional technology	4
T07	PhD	Professor	Physical chemistry	18
T08	PhD	Lecturer	Archaeology and science education	20

Table 9. Information relating to the interviewees who evaluated the framework

Evaluators’ ID	Occupation	Qualification	Educational background	Gender	Age group
ES01	Student	Master’s	Education and technology	Male	25–30
ES02	Student	Master’s	Education and technology	Female	25–30
ER03	Researcher/ practitioner	PhD	Multimodal learning analytics	Male	30–40
ER04	Researcher/ practitioner	PhD candidate	Multimodal learning analytics	Male	25–30
ER05	Researcher/ practitioner	PhD candidate	Multimodal learning analytics	Female	25–30
ET06	Teacher	PhD candidate	Multimodal learning analytics	Male	30–40
ER07	Researcher/ practitioner	PhD	Multimodal learning analytics	Male	30–40

ER08	Researcher/ practitioner	PhD	Multimodal learning analytics	Male	30–40
ER09	Researcher/ practitioner	PhD	Multimodal learning analytics	Male	30–40
EE10	Ethics expert	PhD	Ethics	Male	60–70
ER11	Researcher/ practitioner	PhD	Multimodal learning analytics	Male	30–40
ER12	Researcher/ Practitioner	PhD	Multimodal learning analytics	Male	50–60
ET13	Teacher	PhD candidate	Education	Female	30–40
ES14	Student	Master's	Cybersecurity	Female	30–40
ES15	Student	Master's	Education and technology	Male	25–30
ER16	Researcher/ Practitioner	PhD	Learning analytics	Male	30–40
ER17	Researcher/ Practitioner	PhD	Learning analytics	Male	30–40
ET18	Teacher	PhD	Education	Female	30–40
ES19	Student	Master's	Artificial intelligence and machine learning	Female	25–30
ER20	Researcher	PhD candidate	Multimodal learning analytics	Male	25–30
ET221	Teacher	PhD	Digital learning	Female	30–40
ES22	Student	Master's	Cybersecurity	Female	25–30
ES23	Student	Master's	Cybersecurity	Female	25–30

EP24	Policy maker	PhD	Educational curriculum	Male	40–50
EP25	Policy maker	PhD	Educational system design	Male	40–50
ER26	Researcher/ Practitioner	PhD	Multimodal learning analytics	Male	30–40
ER27	Researcher/ Practitioner	PhD candidate	Learning analytics	Male	30–40

Table 10. Researchers/practitioners who adapted the framework for their RAP application version experiment

Name	Occupation
Federico Domínguez (Interviewed on behalf of the remainder of the group)	Professor of Computer Engineering
Gonzalo Mendez	Professor of Computer Science
Marisol Villacres	Professor of Computer Science
Jhonston Benjumea	Engineer, App development
Leonardo Eras	Engineer, Backend development

3.4 Data Collection Methods

3.4.1 Main Data Collection from the Structured Open-ended Interviews

The study aims to gain a better understanding of the ethical concerns associated with the use of MMLA in higher education and how to mitigate them by collecting comprehensive viewpoints and experiences from relevant stakeholders. This was achieved through individual structured interviews. Due to COVID-19 restrictions, the interviews were conducted via Microsoft Teams, an online video meeting software. The interview protocol was designed to ensure consistency between each interview. Each interview lasted 30 to 60 minutes.

The first set of questions was designed based on the five core ethical principles commonly used in bioethics and AI: beneficence, non-maleficence, autonomy, justice and explicability (Beauchamp &

Childress, 2001). Owing to similarities between bioethics and digital ethics, specifically in terms of the ecological approach taken when interacting with new types of agents, patients and environments (Floridi, 2013), bioethics has become an important method of analysis for many digital ethical reasoning and decision-making processes (see, for instance, Floridi and Cowls, 2019).

The interview sessions had 11 separate sections inspired by the SLR of the field, addressing the following aspects: introduction; background demographic information; privacy; well-being; safety; autonomy; student agency; accountability; trustworthiness; transparency and explainability; and fairness and bias. Since most participants did not have first-hand experience of MMLA, a short, animated video[2] was created to explain the concept of MMLA in education, providing specific examples from real-world applications. The video aimed to simplify and clarify what MMLA is to participants with limited experience. To ensure the participants' privacy, the GDPR were followed and approval was received from the institutional ethics committee. The participants' permission was obtained for the audio and video recording of the interviews via detailed information and consent sheets signed by the participants, providing a legal and ethical basis for processing their data. DocuSign, a secure online signature service, was used to collect e-signatures from the participants. The main structured interview protocol is shown in Appendix 3.

3.4.2 Evaluation of the framework by the Interviewees

The evaluation process necessitated presenting the framework to the interviewees and requesting their feedback with respect to four principal questions: 1) What is your favourite feature of the framework and which aspect of it would you like to remain unchanged? 2) What changes or additions would you like to make to the framework? 3) Does the framework provide a practical guide to increase the understanding of and trust in the use of MMLA? 4) To what extent do you consider this framework to be transparent and easy to use? Could you propose a different approach to present the framework? (See Appendices 4 & 5). Based on the results of the evaluation, the framework was continuously assessed until saturation was attained. In response to stakeholder feedback, the framework was evaluated three times and repeatedly modified.

Furthermore, following its development, a team of MMLA researchers implemented the framework into their research, as illustrated in Table 10. As part of an attempt to understand the team's

[2] https://drive.google.com/file/d/1yL8WXysnQT5SKZFskTmc4jf4GFx8sym6/view?usp=sharing

experience in relation to implementing the framework, Professor Federico Dominguez was interviewed online using Microsoft Teams. The interview questions concentrated on four key themes, comprising clarity, comprehensiveness, effectiveness and practicality. Appendix 5 provides the interview protocol and questions.

According to Professor Dominguez, the purpose of their study was to develop a mobile version of the RAP system used for automatic feedback of oral presentation skills using MMLA (Ochoa et al., 2018). In 2023, the RAP system was introduced at the university. Subsequently, it has been employed on a regular basis by students on several academic courses. Two dedicated rooms were set up where students could deliver presentations and receive immediate feedback. Additionally, a web portal was developed to allow professors to observe the presentations and students to assess their feedback. Professor Dominguez also asserted that the university requested the development of a phone application owing to the high maintenance costs and the space occupied by the existing system. In total, 43 students participated in the experiment. The application developed in the study gives students the opportunity to record video and audio presentations at home and receive feedback on their performance, and the option of uploading their slides, although this is not mandatory as it was in the previous version. The application transfers the video recording to the backend server, which subsequently provides the students with useful feedback. A web portal was also available to the professor to view the results of the presentations. The experiment evaluated the system to ascertain its performance, whether it was beneficial for the students and professors, and to determine the quality of the feedback provided. Concerning the app version of the experiment, the MMLA ethics framework developed in the current study functioned as a guide in support of its design and execution.

3.5 Data Analysis

3.5.1 Interview Analysis

Thematic analysis was adopted for the assessment of the interview data. Thematic analysis, an approach that is commonly used in qualitative research, was chosen for this study because of its flexibility (Braun & Clarke, 2006). Having the flexibility to revise the codes and themes as often as required in a nonlinear approach was beneficial. Moreover, to provide accurate analysis that will answer the research questions and to fit with the exploratory nature of this study, a deductive thematic method was adopted. This involved extensive reading of the data with the aim of identifying themes related to the research question, while also considering themes identified previously and outlined in similar studies (Braun & Clarke, 2006).

In terms of the level of thematic analysis, a latent approach was adopted to identify the underlying ideas. Specifically, prior to starting, analysis transcription software was used to transcribe the interviews into a written form without any modification, except to correct minor spelling mistakes generated by the software. The transcripts were then compared with the original audio recordings for accuracy and were exported to NVivo12, a qualitative analysis software. The analysis process was guided by the six-step Thematic Analysis approach proposed by Braun and Clarke (2006). The first step entailed a meticulous review of the interview data to develop a better understanding, while documenting an initial list of ideas and interesting observations. Each interview transcript was read at least once. In the second step, following the latent approach and looking for underlying ideas, codes were generated for important parts of the data that could help to answer the research questions. The relevant data were linked to each code using NVivo12, according to a systematic approach. During this stage, 21 codes were generated.

The third step predominantly focused on the analysis of the broader themes and sub-themes, and on allocating and combining codes and data to form relevant themes. Owing to the exploratory nature of this study, themes were identified according to a deductive thematic coding approach. This involved extensive reading of the data to identify themes related to the research question whilst identifying themes present in the extant research. A theme is a pattern that captures something significant or interesting concerning the data. Moreover, as Braun and Clarke (2006) underline, there is no standard definition of what constitutes a theme; rather, a theme is defined by its significance. Themes at this stage occasionally appeared to be overlapping with the same data belonging to different themes, but each theme interpreted the data differently. The fourth step was a continuous process of reviewing and refining themes, combining themes or separating them into several themes. These decisions were made based on whether or not there was a clear pattern in the coded data obtained. A clear pattern was defined based on whether there was sufficient data to support a certain theme and whether the data were connected. Additionally, in this step, the dataset was reevaluated to assign any uncoded data to relevant themes or remove any irrelevant coded data. Irrelevant coded data were defined as any coded data that did not belong to any emerging themes or were too insignificant to function as a stand-alone theme.

The fifth step comprised assigning a precise name to each theme, providing a sense of the scope of the theme that would be easy for readers to relate to and understand. Finally, the last step involved writing up the thematic analysis, including evidence of the identified themes, in a non-descriptive way while constructing arguments related to the relationship between each theme and the research questions (Braun & Clarke, 2006).

3.6 Reliability

Reliability is an important concept in quantitative research, but the question of whether and how to achieve reliability in qualitative research is constantly debated (McDonald et al., 2019). According to Kvale (2012, p. 162), “[r]eliability pertains to the consistency and trustworthiness of research findings; it is often treated in relation to the issue of whether a finding is reproducible at other times and by other researchers”. These concerns relate to whether participants might provide different interviewers with different answers, and whether or not a different interview analyst would produce similar results (Kvale, 2012).

Therefore, to guarantee reliable findings and mitigate any potential bias caused by a single researcher, the interview transcripts were reviewed and coded by two researchers individually. Agreement between the two coders was measured by way of inter-rater reliability measures. According to McDonald et al. (2019, p. 2), “inter-rater reliability is a statistical measure of agreement between two or more coders of data”. Although inter-rater reliability is a less common measure of reliability in qualitative research than the statistical data collected in quantitative research, owing to the complex nature of qualitative data which could include reviews and personal emails (McDonald et al., 2019), inter-rater reliability was perceived to be appropriate and feasible for this study. Hence, it was calculated to increase the reliability of the findings.

A variety of statistical methods can be employed to measure inter-rater reliability, including Cohen’s Kappa, Scott’s Pi or Krippendorff’s Alpha (McAlister et al., 2017). Many factors should be considered prior to the selection of a particular inter-rater reliability statistical test, for example the type of data (for example, whether it is nominal, ordinal, interval or ratio), the study design (e.g., whether all the data or only a subset of it will be rated by multiple coders), and the purpose of the inter-rater reliability measurement (e.g., to estimate reliability for individual coders, or find the reliability of the mean ratings from multiple coders) (Hallgren, 2012). Cohen’s Kappa was selected as the most appropriate measure for this study, as two coders were coding the same dataset and the data were nominal, and also because of its popularity as the most commonly-used measure of inter-rater reliability in qualitative research (McDonald et al., 2019). McHugh (2012) asserted that Cohen’s Kappa is a robust statistic in relation to testing inter-rater reliability. Accordingly, the interview transcripts were independently reviewed and coded by two researchers, resulting in a Cohen’s Kappa of 0.76. This agreement was substantial for complex thematic analysis research and is consistent with previous literature (Cheung & Tai, 2023).

To ensure consistency and minimise potential bias, all of the interviews were conducted in English, a language common to each of the participants. The raw audio data from the interviews were transcribed using transcription software without any modification, except for correcting a few minor spelling mistakes generated by the transcription software. The transcripts were compared with the original audio recordings for accuracy. The researcher has declared that there is no conflict of interest in this research, and acknowledges that transparency in reporting how the research was conducted and the rationale for choosing specific methods are important reliability measures, allowing other researchers to adopt and implement the same techniques in their own setting.

3.7 Validity

According to Kvale (2012, p. 162), "[v]alidity refers in common language to the truth, the correctness and the strength of a statement. A valid argument is sound, well grounded, justifiable, strong and convincing. Validity in the social sciences pertains to the issue of whether a method investigates what it purports to investigate". On account of the diverse nature of qualitative research, quantitative criteria have on occasion been used inaccurately by novice researchers to improve the apparent trustworthiness of their qualitative research (Anney, 2014); thus, it is important to adopt appropriate qualitative credibility strategies. There are a variety of "qualitative credibility strategies" (Anney, 2014, p. 276), such as prolonged and varied field experience, time sampling, reflexivity (field journals), triangulation, member checking, peer examination, interview technique, establishing the authority of the researcher, and structural coherence. "Peer debriefing" (Guba, 1981, p. 85) was adopted for this research. Guba (1981) maintained that peer debriefing "provides inquirers with the opportunity to test their growing insights and to expose themselves to searching questions". The perceptions of the researcher's academic supervisors and colleagues were sought during the development of each of the research phases, including the research background, data collection and analysis, and during the review of the findings. Conversely, to prevent group thinking, the researcher evaluated each idea critically, asking for reasons behind each opinion and encouraging discussion.

3.8 Generalisation

The generalisability of research can be assessed based on "whether the results are primarily of local interest, or whether they may be transferable to other subjects and situations" (Kvale, 2012, p. 166). Given that qualitative research is often not based on random sampling or statistical controls, it is often not designed to allow generalisability to the wider population (Niaz, 2007). Moreover, for practitioners, the relatability and auditability of research can be more important than its generalisability (Cukurova et al., 2018). For instance, considerable educational research does not report all relevant contextual information, lessening its impact on educators' practices. A lack of generalisability can prevent research findings from being applied to educators' own contexts, and consequently makes them less relatable (ibid.). Although the findings obtained by this study might not be generalisable to every particular context in higher education, they can still be related to similar contexts.

3.9 Ethical Considerations

To conduct ethical research, it is important to ensure that the participants' privacy is protected, while also being mindful of ethical issues that might appear during the study. Confidentiality can be safeguarded by following the GDPR. Therefore, the researcher completed and passed online GDPR training prior to the beginning of the data collection phase. In terms of ethical issues, UCL ethics approval was granted for this research in keeping with the guidelines of the British Association for Educational Research (BERA). The data protection registration number is Z6364106/2021/06/210. In line with the GDPR, the participants' permission was obtained for audio and video recording via consent sheets signed by the participants, providing the legal basis for processing personal data. DocuSign, a secure online signature service, was used for e-signatures. Moreover, the interview data collection process consisted of three stages to consider: prior to the interview, during the interview, and after the interview. These were as follows.

3.9.1 Considerations Prior to the Interviews

Interview sessions were arranged and scheduled according to the availability of the participants. To allow the participants to familiarise themselves with the questions, they were provided with the interview schedule prior to the interview. A reminder email with an online meeting link was forwarded to the participants one day in advance of the interview. As the participants were all adults, they were all qualified to sign the consent sheet. Although all the participants agreed to the interviews being recorded via a signed consent sheet, they were asked to confirm their decision at the beginning of the interviews. The aim of the study and the structure of the interview were clarified before each interview, both in the invitation email and at the beginning of the interview. Questions were combined with the definitions of unfamiliar terms, examples and explanations, as necessary. The interview questions were planned to safeguard the well-being and comfort of each of the participants and no sensitive questions were included.

3.9.2 Considerations During the Interviews

To allow the participants to feel comfortable and welcome during the interviews, the sessions were structured and presented in a friendly and informal manner. The interviews started with icebreaker questions pertaining to the participant's city and the weather. During the interviews, the participants were frequently asked whether they required any clarification. The researcher showed interest in the participants' answers through nonverbal gestures such as smiling and nodding. To avoid influencing the participants' answers, the researcher maintained a neutral position at all times during the interviews. By employing an active listening approach, the researcher was able to identify important answers, direct the interviews in a specific direction and ask participants to elaborate on specific points.

3.9.3 Considerations After the Interviews

To ensure that the confidentiality and anonymity of participants were protected according to the ethical principles, the participants' identities were completely anonymised by giving each participant a unique individual code, e.g., S01, S02, as shown previously in the participant information table. Likewise, personal identifiers were removed from the data. The participants' consent sheets, the recorded interviews and interview transcript records were all stored securely on password-protected files. Only data that were relevant to the research were retained. Although some of the results have been published in academic articles, the participants were not individually identifiable. At present, the encrypted data are securely stored in UCL's Data Safe Haven and will be kept for future use for a period of up to 60 months. Restricted access by other authenticated researchers will be allowed for further data analysis if required.

3.10 Chapter Summary

This chapter has presented a detailed overview of the methodological approaches employed in this study, including the sampling approach, data collection method and the data analysis technique, together with discussing reliability, credibility and ethical considerations. The interview findings will be presented in detail in the following chapter.

4 Chapter Four: Findings from the Thematic Analysis of the Main Data Collection

4.1 Introduction

This chapter presents the participants' responses, organised in terms of the common themes and sub-themes. As mentioned in Chapter Three, given that the nature of this study is exploratory, a deductive thematic coding approach was adopted in this thematic analysis. This involved extensive reading of the data to identify themes related to the research question while relying on earlier identified themes presented in previous research (Braun & Clarke, 2006).

4.2 Themes

According to the thematic analysis of each stakeholder interview, a number of themes were determined to be common across stakeholders (see Tables 12, 13, 14 & 15). Consequently, nine themes emerged as shared concerns among different groups of stakeholders. The nine emerging themes are summarised in Table 11. The themes are presented with regard to how many participants mentioned or agreed with them.

The selection of quotes was made based on their relevance to the theme discussed as well as the prevalence of similar opinions in the data analysed.

Table 11. General unified themes

Theme 1: The increasing need for an ethical framework for MMLA	Theme 2: Privacy, surveillance and intrusiveness issues with MMLA	Theme 3: Student agency over their learning and data ownership
Theme 4: Trustworthiness of MMLA result	Theme 5: Fairness and bias issues in MMLA systems	Theme 6: Transparency and explainability of MMLA systems
Theme 7: Accountability of MMLA systems	Theme 8: Level of awareness of the benefits and risks associated with MMLA use	Theme 9: The benefits of MMLA and the ethical issues associated with failing to use it

Table 12. Thematic analysis coding schemes for the students' interviews

Themes	Code	Description
The increasing need for an ethical framework in MMLA.	The importance of an ethical framework for MMLA.	Explains why an ethical MMLA framework is essential, as perceived by students.
	Recommendations for future framework.	Explains the students' recommendations regarding the future framework.
Potential benefits of MMLA and the ethical issues associated with failing to use it.	Potential benefits of MMLA.	Describes how the learning and teaching process can benefit from using MMLA, as perceived by students.
Accountability for MMLA systems.	Accountability for the effectiveness of MMLA systems and the protection of data.	Explains the students' perceptions of who takes responsibility for the effectiveness of MMLA systems and data protection, and the consequences of a data breach and system failures.
	Suggestions to promote accountability in MMLA.	Recommendations from students to promote accountability within MMLA.
Trustworthiness of MMLA results.	Negative attitudes towards modelling or predicting with MMLA.	Discusses students' trust issues in relation to MMLA making assumptions/predictions.
	Trust in MMLA results.	Describes how trust in MMLA results can be promoted, as perceived by students.
	Views on using MMLA results for assessments.	Views on whether MMLA results should be used for assessments as perceived by students.
Fairness and bias issues in MMLA systems.	Potential risk of bias.	Describes potential risk of bias issues in MMLA systems as perceived by students.
	How to mitigate bias.	Provides recommendations on how to mitigate bias as perceived by students.
Transparency and explainability of MMLA systems.	Students' views concerning transparency within MMLA systems.	Describes students' opinions regarding the transparency of MMLA systems.
	Students' attitudes towards the explainability of MMLA systems.	Explanation of students' attitudes towards the explainability of MMLA systems.

	Risk of gaming the system.	Describes the possible risk of students gaming the system due to over explainability and transparency.
Students' agency in relation to their learning and ownership of data.	Attitudes regarding students' agency in relation to their learning.	Understanding students' rights to gain access to, change or delete their MMLA results.
	Students' attitudes regarding ownership of their data.	Understanding students' rights to gain access to, change or delete their MMLA data.
Level of awareness of the benefits and risks associated with MMLA use.	The effect of the type of MMLA data and the purpose of the study on students' willingness to participate.	Explains the impact of the type of MMLA data and the purpose of the study on students' willingness to participate.
	The effect of students' educational background on their willingness to participate.	Describes how students' educational background affects their willingness to participate.
	Relationship between students' understanding of the consent form and their willingness to participate.	Explains the positive correlation between the students' level of understanding of the consent form and their willingness to participate.
	Views on students' understanding of the information sheet.	Provides an overview of student attitudes regarding the information sheet's comprehensibility .
	Relationship between students' trust in the institution and their willingness to participate.	Explains the positive correlation between students' trust in the institution and their willingness to participate.
	Expectations concerning the information sheet.	Suggests what should be included in the information sheet and how the information should be presented from students' perspectives.
	Problems with consent form.	Identifies the issues related to the content, layout and language used in the consent form and the effect they may have on students' willingness to provide consent.
	Attitudes towards MMLA data sensitivity.	Describes how students feel about the sensitive nature of the MMLA data
	Potential physical and psychological harm.	Explains the potential physical and psychological harm associated with the use of MMLA tools.

Privacy, surveillance and intrusiveness issues with MMLA.	Potential behavioural and psychological effects of surveillance.	Describes the behavioural and psychological changes which may occur with students as a result of being constantly observed.
	Different interpretation of data identity.	Different definitions or understandings of data identity.
	Trade-off between privacy and the benefits.	Explains being obliged to provide data or relinquish privacy to gain benefits from using a tool or technology.
	Data sharing.	How data are shared with others (other parties, researchers, organisations, authorities, etc.).
	Data handling and storage strategy.	Perceptions on how, when, where and how long the MMLA data should be stored.
	Further protective measures.	Describes further measures that can be implemented to reduce the risks associated with the use of MMLA in educational settings.
	Attitudes towards the intrusiveness of MMLA data and collection techniques.	Describes the students' attitude towards the intrusiveness of MMLA data and collection methods.
	Potential risk of exploiting MMLA data.	Describes the possible risk of misusing MMLA data.

Table 13. Thematic analysis coding schemes for the teachers' interviews

Themes	Code	Description
Privacy, surveillance and intrusiveness issues with MMLA.	Teachers' views on sharing and storing MMLA data and confidentiality protections.	Describes teachers' opinions on sharing and storing MMLA data, together with the privacy measures implemented to protect it.
	Potential physical and psychological harm.	Describes the potential physical and psychological harm associated with the use of MMLA tools as perceived by teachers.
	Potential behavioural and psychological effects of surveillance.	Examines the behavioural and psychological shifts that can occur in students due to continuous surveillance, as perceived by teachers.

	Teachers' opinions regarding the sensitivity of MMLA data.	Describes how teachers feel about the sensitive nature of MMLA data.
Level of awareness of the benefits and risks associated with MMLA use.	Teachers' perspectives on the effect of the type of MMLA data and the purpose of the study on students' willingness to participate.	Investigates teachers' views on the effect of the type of MMLA data and the purpose of the study on students' willingness to participate.
	The correlation between the students' understanding of the consent form and their willingness to participate.	The correlation between the students' understanding of the consent form and their willingness to participate
	Teachers' views on the students' understanding of the information sheet.	Describes teachers' perceptions of students' comprehension of the information sheet.
	Problems with the consent form.	Identifies issues related to the content, layout and language of the consent form, and their perceived impact on students' willingness to provide consent, from the teachers' perspectives.
	Expectations concerning the information sheet.	Suggests what should be included in the information sheet and how the information should be presented from teachers' perspectives.
Student agency in relation to their learning and ownership of data.	Teachers' attitudes in relation to students' agency over their learning.	Understanding teachers' perspectives related to students' rights to gain access to, change or delete their MMLA results.
	Teachers' opinions in relation to students' ownership of their data.	Understanding teachers' perspectives related to students' ownership of their data.
Trustworthiness of the MMLA result.	Negative attitudes towards modelling or predicting with MMLA.	Discusses teachers' trust issues in relation to MMLA making assumptions/prediction.
	Trust in MMLA results.	Describes how trust in MMLA results can be promoted, from the perspectives of the teachers.
	Views on using MMLA results for assessment.	Views on whether MMLA results should be used for assessments, from the viewpoint of the teachers.

Accountability for MMLA systems.	Accountability for the effectiveness of MMLA systems and the protection of data.	Illustrates the teachers' perceptions of who takes responsibility for the effectiveness of MMLA systems and data protection and the consequences of a data breach and system failures.
Fairness and bias concerns in MMLA systems.	Potential risk of bias.	Describes the possible risk of bias issues in MMLA systems, as perceived by the teachers.
	How to mitigate bias.	Provides recommendations on how to mitigate bias, as perceived by the teachers.
Transparency and explainability of MMLA systems.	Teachers' views regarding transparency within MMLA systems.	Describes teachers' opinions on the transparency of MMLA systems.
	Teachers' attitudes towards the explainability of MMLA systems.	Explanation of teachers' attitudes towards the explainability of MMLA systems.
Potential benefits of MMLA and the ethical issues associated with failing to use it.	Potential benefits of MMLA.	Describes how learning and the teaching process can benefit from using MMLA, as perceived by teachers.
The increasing need for an ethical framework for MMLA.	The importance of an ethical framework for MMLA.	Explains teachers' perceptions of why an ethical MMLA framework is essential.

Table 14. Thematic analysis coding schemes used for the researchers' interviews

Themes	Code	Description
Privacy, surveillance and intrusiveness issues with MMLA.	MMLA data sharing, storing and privacy protection measures.	Describes researchers' attitudes toward MMLA data sharing, storing and the privacy measures implemented to protect MMLA data.
	Potential behavioural and psychological effects of surveillance.	Explains the behavioural and psychological changes that occur with students as a result of being constantly observed, as perceived by the researchers.
	MMLA data sensitivity.	Describes the researchers' opinions of the sensitivity of MMLA data.

	Researchers' views on the intrusiveness of MMLA collection methods.	Describes the researchers' views on the intrusiveness of MMLA collection methods.
	Potential misuse of MMLA data.	Illustrates the potential risk of MMLA data being misused, as perceived by the researchers.
Level of awareness of the benefits and risks associated with using MMLA.	Researchers' views on the students' understanding of the information sheet.	Describes researchers' perspectives on students' comprehension of the information sheet.
	Expectations concerning the information sheet.	Suggests what should be included in the information sheet and how the information should be presented from the researchers' perspectives.
	Researchers' perspectives on the effect of the type of MMLA data and the purpose of the study on students' willingness to participate.	Investigates researchers' views on the effect of the type of MMLA data and the purpose of the study on students' willingness to participate.
Students' agency regarding their learning and data ownership.	Researchers' attitudes in relation to students' agency over their learning.	Understanding researchers' perspectives related to students' rights to gain access to, change or delete their MMLA results.
	Researchers' opinions in relation to students' ownership of their data.	Understanding researchers' perspectives related to students' ownership of their data.
Trustworthiness of MMLA result.	Negative attitudes towards modelling or predicting with MMLA.	Discusses researchers' trust issues in relation to MMLA making assumptions/ predictions.
	Trust in MMLA results.	Describes how trust in MMLA results can be promoted, as perceived by researchers.
	Views on using MMLA results for assessments.	Views on whether MMLA results should be used for assessments, as perceived by researchers.
The accountability of MMLA systems.	Accountability for the effectiveness of MMLA systems and the protection of data.	Explains the researchers' perception of who takes responsibility for the effectiveness of MMLA systems and data protection and the consequences of a data breach and system failures.

	Recommendations to promote accountability in MMLA systems.	Presents researchers' recommendations to promote accountability in MMLA systems.
Transparency and explainability of MMLA systems.	Researchers' views about transparency within MMLA systems.	Explains researchers' opinions of the transparency of MMLA systems.
	Researchers' attitudes towards the explainability of MMLA systems.	Explanation of researchers' attitudes towards the explainability of MMLA systems.
	Risk of gaming MMLA systems.	Describes the researchers' concerns about the potential risk of students gaming the system due to over explainability and transparency.
Fairness and bias issues in MMLA systems.	Potential risk of bias.	Describes possible risk of bias issues in MMLA systems, as perceived by researchers.
	How to mitigate bias.	Provides recommendations on how to mitigate bias, as perceived by researchers.
The importance of an ethical framework for MMLA.	The importance of an ethical framework for MMLA.	Explains why an ethical MMLA framework is important, as perceived by researchers.
	Recommendations for the future MMLA ethical framework.	Describes researchers' recommendations concerning the future MMLA ethical framework.

Table 15. Thematic analysis coding schemes for the educational technology company interviews

Themes	Code	Description
Privacy, surveillance and intrusiveness concerns with MMLA.	Potential behavioural and psychological effects of surveillance.	Explains the behavioural and psychological changes that occur with students as a result of being constantly observed, as perceived by an educational technology company.
	Privacy concerns.	Describes the privacy concerns associated with using MMLA, as identified by an educational technology company.
	MMLA data sharing, storing and privacy protection measures.	Describes an educational technology company' attitudes towards MMLA data sharing, storing and the privacy

		measures implemented to protect MMLA data.
Level of awareness of the benefits and risks associated with MMLA use.	Views on the students' understanding of the information sheet.	Describes an educational technology company's perspectives on students' comprehension of the information sheet.
Accountability for MMLA systems.	Accountability for the effectiveness of MMLA systems and the protection of data.	Denotes an educational technology company's perception of who takes responsibility for the effectiveness of MMLA systems and data protection and the consequences of a data breach and system failures.
Trustworthiness of MMLA results.	Trust in MMLA results.	Describes how trust in MMLA results can be promoted as perceived by an educational technology company.
	Views on using MMLA results for assessment.	The educational technology company's views on whether MMLA results should be used for assessments.
Transparency and explainability of MMLA systems.	Researchers' views of transparency within MMLA systems.	Describes an educational technology company's thoughts regarding the transparency of MMLA systems.
	Researchers' views of the explainability of MMLA systems.	Explanation of an educational technology company's opinions of the explainability of MMLA systems.
Fairness and bias issues in MMLA systems.	How to mitigate bias.	Provides recommendations on how to mitigate bias, from the perspective of an educational technology company.
The importance of an ethical framework for MMLA.	The importance of an ethical framework for MMLA.	Explains why an ethical MMLA framework is essential, as perceived by an educational technology company.

In the following section, themes will be identified in bold, whilst participants' quotes will be provided in italics. The interviewees' names are anonymised using letters and numbers: (S) for students; (T) for teachers; (R) for researchers; and (C) for technology companies.

4.2.1 Theme 1: The Increasing Need for an Ethical Framework for MMLA

To reduce the likelihood of harm occurring from the use of MMLA and to ensure the fair and ethical treatment of its users, the establishment of a unified ethical framework tailored specifically for MMLA may be beneficial. Thus, this theme provides an opportunity to assess the framework's level of acceptance and the specific requirements among different stakeholders.

Most of the participants (58 out of 60), concurred that the establishment of a unified ethical framework specifically designed for MMLA is essential, and they gave the following reasons. First, the development of an ethical framework for MMLA is essential to protect end-users from any potential harm by increasing users' awareness of ethical issues and how to minimise the potential harm associated with the use of MMLA system and tools: "*Both parties like teachers and students will really understand what and how to minimise any potential harm that might not be expected*" (S21, p. 22). An ethical framework is paramount. R09 reported that only four out of 60 Edtech companies have reasonable policies in place to protect student data, with those policies being limited:

> *There was a report from the US fairly recently where they looked at 60 educational technology companies who are using data. And regarding each one of them, they found only four had reasonable policies to protect student data. Now, I think probably those four, the policies they have in place are actually quite limited* (R09, p. 9).

Second, the existence of an ethical framework is important to increase users' trust in MMLA tools: "*People are afraid of these kinds of new technology when they do not fully understand them [MMLA systems]. So if there is a framework, that could make sure that it's good for all*" (S07, p. 33). Third, recognising that a number of MMLA researchers reside in foreign countries and are therefore bound by their national data protection laws rather than GDPR, it is likely that a unified ethical framework will simplify the standardisation of a safe method in relation to using MMLA in education: "*[We are] doing these experiments in [country name] where we do not have GDPR legal requirements, but the government is currently preparing a law regarding data protection*" (R06, p. 3).

A number of recommendations have been made regarding the creation of a future framework. First, it is essential that a framework be easy for most people to understand. Having a framework that is simple enough for the majority of users would significantly increase its acceptance and use: *"Any kind of ethical guidance that a common person without much understanding about ethics or data could understand, it would be vital"* (S06, p. 16). Second, a concern was raised regarding the practical application of the framework: "*How do you apply the framework in practice? That's where it becomes really important"* (R09, p. 43). Accordingly, including a real-life case within the framework was considered essential to promote its practical application: *"It requires practice with the system as well working on different scenarios"* (S05, p. 26). Third, it should be legally binding by making it compulsory, and thoroughly tested for its usefulness: *"Legally binding, and I think that it should definitely be validated and tested and proven to be useful"* (S34, p. 24). Fourth, the framework should be regularly updated: *"This would need to be revisited throughout the process […] needs to be looked at regularly"* (S38, p. 12). This is particularly important to ensure that the framework is up to date with any ethical issues that may emerge as a result of new MMLA tools: *"It [the framework] should probably be evaluated and reviewed from time to time. As long as technology changes, it needs to change with it. You need to assess its [the framework] value and its impact over time*" (S37, p. 29). Fifth, the framework should be reviewed and approved by the entire research community before it can be considered mature enough for use:

> *I would like to stay informed on what is important. When it reaches a level of maturity that can be accepted and adopted by all of us, I'll probably use it this way, but right now it sounds like it is quite premature in my eyes* (R01, p. 16).

Finally, there should be a training session for end-users on how to use and adopt the framework: *"I think they [end-users] need training sessions to improve the experiences"* (S28, p. 23). These training sessions will undoubtedly encourage the adoption of the framework.

4.2.2 Theme 2: Privacy, Surveillance and Intrusiveness Issues with MMLA

There was convincing agreement among the interviewees (55 out of 60), that MMLA data are highly sensitive for several reasons.

First, MMLA data includes users' voices and faces, which suggests that they are more likely to be identified. S01 asserted: *"For me, faces require a higher level of protection because people will certainly be able to recognise your identity"* (S01, p. 21). Moreover, as noted by R08*,* facial recognition and the data that it is linked to would increase the data's sensitivity:

> *What the facial recognition data is linked to, I think [is more important] than the fact that it's MMLA data itself. I think that's probably where the problem lies. So, what I typically worry about is not so much the nature of the data itself, but rather what the data is linked to* (R08, p. 4).

However, there was controversy among the interviewees regarding the traceability of MMLA data. A representative from a technology company (C01) confirmed that the MMLA system they developed does not present any additional privacy concerns as it does not collect any biometric information, only motion data. He stated: "*With us at least, it appears that neither the camera nor the motion sensor device capture any biometric data*" (C01, p. 1). This is in accordance with S07, who concurs that video and audio data can be traced, although, other data, such as brainwaves and physiological data, cannot: *"For now the most common data is used to identify people's face and voice because the accuracy is quite high, achieved by the algorithm. But for physiological data, I think it is a little bit hard [to identify people]"* (S07, p. 8). The controversy concerning the traceability of MMLA data among the interviewees raises serious concerns. Although brainwaves and heartbeats cannot be traced as easily as visual or audio data, they are exceedingly sensitive data, given that they can reflect not only cognitive states, but also emotional responses:

> *There is a whole different set of implications about collecting data from physiological processes that are occurring in someone, especially data which has a connection or potential implications in terms of understanding how people think, how their metacognitive and emotional processes take place and their awareness of the situation, as well as physical and psychological well-being* (T01, pp. 4-5).

As reported by S01, the collection of sensitive information, such as eye gazes and heartbeats, may disclose personal health information: "*If I have medical problems in my body, then ... I think heartbeat data could reveal a lot of things*" (S01). In particular, this is important if the student has a mental health problem and does not wish to reveal it to others:

> *If I have a health issue, I do not want to tell someone, right? If I am not feeling emotionally well and I am going through therapy, I would not want to come and reveal it to an educational institution* (S04, p. 8).

Owing to this, MMD must be handled carefully, as reported by R05*:"Some of the data potentially might be sensitive personal information because it's medical data […] So, yes, I think you would treat it with a greater degree of care"* (R05, pp. 6-7).

It appears, however, that there is uncertainty over what MMD can and cannot reveal in educational settings. Participants with medical backgrounds, for instance, argued that MMD could potentially diagnose functional diseases, such as dyslexia, but not organic diseases: "*MMD is sensitive data because it can be used to diagnose functional diseases, such as dyslexia, but not organic diseases*" (S11, p. 14). Nevertheless, we must treat this MMD very carefully due to the fact that it may indicate any health condition. Second, due to cultural considerations, it might not be feasible to capture the face of a woman in some countries. Consequently, video data acquired by MMLA for the analysis of facial expressions is extremely sensitive: *"It [collecting MMD] has a social or traditional aspect"* (S12, pp. 7-8). Third, students dislike having their faces recorded, as confirmed by S13: "*They [students] don't want to be recognised*" (S13, p. 5).

Considering all the previous reasons, students are more comfortable with data that cannot be identified at personal levels, such as heartbeats, rather than faces and voices: "*capturing a heartbeat or something psychological, those that I don't really care about [...]. Capturing my face that would be a much greater intrusion of my privacy*" (S14, p. 5). Therefore, the interviewees preferred a log data study over an MMLA study: "*Maybe I will be more willing to give my log data*" (S21, p. 6).

The interviewees expressed the concern that the results of MMD might be misused or abused if they were employed for any other reason than educational purposes: *"If it is [the collection of MMD] for development for the institution itself, I am fine with that. But as long as it is commercial, I think it will be different*" (S02, p. 9). For example, eye trackers could be worrying if data are misused: *"Eye tracking could be terrifying in a non-teaching sense"* (R08, p. 4).

S03 also expressed concern that MMD might be used by teachers to negatively label students: "*[MMD] could affect where I'm going to be in the class"*. Students from different religious backgrounds expressed concern that certain sensing technologies, including EEG caps, might discriminate against them because their religious customs prevented them from using these particular devices. This is problematic because students cannot be forced to remove their religious clothing to use MMLA data collection tools, but likewise, they cannot be excluded from the remainder of the cohort. One student (S03) explained: "*I think that also might cause abuse or bullying because you will be different from other groups"* (S03, p. 9). Moreover, several thought that MMLA might be too intrusive to comprehensively monitor students' emotions:

> *It is a bit more extreme in the sense that we are using invasive technology that is specifically submitting the students to a bit more comprehensive surveillance of their own emotions and this is then used not only to support them but for other reasons too* (R10, p. 5).

Moreover, most students claimed that being observed by MMLA for a prolonged period of time would lead to anxiety and nervousness: "*It will make me nervous because you feel that you are examined the whole time in the class"* (S02, p. 11). In spite of this, individuals such as S10 reported that once they became accustomed to being observed by the MMLA, it might become routine: "*Maybe not so weird after 2-3 class meetings*" (S10, p. 8). It is imperative to note that when students are being monitored, they exceed the norm in order to give their best, although this is not really reflected in their daily learning activities: "*When they know they're being monitored, they will act differently … Maybe they give their best, although it is not really reflected in their daily learning activities"* (S10, p. 15). Conversely, others such as R10 argued that students are fine being constantly observed if it helps to improve their learning:

> *If I am a student that is studying medicine and I want to become a surgeon, I would be totally OK with being constantly observed while I practise that procedure, because I know that I would get valuable feedback to help me improve* (R10, p. 11).

This comment indicates a difference in how students and researchers view being constantly monitored. Although the majority of the interviewees claimed that MMLA tools are safe in general, a number argued that the long-term effects of MMLA tools remain uncertain: "*We do not know the long-term effects of [MMLA tools]. So even cell phones, we have been using them for a while, but still there are no studies that show what will happen in like 50-60 years"* (S11, p. 15).

For example, S31 claimed that "*physical stiffness"* could be physical harm resulting from constant observation by certain MMLA tools (S31, p. 11). As for the mental health issues associated with MMLA use, S31 asserted that the use of MMLA tools might create *"stress and anxiety related to mental health"* (S31, p. 11). Therefore, MMLA tools should be thoroughly examined for an extended period to determine if they cause any harm. MMLA tools should undergo the same accreditation process as medicine does prior to approval, as suggested by R09, who stressed that:

> *A company cannot simply take a new medicine to a hospital when it creates it. So why is this different when we talk about multimodal learning analytics? [...]. There should be a central body to which the learning analytics company can report. Look, this is the intervention we wish to conduct. For these tools to be effective, they must be registered, make them public and then conduct three studies to prove they will not do things that are harmful* (R09, pp. 12-13).

In spite of the sensitive nature of MMLA data, R10 believed that both log data and MMLA require the same level of privacy protection:

> *I could think of a learning analytics method that would be very invasive and a multimodal learning analytics [system] that is not as invasive and the other way around. I think to generalise this, I would think the same principle should apply to both. […]. There must be the same level of scrutiny and transparency* (R10, pp. 7-8).

These views were influenced by the fact that MMLA functions as a standalone system and does not rely on a web-based server to operate, thereby preventing threats related to unauthorised access to data: *"Currently it [MMLA system] is a standalone system. It runs on a computer; it does not run on the web. So whatever data is collected, it is placed on your hard drive. It is never openly offered to anybody"* (R02, p. 8).

Additionally, most researchers stated that no additional measures were taken to ensure the anonymity of MMLA data, given that the data are not traceable. The traceability of MMLA data was the subject of considerable discussion amongst the interviewees. According to one interviewee, MMLA data are not traceable due to their raw and unintelligible nature, which implies that users cannot be identified:

> *I think you don't need it. Because if you look at the data, it's an absolute mess. I mean, it's not understandable at all […]. If you're just using the recognitions, like in second number three, somebody smiles. If that's your data, I think that's completely anonymous, or it's very rare. It will be very, very difficult to know, to trace back from how many seconds somebody frowns and smiles* (R02, p. 5).

Additionally, it is contended that only video and audio data can be traced, and that it would be difficult to trace back data such as brainwaves and physiological data: "*For now, the most common data are used to identify people's faces and voices because it's quiet and the accuracy achieved by the algorithm is quite high. But when it comes to physiological data, I think it's a little bit hard"* (S07, p. 8).

R04 suggested differential privacy as an approach to anonymisation, although he had not yet adopted that approach himself:

> *Student ID to be replaced by a symbol. However, I think it's not the best and only way to ensure anonymisation. I know that that can be easily hacked [...]. So, as far as I know, the best anonymisation approach is to differentiate privacy, but I haven't used that in a study setting* (R04, p. 6).

Other approaches were proposed to de-identify MMLA data, including introducing noise to large datasets:

> *There are new approaches, particularly for larger datasets, that introduce noise into the data directly, so that you can't connect it back to the original, which may be appropriate in some contexts. But it does depend on what the context is, I think* (R05, p. 8).

Despite the fact that it is generally regarded as good practice to share data among researchers with the aim of advancing the field of educational research, this area may require in-depth consideration in the context of MMLA, because the data may contain sensitive and private information. However, the majority of researchers indicated that they had not implemented any additional data-sharing measures beyond the standard measures used with traditional data. Nonetheless, if student data are to be shared, this should be undertaken only if it directly benefits the students:

> *I think it should be shared only on the basis of direct benefit to the students. So if I had concerns about students' welfare, I might be able to share it with the student support and wellbeing team, ideally with the consent of the student. Or if it was an extreme situation and I thought there was a danger to the student or other people, maybe I could share it without their consent, but that would be it* (T01, p. 9).

In conclusion, it is important to consider the concerns associated with the collection of sensitive data, such as psychological and biometric data, together with the issues of continuous surveillance and the intrusive nature of MMLA's data collection procedures, to ensure that data acquisition is respectful of privacy and promotes positive learning.

4.2.3 Theme 3: Student Agency Over their Learning and Data Ownership

Of the 60 stakeholders interviewed for this study, 54 believed that learners should be able to control their learning and own their data. A difference in opinion was observed among the interviewees regarding the degree to which students should have control over their data and agency related to their learning. For instance, researchers such as R09 claimed that students should have access to, and be able to modify and delete their own personal information, which includes any inaccurate data that may have been collected by the system. "*So they [students] should be able to add, modify, delete and remove it [MMD]"* (R09, p. 18).

In a researcher's opinion, students must be permitted to control their own data, as they are the lawful owners of the information, which is in keeping with the principles of data ownership: *"Access to the data is unconditional, because they are actually the ones who are producing the data. It is a little bit contradictory to collect that data and then keep it hidden from the owners of that data*" (R10, pp. 14-15). While allowing students to control their data provides them with the ability to manage their personal information and ensure that their data are accurate, it poses challenges for researchers: *"I understand that it gives challenges to learning analytics researchers, but that's still the way it should be"* (R09, p. 18). In this regard, it is extremely important that any changes made to the MMD be communicated to the teacher. It is also essential that the system tracks these modifications, as argued by S37, who maintained:

> *Even if a student makes a choice that I wish to conceal, it [the MMD] is accurate. But if I wish to conceal it [MMD], there must be some evidence of that [to support the claim]. The system*

needs to show the teacher that the student deleted this information around this time (S37, p. 18).

While both students and researchers generally support giving students control over their MMD, including the ability to access and modify the data, teachers such as T02 argued against any modification of MMD: "*I don't think modifying it [MMD] is a good thing to do with these types of data, but I think they [students] can have access*" (T02, p. 20). Moreover, the interviewees argued that engaging students in the process and explaining what the data means would lead to more effective learning. However, S22 believed that students should be able to contribute to their learning by means of a comment box:

> *I would like to be able to access to understand what's happening in my learning as a learner. But when you give me access to modify it, I might manipulate it [MMD] because not everyone has the same ethical code, so I would suggest a comment section* (S22, p. 14).

Moreover, the level of control that students should have over MMLA tools should be limited to a certain extent, such as not pausing or interrupting the data collection:

> *I think students should have control to a certain extent. I don't want to be able to just pause the tracking and look away and talk to my friend and then resume or something, because it will show. I'm focused all the time* (S39, p. 10).

An added concern was raised by T01, who commented that although giving students control over their data and learning in a predictive manner can be valuable, it may also have an adverse impact on their psychological well-being: "*Some students could use it [MMLA system result] in a really productive and useful way [...]; some students, however, might actually be negatively psychologically affected*" (T01, p. 15).

To conclude, it is essential for students to have a sense of ownership over their learning and data to encourage trust in the educational system, as it can enable a better understanding and more meaningful learning experiences. Control measures must prioritise ethical considerations and data integrity to maintain students' learning outcomes and psychological well-being.

4.2.4 Theme 4: Trustworthiness of MMLA Results

A significant ethical concern is the trustworthiness of the MMLA system and its results. Most of the interviewees (53 out of 60) agreed that there is insufficient trust in MMLA's fully automated decisions. For example, (R09) revealed: "*I am uncomfortable with these [MMLA] systems making fully automated* *decisions*" (R09, p. 25). They gave several reasons for their arguments, including: (1) it is possible that MMLA data might not be an accurate demonstration of the actual status of the learner, as it is based on a brief period:

> *I would not trust it [MMLA system] because I may be a different person when I know that I am being observed. Many of us might be slow learners, might learn in our own comfort zones, [….], so the brief time that I am performing in front of the cameras, that should not be used to judge me* (S08, p. 30).

(2) S10 claimed that although MMLA systems may be trusted to be entirely automated in online and synchronous activities, in face-to-face learning, they are dependent on the interaction between the teacher and the student. Therefore, these systems cannot be relied upon without the teacher's interpretation:

> *In online learning or asynchronous sessions where the learner is learning by themselves [...] I think the system can be made fully automated [...] but in face-to-face learning, I believe the teacher plays an important role; an IT tool is just a tool but how to use it effectively depends on the teacher and the student and their interaction, I think* (S10, p. 17).

MMLA alone may not be able to accurately portray students' actual emotions, or the external environmental influences that impact their emotional state at the time. C01 remarked: *"The eye of the teacher is very important because you cannot capture, you know, the engagement, the happiness or the boredom or any distractions that might happen"* (C01, p. 4).

(3) It was reported that some human elements can only be judged by people. Hence, S32 asserted that MMLA data are incomplete: "*Human skills, human capacity and human relationships can only be judged by other human [teacher], it can't be judged by machines*" (S32, p. 16).

In this regard, a number of recommendations were made by the participants. First, among the major ethical concerns with technology in general and predictive systems specifically, is the tendency for people to instinctively trust them and accept their predictions as facts. Therefore, it is vital to stress the importance of incorporating human decision making based on genuine observations, rather than relying solely on machine predictions. Thus, autonomous decisions should act as a source of recommendations and information for teachers and not be taken for granted: *"Maybe as a recommendation, to give the future a heads up before doing anything, but I would not recommend taking it for granted"* (S25, p. 11). Therefore, the results of the MMLA decisions should always be supplemented by observations, opinions and interpretation from teachers to guarantee their accuracy: *"I'd say it can account for a maximum of 90% because at the end of the day, we need human interpretation of this kind of data to make sure that it's accurate"* (S23, p. 11). It is also essential that MMLA decisions are reached in consultation with the student, considering that they are the person affected by these results: *"It still falls to the user [student] to assess whether those conclusions are accurate and helpful*" (S37, p. 5). Likewise, it is particularly important to provide students with a sense of confidence concerning MMLA and the outcome: "*I think, I think, teachers should be in the loop. I'm not very comfortable with machines making fully automatic decisions"* (S08, p. 27).

Second, the results of a MMLA prediction should be perceived as feedback as opposed to an assessment or a classification tool:

> *No, I think we should not use them for grading. Perhaps, and not to give a final assessment. But they can definitely be useful for other types of recommendations and predictions that do not necessarily put them in a box, but support them more with their learning* (R4, p. 14).

Consequently, this ensures that the system is designed in a way that supports students and does not exclude or criticise them. With the emphasis on feedback, MMLA identifies areas where students require further assistance or intervention without labelling them, based on their current data patterns:

> *Using prediction systems might result in the expulsion of 10% of our students because we thought they were going to fail at the end of the year, anyway, so let's get rid of them now. I don't think it would be ethical to use such a system [prediction system]. Using these systems to invite these people for additional support is probably more acceptable* (P05, p. 15).

Third, MMLA predictions would be more trustworthy if they were verified in advance. It is essential that autonomous systems undergo long-term testing and comparison against human interpretation before they can be trusted: *"They should initially validate it [MMLA system and its result]. So, we could start with the computer and then validate it with the human interpretation and then we see whether or not it is comparable"* (S11, p. 16). S24 recommended that MMLA tools be validated in a similar manner to hospital machines: "*The MMLA system should be tested first for its repeatability and reproducibility before it's used*" (S24, p. 22).

Fourth, it is essential that the human relationship between teacher and student is not compromised when using automated systems. To provide meaningful and ethical education, it is necessary to balance automation with an irreplaceable human element: "*What's really important is the human* *relationship, the human relationship between the teacher and student, between colleagues within a place. We cannot relinquish our human decision making, our human relationship*" (S32, pp. 14-15).

Fourth, it is imperative that MMLA remains transparent and fair as a way to develop trust. MMLA systems should be transparent regarding how decisions are made and how students will be supported:

> *If we provide evidence about what we can do and how we can help the students with the MMLA systems they are using, that will increase their accountability, which would increase their trust. [….]. It is critical for the end-user to understand how these systems work and how they end up with a decision or a recommendation* (P01, p. 10).

Moreover, it is imperative that the data collected are transparent to the end-users, including allowing them to access the data and the results:

> *I don't think the students will be able to trust the system without full transparency. And full transparency means that they should be able to make these assessments as to whether or not the system is accurate. So, I think that students should have complete access to and control over their recorded data, allowing them to review it and assess its accuracy for themselves* (S37, p. 18).

Additionally, to promote trust in MMLA systems, it is necessary to address the fairness and the issue of bias because these bring into question the ability of the system to produce equal and fair results for different populations. A lack of trust in this could negatively affect its usability: *"This might raise a concern in regard to the owner's trust [students] in the MMLA system, questioning its ability to produce an equal and fair result for every different population, regardless of any demographic differences*" (R02, p. 12).

Finally, in terms of the development of productive learning environments, the trustworthiness of MMLA is essential. By ensuring the transparency of both the data collected and the process by which decisions are reached, as well as the fairness and accuracy of the result, trustworthiness can be promoted. Equally, users must feel confident that the system will perform as expected in order for learning to be effective.

4.2.5 Theme 5: Fairness and Issues of Bias in MMLA Systems

It is imperative that the MMLA system be fair, with the aim of ensuring that all students are treated equally and that the results generated by the system are accurate and free of bias in favour of any particular group of students. Nevertheless, 50 out of 60 participants who were interviewed expressed concerns regarding potential bias in MMLA systems for the following reasons:

First, it is possible that the MMLA system, which was initially developed for a specific population, might be biased when applied to a different population. This may be the result of the algorithm and prediction models, which were developed and trained by the system on the basis of the race, gender, cultural and physical characteristics of the original group, which may not be representative of other groups. R01 stated: "*It is not fair to make decisions about some students based on predictions that were made for samples with different characteristics*" (R01, p. 12). Therefore, MMLA systems may be prone to bias, particularly when combined with facial recognition to predict emotions, for instance boredom or enthusiasm. A significant source of bias in facial recognition algorithms arises from the way algorithms interpret emotional expressions, which is influenced by a wide range of factors, including skin colour and facial features, as clarified by R08, who stated:

> *If you're using a multimodal system looking for emotion, boredom or affective states and you were not up to date with some of this stuff [bias issues] around different skin colours or how various kinds of facial features might sort of impact that [the fairness of the result], it's quite likely that most of the effective state prediction stuff [algorithm] has been designed with young white college boys in mind. So, it is highly unlikely to work with probably everyone else, including women* (R08, p. 14).

It is essential to note that MMLA systems may encounter bias beyond physical characteristics. This includes an inability to identify certain accents due to the fact that they were developed and trained for a particular accent. This issue is particularly significant in the context of the MMLA system that employs speech recognition, given that speech technologies can be biased if they are trained in a limited range of languages. MMLA systems therefore struggle to aid students from different linguistic backgrounds fairly and appropriately. In fact, S06 remarked: "*I would absolutely question the [MMLA] results. Can you pick up my accent? Because it could misinterpret what I am saying*" (S06, p. 16).

Also, bias may arise from the implicit values of algorithm designers. Algorithm designers typically incorporate their own values and perspectives into the design process. Therefore, algorithms developed by a group of designers with similar values, cultures and norms may represent the values and norms of a particular culture, which may not be applicable to every student:

> *The algorithms themselves are not neutral. So, it is not just about the data that it is based upon, it is also the algorithms and the way they are written and constructed and who*

> *constructed the algorithms. As you well know, the vast majority of people in the AI community are white men* (R09, p. 37).

The results of the MMLA could be biased in the absence of information regarding external environmental factors, such as personal circumstances or social context, which could only be captured by the human eye. This limitation can result in inaccurate feedback or erroneous interventions regarding student engagement, motivation or emotional state as a result of false readings: *"It does not measure the environment, does not measure my condition; it is a measure only of the action, which could give a wrong result*" (S03, p. 32).

Furthermore, MMLA systems may be biased when they fail to take into account factors such as learning disabilities. Failure to include special education professionals and psychologists in the design and implementation of MMLA systems can indeed affect the validity of the results:

> *There are multiple biases involved as well. But a [learning] disability, I think one of the major ones, specifically mental illness and generally the inability of individuals to understand, to respond, is not taken into consideration when these systems are built* (S04, p. 32).

Several recommendations were made in relation to how to mitigate bias, including:

1) The system developer may be able to increase MMLA's fairness via the implementation of a transparent and explainable protocol and algorithm. The transparency of algorithms and decision-making processes will provide educators and stakeholders with a better understanding of how outcomes are determined. Accordingly, it is easier to identify potential biases and ensure that the educational objectives are achieved: "*It's up to the researchers to do their best to ensure that this doesn't happen [bias]. It should be done [algorithms] in a transparent way and also use protocols and algorithms that can be explained*" (R09, p. 38).

2) To mitigate bias in MMLA systems, it may be beneficial to increase the training dataset by including a wide range of age, sex, cultural and contextual data, as well as to regularly update this dataset. With the assistance of a larger and more diverse dataset, algorithms that are more representative of the various learner populations they are designed to support can be developed and trained: For example, (S09) stated: *"It depends on the data. If it is weak and very small, then I will expect it to be biased. If your datasets include a lot of students from different backgrounds from different cultures, I will trust it more"* (S09, p. 31).

3) The dataset might need to be trained for a long time before it can reach the level of credibility necessary to generalise the results for a varied population. To achieve a trustworthy result, the model

must be fed with a dataset over an extended period and be tested within different educational settings:

> *If you told me that a system has been running for ten years, I will trust it more because I know the training data will be more efficient because they go through different situations, different cases. Feeding the model with more data would lead to considerable improvement and accuracy* (S09, pp. 20-21);

4) Creating an ethics panel prior to the establishment of MMLA systems is a proactive and crucial step in ensuring the fairness of the results. A panel can be crucial to the success of a project as it can raise important questions related to the data quality and whether the dataset represents a diverse group of learners.

> *There is a need for ethics panels that look and actually ask the questions. Is there a broad enough dataset? If the dataset is clean, how did you clean the data? This should be done even before the programme [MMLA system] is being created or whilst the programme is being created* (S32, p. 21).

5) To mitigate bias and enhance fairness, the MMLA system must be developed by multidisciplinary teams. By integrating diverse perspectives, experiences and skills, a multidisciplinary team can contribute to the development of a system devoid of bias:

> *It [MMLA system] will be so biased if it only considers the cultural experiences of white people and not those of people of colour, right? That is where the bias issues arise. So, we should look at who was involved in the design and how representative is this process to decide fairness* (S30, p. 23).

6) It is essential to validate and modify the MMLA results using human observation, which in this case is that of the teacher, with the intention of ensuring that the results are unbiased. This would make sure that MMLA automated decisions do not make a decision in isolation and consider the individual students' distinct circumstances or learning disabilities, which algorithms frequently fail to notice: "*So it's [MMLA result] basically fair but I think also it needs to be involved with a human decision. So as to take into consideration the other things that aren't measured*" (S25, p. 14).

To summarise, fair and unbiased systems will increase confidence in their results and make fair decisions. For this to be achieved, we must address the potential biases and limitations of MMLA systems, including data, algorithms and design processes. The use of multidisciplinary teams, the supplementing of automated results with human observation, the selection of diverse and representative datasets, along with regular audits of the system are all essential aspects of the design and validation process. These steps will help mitigate bias and provide a MMLA system that is reliable and trustworthy.

4.2.6 Theme 6: Transparency and Explainability of MMLA Systems

It was noted that most participants (47 out of 60) concurred with the significance of transparency within the MMLA system.

The term 'transparency' was defined by participants such as R10 to mean disclosing information regarding where the data come from as well as establishing what correlations exist between specific actions and learning outcomes:

> *Assessing the students is completed by virtue [making use] of their brain activity. There should be total and absolute transparency on how that is assessed and calculated. How is that [data] obtained and how is that related to the skills we want them to acquire?* (R10, pp. 19-20).

Several participants, including R01, argued that increased transparency in MMLA systems would enhance users' accountability by enabling a better understanding of how decisions are made, why certain results are produced, and the underlying logic and processes pertaining to the analytics system.

> *If we provide evidence about what we can do and how we can help the students with the MMLA systems they are using, that will increase their accountability […]. It is crucial for the end-user to understand how these systems work and how they end up with a decision or a recommendation* (R01, p. 10).

Transparency is fundamental in a MMLA system in the event of an unexpected outcome. It is only through transparency that users are able to trace and understand the reasons for unexpected or contrary results produced by a system: *"I do absolutely believe in transparency, and, yes, if an unexpected result was coming out, then yes, I think an explanation should be provided"* (P081, p. 10). Furthermore, S07 noted that understanding how decisions are made will enable users to interpret the results and apply them to their learning, and thus take ownership of their learning: "*If I know how this decision is made, I can improve my result"* (S07, p. 29).

While participants discussed the importance of transparency, allowing users to observe how data are collected, algorithms are employed, and decisions are made, a significant emphasis was also placed on the explainability of the results. An explainable system not only reveals its inner workings; it actively explains how the system operates in a way that humans can comprehend. Providing detailed information without considering the way in which it is presented could potentially cause various problems. For instance, explaining how the MMLA system reached a decision may require additional explanation, which could become over-complicated: *"At what point do you make it transparent? The explanation will become more complex than the black box itself, I would say. So, there should be a new explanation, yes, but to what degree?"* (R2, p. 9). Therefore, explanations should be presented in a straightforward manner that does not include technical details in order to make the decision more understandable. C01 maintained:

> "*Not technical details, because they don't care. But how it works and also how we calculate the score […] first of all, we try to make it simple [the explanation]. So, no matter how complex it is, it should be simple*" (C01, p. 6).

Although most interviewees agreed on the importance of transparency and explainability in the MMLA system, others argued that too much explanation could allow students to game and manipulate the system. For example, students who understand the relationship between specific actions and their outcomes may behave in an unusual way, as the researchers discovered during their research into presentation skills: "*In our experience, some students maintained a [specific] posture throughout the entire presentation, watching the screen and looking at the audience the entire time*" (R06, p. 10).

For the MMLA system to be reliable and trustworthy, both transparency and explainability are essential. To achieve this goal, it is mandatory to be transparent regarding the data collected, the methods used to collect the data and how the decisions are made, while the information is presented to end-users in an understandable way.

4.2.7 Theme 7: Accountability of MMLA Systems

A primary concern that stakeholder groups (42 out of 60) raised pertains to the issue of accountability. They argued that accountability is a key consideration when using MMLA in educational settings. According to all of the stakeholders, educational institutions should be held accountable for any problems associated with MMLA systems: "*I think it should be entirely the responsibility of the institutions"* (T01, p. 16). Consequently, it is believed that experienced individuals/staff should be available within institutions, so that problems can be resolved. For example, S20 argued that safety guardians should exist in any situation: *"I think each institute must have a safety [officer] who is responsible for issues in case of unauthorized access"* (S20, p. 16). Moreover, S17 reasoned that educational institutions should have an information technology department: "An *IT department […] institution of the school*" (S17, pp. 16-17).

To ensure accountability in the MMLA system, it is imperative to include each relevant stakeholder in the development process, as they may provide valuable information that is not apparent to the individual system developer. It is recommended that teachers, students, experts, as well as institutional representatives, participate in this process of designing the MMLA system: *“End-users should be in the loop […] experts in this area […] and if possible., the institutional authorities”* (R06, p. 12). To ensure accountability, the system’s goals and target audience should help to determine which stakeholders should participate in the MMLA design process. Different stakeholders provide distinctive points of view and knowledge, which guarantees that the system is fair and efficient. For example, a company representative reported that their MMLA system was designed for special education. Therefore, their design process comprised students and special education teachers, as well as occupational therapists:

> *This system has been designed by special educators and occupational therapists, but also in the better version, we test them in real classrooms or therapeutic environments in order to get feedback from the students, and other therapists. So definitely we do consider their thoughts at different stages* (C01, p. 5).

Although most of the interviewees believed that providing information about the individuals involved in the design process was important to increase users’ trust in the system, ordinarily, the actual end-users, namely teachers and students in the real world, are not provided with these details. For instance, (R06) said:

> *I guess the educator could mention who was involved in the design of the system. Yeah, to be honest, we never told the educators that they should mention this. I should say, I’m unsure, some of them did mention this but [...] I cannot be certain* (R06, p. 11).

Accountability is essential to verify fair and ethical use of MMLA systems. It is important to include a variety of perspectives in the design process, and to define who is responsible for resolving any issues that may arise in relation to these systems, as well as how the data collected will be managed and used ethically. These actions would enable MMLA systems to guarantee a trustworthy, safe and accountable learning environment.

4.2.8 Theme 8: Level of Awareness of the Benefits and Risks Associated with MMLA Use

A total of 40 out of 60 interviewees considered that learners should understand the impact of the MMLA recommendations and predictions on their learning. To guarantee that informed consent is given, adult learners must be capable of understanding the benefits and potential issues associated with the collection of MMLA data and the results. However, various limitations have been identified with respect to the current consent forms that prevent them from achieving their objective.

As a general finding from the interviews, the participants agreed that students are not sufficiently aware of the type of data that is collected from them or the sensitive nature of the data collected. This was reported by R06, who claimed:

> *We tell them about the experiment and what it entails. We tell them and we ask them to sign a paper, but to be honest, our students really don't care. So, I don't know, some of them are aware, whilst I'm pretty sure that some of them are not aware, as they don't care* (R06, p. 4).

Although students are not generally interested in consent forms or understanding MMLA data, maintaining consent is essential for reasons of accountability: *"I don't think most participants are actually interested but you are obliged to put it in and I think it is important because it's considering accountability"* (P05, p. 5).

Data visibility was identified in the interviews as an important factor affecting student awareness. R02 observed that students are more aware of their participation in the data collection process when they are allowed to observe the technology in use, such as cameras or eye trackers: *"I think in my cases, they always know the technique because they see the camera and when you see okay, this is a 3D camera, they see their skeleton being tracked by the camera, [….] or the eye tracker. So, to them, it's pretty obvious"* (R02, p. 4).

Although students might recognise that eye-tracking devices collect data from students' eye gaze, they still might not fully comprehend what that data can provide. (P03) asserted: *"Of course they understand when we say we collect the audio or video but when you use wearables, how you are associated with things, it's getting a little bit more complicated"* (P03, p. 4).

According to the interviewees, students' awareness of the benefits and risks of using MMLA may have a direct impact on their willingness to use it. Specifically, the students suggested that there is a positive correlation between increasing their level of understanding and their willingness to participate. For instance, it was determined that students who are more familiar with MMLA and the risks associated with it are more likely to agree to participate:

> *Personally, because I understand the risks involved [in using MMLA systems], I also understand that potentially, this [MMLA system] can be used to predict, understand, quantify and*

> *essentially aid my outcome. So, if this [MMLA system] could help then I'm all for it* (S35, pp. 5-6).

It is thought-provoking that there appear to be contrasting views on MMLA ethics held by teachers and students. For example, T08 presented an opposing view, suggesting that increasing learners' comprehension may result in a decrease in participation: *"I think it [students' participation level*] *will be reduced, [...] when you explain that the data will be taken away from you and that you will need to wear a headset; you are going be monitored, and especially if it can possibly affect your grades"* (T08, pp.7).

A decrease in participation might also be noted for students from particular backgrounds, such as law, as they are more concerned with privacy issues than others: "*As far as I am concerned, it [the participation level] will decrease due to privacy concerns, but for someone else, it will increase due to their desire to participate in education and society"* (S28). This comment contradicts the initial statement that increasing students' comprehension level would increase their participation (S28, p. 12).

It was interesting to note that the students were more concerned about the data when they were related to their learning or had the potential to impact their learning outcomes. R05 explained that since data are not used for grading, students appear to be quite relaxed about their data:

> *I think it depends on what the context is and whether or not we've clearly articulated what the aims of their search algorithms are, if they support learning and what they should be. Obviously, explaining what's been collected and why, and how it will be analysed, that is certainly the ethics process in this case. I mean, we're typically not using data in a way that will have an impact on the students* (R05, p. 4).

With consent forms, the principal challenge is creating a balance between making them comprehensive and keeping them simple. This challenge arises from the need to include technical descriptions and legal requirements while ensuring that students are able to understand the information:

> *I think the main difficulty with consent forms is that they have to aim at being very effective. This is by conveying to students with clarity and conciseness what they are being asked for and what the data is going to be used for. So I think it's a bit challenging for consent forms to hit that balance between making it understandable to the students but at the same time providing*

a comprehensive description of what the experiment is all about and what is required from them (R10, pp. 12-13).

Basically, to achieve a balance between designing a consent form that is comprehensive and straightforward, and improving the quality of consent and student understanding of MMLA, the following recommendations were made:

1. For students to genuinely comprehend what they are consenting to, MMLA should be presented in a variety of ways, including visuals and videos: "*So I think that some form of video is definitely more useful than just text*" (R11, p. 14). Therefore, adding a mandatory video about MMLA to the consent form may improve student comprehension: "*Maybe make the video mandatory. They cannot proceed with the consent form or agree without seeing it first*" (S17, p. 8).

2. It is possible to increase students' awareness of the benefits of MMLA through a pre-session or lecture that explains its role in improving student learning:

> *A class or session that explains the advantages of this MMLA system. So, when they realise that the MMLA is actually beneficial for their learning journey, learning progress, or to achieve their learning outcome, I think it will increase their awareness and understanding about informed consent* (S10, p. 11).

It has been established that this approach is effective, as students have demonstrated high levels of consent comprehension. S08 (p.19) stated: *"Because we were talked into it and we were told that this is what is going to happen to you".*

3. To improve students' understanding of MML by way of the consent form, they could be asked to answer a set of questions after reading the information sheet: "*Like completing a multi-choice question and then having the students go through it*" (S34, p. 13).

4. In the consent form, students should be asked whether they would like to be informed if abnormalities are observed during the study. As students are the owners of the data, they should be entitled to know what they contain, as well as what can be learned from them:

> *Write at the beginning of the consent form that if we observe something, do you want to know? Because I think it will be there as medical–legal stuff. I don't understand its*

application, but to protect the researcher, it's better to have it in the consent form (S11, p. 14).

5. To encourage greater participation, consent forms should emphasise how MMLA develops students' learning: *"Students are open to collect their MMLA data as long as it is to improve their learning"* (S07, p. 7). Nevertheless, students should also be informed about the degree of risk associated with their collected data: *"I think that should be commensurate to some extent with the degree of risk associated with that data. So if we think that MLA data is riskier, then probably there needs to be more detail given about that"* (R05, p. 9).

Lastly, it is mandatory to increase transparency regarding which data will be collected and for what purpose, as well as how they will be stored, anonymised and used. Consent forms should contain all of this information clearly and make it easily accessible to students:

> *I completely agree that we should be transparent with the participants about what kind of data is being collected. [….]. I think we should be clear about what kind of device they have to wear and for how long it has to be worn in the research* (R04, p. 4).

4.2.9 Theme 9: The Benefits of MMLA and the Ethical Issues Associated with Failing to Use It

Although the primary objective of this study is to examine the ethical issues connected with MMLA use, several individuals from various stakeholder groups discussed the ethical benefits of MMLA (26 out of 60). Consequently, the following theme emerged.

Based on the claim made by S04, by providing objective, data-driven information about student performance, MMLA may reduce bias and favouritism in classrooms: "*There's a lot of favouritism in classrooms […] I think with these systems [teachers] become more unbiased"* (S04, p. 34). For example, MMLA can be extremely useful as an objective measure and additional feedback for students who are undergoing practical assessments, such as the OSKI examination in medical school:

> *In the medical school exams, with the OSKI exams, an objective exam, the students should pass through different stations and the doctor will evaluate them. I think using artificial intelligence in those sorts of exams might be helpful because the marking of the exams is quite objective and also depends on the person who is marking* (S11, p. 6).

This is particularly important when racism is present, as suggested by S02 (p.28), who stated: "*Maybe if the teacher is racist*". Additionally, it may assist teachers in identifying any learning differences, as T01 remarked:

> *If you notice an issue with a student's concentration, if you are a teacher that is aware of the phenomenon of ADHD, you might be able to deal with that issue in a sensitive way that actually helps that student progress in their life, in their future and in that career* (T01, p. 6).

As discussed by S25, MMLA provides an effective method to improve the learning experience of students with special needs, including those who are diagnosed with ADHD: "*It is a great tool to enhance the education of students with learning disabilities such as ADHD"* (S25, p. 4).

Moreover, students observed that MMLA might reduce harassment between students in the classroom, "*It might be helpful to minimise many kinds of abuse and harassment, maybe, because they would understand that everything is monitored*" (S11, p. 25), as well as protect students' safety, "*so everything recorded […] that puts me in a safe place*" (S20, p. 8).

Moreover, MMLA may assist in monitoring students for any instances of academic misconduct and "*Prevent people from cheating*" (S12, p. 25). This was particularly important in certain circumstances such as during COVID-19 and the online tests: "*Maybe in some cases, for example during COVID, they were monitoring students, so they would not cheat*" (S13, p. 13). In addition, as mentioned by S26, student discipline could be improved as students are required to concentrate or be there on time: "*Discipline*" (S26, p. 17).

To conclude, MMLA should only be judiciously used for well-defined and justified reasons. It is also important to make sure that end-users are aware of the potential consequences of not using MMLA.

4.3 Divergent Stakeholder Perspectives on Ethical Concerns in MMLA

Although stakeholders expressed a number of common concerns about the ethical implications of MMLA, the interviews also revealed that students, researchers and teachers occasionally held opposing views. These differences were particularly evident in discussions pertaining to the sensitivity and traceability of MMLA data, as well as the perceived impact of enhancing students' understanding of consent.

In relation to the sensitivity and traceability of MMLA data, the interviews revealed that the stakeholder groups had conflicting opinions. Students frequently regarded physiological and biometric data such as voice recordings, eye gaze and heart rate as highly sensitive. Their concerns focused on the risk that these sensitive data could reveal personal health conditions or emotional states, affecting their emotional well-being and sense of privacy. Many students preferred less identifiable types of data, for instance heart rate or log files, and considered audio-visual recordings to be particularly intrusive because of their traceability in terms of individual identity. Teachers agreed with students' concerns, particularly in relation to the sensitivity of MMLA data. Researchers, however, held more disparate views. While several acknowledged the sensitivity of MMLA data, others argued that raw data are frequently decontextualised and not easily attributable to individuals unless combined with contextual identifiers. Specific researchers even suggested that log data and MMLA data should receive the same level of privacy protection, pointing out that many MMLA systems operate as standalone systems, hence the risk of unauthorised access is reduced.

The interviews also revealed distinct differences in how stakeholders viewed the relationship between informed consent and student participation. Many researchers and students supported making consent information more accessible by way of using visual aids, simplified language or videos. They believed that increased understanding would develop trust and encourage participation, as students would be better informed of the benefits and risks. However, several teachers expressed concern that raising awareness of data collection practices and potential risks might deter students from participating. They noted that awareness of surveillance, data sensitivity and the potential academic consequences could increase anxiety, notably in cases entailing wearable technologies and continuous monitoring.

On the topic of data ownership and student agency, many researchers argued for full student control, including access, editing and deletion rights. They framed this as both a legal and ethical obligation, given that students are the primary producers of the data. Students predominantly agreed, although several suggested alternative approaches, such as adding comment sections, to avoid compromising the accuracy of the data. In contrast, a number of teachers opposed allowing data modifications, supporting limited access while cautioning against changes that might affect pedagogical feedback or data integrity.

Although all the stakeholders agreed that accountability is crucial for building trust and ensuring ethical MMLA use, they differed on how accountability should be implemented. Students prioritised safeguards to protect their identities and well-being, while teachers focused on institutional responsibility and the need to employ support staff who can deal with any issues. Likewise, researchers highlighted the role of transparency in system design and the inclusion of diverse stakeholder input to ensure fairness and ethical use.

Similarly, while there was strong agreement that transparency is essential for trust, opinions varied regarding the level of detail that should be shared. Students valued transparency as a tool to understand how decisions are made and to gain greater control over their learning. Teachers supported transparency but worried that students might struggle to interpret complex outcomes, while researchers warned that too much detail could cause confusion or manipulation, and they wanted a balance between clarity and simplicity.

Concerns relating to fairness and bias in MMLA systems were widespread, although stakeholders emphasised different issues. Researchers stressed how algorithmic design often exhibits the characteristics of limited populations, potentially excluding others based on race, gender or cultural background. Students voiced concerns regarding being misrepresented due to their accents, facial features or learning disabilities, questioning the fairness and accuracy of MMLA outputs. Teachers supported inclusive system design and emphasised the need to consider students' different learning needs and contexts. Generally, stakeholders sought broader involvement in the design process and increased attempts to manage bias and promote equity.

Despite shared concerns over the trustworthiness of MMLA systems, stakeholders differed in their reasoning. Researchers were cautious about relying on automated systems without human oversight, noting the limitations in portraying the circumstances. Students felt that short-term data collection could misrepresent their true learning behaviours or emotional states, whereas teachers stressed the importance of human interpretation, particularly the role of educators in understanding student engagement.

Essentially, while researchers, teachers and students expressed differing ethical concerns concerning MMLA, they confidently agreed on the importance of establishing an integrated ethical framework to ensure responsible and equitable use of these technologies in education.

4.4 Discussion of The Main Findings of the Study

Owing to the substantial increase in the use of MMLA, it is necessary to establish a guidance framework in order to ensure that it is utilised ethically and effectively, which is the main motivation for this research. Upon reviewing the research findings, it became apparent that an MMLA ethical framework is essential to safeguard MMLA users, including students and teachers, and ensure the fair and ethical use of MMLA tools. During the interviews, a number of interesting findings were revealed concerning the ethical issues related to the MMLA tools, researchers' level of awareness of these issues, and recommendations for mitigating some of these pressing issues. The interviews resulted in eight recommendations, which were used to draft the initial framework.

First, considering the invasive nature of MMLA tools, it was surprising to ascertain that most interviewees believed that the methods used to collect MMLA data were non-invasive. This may be indicative of a need for researchers to become more aware of these issues. In their opinion, their belief was justified because the sensors can be seen and touched. Thus, they cannot be considered to be invasive unless they involve a more invasive procedure such as inserting something into the body, which conflicts with the students' viewpoints. For instance, MMLA uses sensors such as EEGs. Previous research has established that students experienced distraction, discomfort, irritability, headaches and that they were unable to move freely when they using MMLA tools (Mangaroska, Martinez-Maldonado et al., 2021). Likewise, the degree to which MMLA was perceived as invasive differed among various stakeholders. Along with the safety concerns raised during the interviews, some students might also find it inconvenient to use EEG sensors on account of cultural differences, for instance students who cover their heads. However, these issues were not mentioned in the interviews. Thus, it is imperative to consider this issue when using MMLA in real-life educational settings, as some of these issues might not arise in a laboratory setting.

The second concern is that MMLA may present a number of privacy concerns given that it collects sensor data that are exceedingly personal (Martinez-Maldonado, Echeverria et al., 2020) and may reveal details concerning a person's daily routines and habits (Kröger, 2018). The interviewees deemed MMLA data to be highly sensitive, given that facial recognition and associated data, as well as images and videos, can easily reveal participants' identities. Other concerns were expressed about the misuse of sensor data, for instance eye-tracking in non-teaching environments. Additionally, selected sensors may reveal sensitive information, such as health information. Considering the sensitive nature of MMLA data, additional privacy protection measures and a better understanding of how sensitive data are handled may be necessary for all of the stakeholders involved.

Third, a further concern is that students may lack awareness of the data collection process, including the types, volume and sensitivity of their own data. The interviewees mentioned that, in some circumstances, students were aware of their data, as both the tool used and the data collected were visible. Data visibility can therefore have an impact on students' perceptions of content. However, several students might still not understand what the data show, despite recognising the type of data. It is therefore essential that students understand how sensitive their own data actually are, because this information has to be protected for reasons of accountability, as well as to allow them to make an informed decision regarding its collection. In a recent paper pertaining to MMLA, Beardsley et al. (2020) ascertained that, with the introduction of an informed consent comprehension test to improve students' and teachers' awareness of their collected multimodal data, participation levels decreased. Irrespective of concerns about losing participants, the interviews highlighted the value of providing detailed information regarding data collection to ensure genuine informed consent. Moreover, as the official informed consent form may not be sufficient for participants to comprehend how sensor data are collected or how algorithms work, an additional, simplified verbal explanation appropriate to the participants' background knowledge may be required. Their study also established that students were predominantly concerned with their data only if they affected their learning outcomes. Thus, it is also important to clarify the exact implications of the MMLA data collected from participants (Mangaroska, Martinez-Maldonado et al., 2021).

Fourth, significant concerns were raised regarding the need to heighten trust within MMLA systems. Hence, it is essential that students are provided with detailed explanations that encourage them to consider more quality indicators that can help them to examine their learning and behaviour. However, explainability with regard to MMLA must be constrained by certain guidelines. Initially, explaining how the decision was reached by the MMLA system should be evident and simple. Furthermore, explanations must contribute to the student's learning rather than providing them with a way to manipulate the system. For instance, if students are provided with information on how student behaviour impacts the outcome of the system, they may be able to game the system and consequently cheat. Abdi et al. (2020) investigated the impact of incorporating transparent explanations into educational recommendation systems. The findings showed that they had a positive impact on engagement and perceived effectiveness, although they also generated an increased sense of unfairness when students did not agree with how their skills were demonstrated. Therefore, the level of transparency of an algorithmic system is a fundamental consideration that will determine the degree to which users will trust both it and the results produced (Kizilcec, 2016).

The fifth concern relates to the issue of bias in the MMLA system, resulting from its design for certain demographic groups. As an example, MMLA may acquire a bias when used in conjunction with facial recognition to predict emotion when the facial recognition algorithm has been designed and trained using a specific dataset. This is due to the fact that the colour of the skin and facial features can vary. Thus, algorithms should be developed and trained based on the different characteristics of a population, with all of this information made available to the end-users as a source of immediate accountability. To reduce algorithmic bias, it is necessary to have access to demographic information pertaining to students and to retain this information to determine student outcomes. However, as concerns over student privacy have increased, retailers of educational technology are under increasing pressure to refrain from collecting identifying information or demographic data, to discard the information after a year, or to desist from sharing it with third parties (Baker, 2023). Therefore, Holstein et al. (2019) recommended investigating approaches to support fair auditing by using only coarse-grained demographic data (e.g., neighbourhood or school demographics) in the future. Moreover, Baker and Hawn (2022) discovered that algorithmic bias reveals itself not only among the variables commonly associated with algorithmic bias (race, ethnicity and gender), but also among a variety of other variables (rural learners, native language, parental education background, international students, military-affiliated students).

Sixth, MMLA prediction systems should be used carefully as they are currently the subject of considerable debate, because they may have a negative effect on students. Consequently, MMLA prediction systems are not recommended for classifying students, but rather for providing feedback. MMLA is intended to support rather than to evaluate, therefore it should not be used for grading. In addition, as these prediction systems do not have access to the students' personal information or background, they may be biased and inaccurate. Hence, MMLA predictions should be augmented by observations rather than depending solely on machine prediction.

The seventh concern pertains to accountability, which is one of the most important aspects regarding MMLA, notably in educational settings. It is important to ensure accountability by including each of the relevant stakeholders in the development of the MMLA system, since they may bring information that is not readily apparent to the developer alone. Preferably, students, teachers, researchers, experts and institution authorities need to be involved. Although the interviewees varied in their opinions of involving stakeholders, it is essential to actively engage all stakeholders throughout the entire design process. Additionally, to increase users' confidence in MMLA, it is necessary to provide information about the individuals involved. Moreover, in accordance with Baker (2023), it may be possible to increase accountability by allowing researchers from the school or external parties to conduct algorithmic bias analyses. However, achieving this can be challenging with the current data infrastructure and may present privacy risks during data transfer. An excellent compromise between privacy and reducing algorithmic bias will be achieved if vendors are encouraged to develop or adopt data infrastructure that allows analysis while safeguarding data.

The eighth concern is related to MMLA's data privacy measures. The findings obtained from the interviews indicate that researchers take privacy, including the methods used to store, anonymise and share user information, very seriously. However, a number of researchers stated that MMLA data did not require additional privacy protection, nor did it require further anonymisation compared to conventional data. Several interviewees asserted that MMLA data had been used solely for research and not yet for research tool production. Therefore, certain privacy concerns can be addressed later, once these tools are being produced. Additionally, MMLA is a standalone system that cannot be accessed via a webserver, preventing unauthorised access to data. The traceability of MMLA data has also been the subject of controversy. It appears that this issue needs to be raised as an ethical matter, given some researchers' assertions that MMLA data do not require additional privacy protection or anonymisation. In the interviews, two approaches to anonymisation were suggested, including differential privacy and adding noise to large datasets. It is important to note that some interviewees may only be familiar with this topic in a research and laboratory setting. The procedures for implementing MMLA tools in real-world environments are still poorly understood. One argument focused on the anonymisation of students, as one respondent proposed that retaining students' identifiers is essential for personalised feedback. It was interesting to observe that researchers held differing views on whether MMLA data could be made open-source or shared exclusively with researchers, owing to the potential risk of re-identification.

In view of the eight concerns outlined above, it is vital that a unified ethical framework be established, one that addresses all of these concerns while being tailored specifically to MMLA. Although it will be difficult to address every single aspect of MMLA systems and to develop a framework that could be applied consistently, in every situation, a unified ethical framework would assist in standardising a safe approach to MMLA use in education. Finally, it is important to underline that at present, these eight points are preliminary. Nevertheless, they provide an excellent starting point for the development of a final framework. Additionally, while concerns such as privacy, accountability, transparency and fairness are not entirely new, the significance of this study lies in tackling these issues within the context of MMLA. At present, there is no comprehensive ethical framework for MMLA researchers and practitioners that incorporates all of the aforementioned considerations.

The main data collection process resulted in the development of the first ethical MMLA framework (see Table 16). This will be further developed by means of an ongoing evaluation process in the following chapters.

Table 16. Draft of first MMLA ethical framework

Objective	Criteria	Guiding Questions to be Considered
Beneficence	Establish the benefit that MMLA brings to the learning and teaching process	• what are the consequences of not using MMLA?

Privacy The use of data should be balanced with the protection of privacy.	It is imperative that students' confidentiality is protected due to the sensitive nature of MMD	• To what extent is the privacy of each student is protected? • What proactive measures are taken to protect the privacy of students? • What steps should be taken if sensitive information (i.e., health conditions) are discovered during the analysis of MMD?
	MMD should only be collected, stored, and shared if there is a clear benefit to the student	• Are there clear reasons why MMD are collected? • Is there a theoretical argument to support the collection of these particular MMD? • When sharing student data, have you ensured that it is for the benefit of students? • Will the data of students be used only for educational purposes?
	If the use of MMLA system is likely to become a form of surveillance, there should be evidence that the benefits to a student outweigh the potential negative impacts and should not in any way harm them	• If MMLA system is used for surveillance at any time, and assuming that the students allow informed consent for this, what is the evidence to support that its benefits outweigh its negative impact?
Safety Safety of students while using MMLA systems should be a priority.	Mitigating any physical or mental harm is non-negotiable	• Is there any chance that the MMLA system could cause physical or mental harm to students? • What proactive measures were taken to avoid any physical and mental harm that could occur through the use of the MMLA system?

Comprehension level Students should be aware of the potential benefits and risks associated with the use of MMLA.	Making sure that students understand what MMLA is, for what purposes exactly it is used, and what are the potential benefits and risks associated with its use	• Has a training session been conducted for teachers and students regarding the practicalities of using sensor technologies like MMLA, the importance of MMLA in improving students' learning, and the associated risks? • What attempts have been made to ensure the accessibility of all information presented in the training appropriate to the background of participants including students? (i.e., visual aids to explain the concepts, avoiding jargon, accessible terminology etc.)
Students' agency Empowering students to own their learning.	Empowering students to own their learning	• To what extent do students have control over their data, including access, modification, and deletion? • To what extent are students able to challenge and modify the results generated by MMLA systems?
Transparency and explainability End users should have a clear understanding of how a decision was made.	MMLA systems should have the features to provide reasons and accessible interpretations for any autonomous decisions taken	• Have stakeholders of education been provided with accessible information regarding the training dataset and how the results are generated by the system developers? • Are the justifications provided by the MMLA system understandable to all relevant stakeholders at different levels? • What are the implications of transparency on further system implementations and learning designs? Do you note any instances of gaming the system and how this can be addressed?

Fairness and bias The lack of system bias.	MMLA should be built in a way that its fairness is evidenced (i.e., trained and tested on a sufficiently broad sample of multicultural populations)	• Has the system been trained and tested on a sufficiently broad and diverse sample of the multicultural population that is representative of the population of students on which the system will be used? • Has the dataset been trained for an adequate period of time? • Did the system developers implement a transparent protocol and algorithm? • Was the MMLA system designed by a multidisciplinary team?
	MMLA analysis results should be validated by all relevant stakeholders	• Have the MMLA results been validated by all relevant educational stakeholders?
Trustworthiness Confidence and trust in the results.	Ensuring the trustworthiness of MMLA result	• What are the implications of MMLA-driven assessment? • To what extent were MMLA assessment results implemented are validated with other sources of information? • Have the results of the system been verified against the interpretation of a human over time? • Were the results validated by students and teachers?

Accountability	Educational institutions should hold responsibility for the MMLA systems used	• Has your institution conducted a risk assessment prior to implementing the MMLA? • Do you have an action plan in place in the event that any system-related issues arise? • Is there a safety guardian or interdisciplinary team of people e.g., ethical experts, lawyers, IT and educators within your institution that can assist with any MMLA-related issues?

4.5 Chapter Summary

This chapter presented a thematic analysis of the primary data collection method using the interviews. The analysis generated numerous themes; however, I concentrated solely on the nine primary themes that were pertinent to the research questions and which directly addressed the objectives of the study. Additional emergent themes, for example discussions surrounding the technical aspects of MMLA tools and peripheral topics were excluded from the detailed analysis due to their limited relevance to the principal aims of the research. In conjunction with the findings of the systematic review in Chapter Two, these themes have enabled the development of the draft of the first MMLA ethical framework, which will be further improved in Chapter Five, the evaluation chapter. The results and discussion chapter will consider how the themes examined in this chapter, as well as the findings from the previous study in Chapter Two, influenced the development of the final framework.

5 Chapter Five: Evaluation of the Framework

5.1 Introduction

This chapter presents the evaluators’ responses with regard to the draft version of the first ethical framework presented in Table 16 in Chapter Four, organised in terms of the common themes and sub-themes. As mentioned in Chapter Three, given that the nature of this study is exploratory, a deductive thematic coding approach was adopted in this thematic analysis. This comprised extensive reading of the data to identify the themes related to the research question, while relying on themes identified and presented in previous research (Braun & Clarke, 2006). The final section provides a discussion of the findings.

5.2 Results

This section presents the evaluators’ responses, organised according to common themes. Four themes emerged from the evaluators’ perceptions of the framework. These themes are presented in the order that many of the interviewees mentioned or noted them: practicality and usefulness of the MMLA framework (Theme 1); comprehensiveness of the framework (Theme 2); novelty of the MMLA framework (Theme 3); and comprehension and clarity of the framework (Theme 4). A selection of quotes is provided for each theme based on their relevance to the particular topic, as well as the prevalence of similar opinions in the data analysed. A summary of the four emergent themes can be observed in Table 17 below. The coding scheme can be seen in Table 18 below.

Table 17. Evaluation themes

Theme 1	Theme 2	Theme 3	Theme 4
Practicality and usefulness of the MMLA framework	Comprehensiveness of the framework	Novelty of the MMLA framework	Comprehension and clarity of the framework

Table 18. Thematic analysis coding schemes for the evaluation interviews

Theme	Code	Description
Practicality and usefulness of the MMLA framework.	Cases or examples of MMLA applications.	Describes the evaluators’ opinions of supplementing the framework with cases or examples of MMLA applications.
	The practicality and usefulness of the MMLA framework.	Discusses the evaluators’ opinions regarding to what extent it is feasible to employ the framework in real-world settings to increase peoples’ awareness while providing recommendations for improvement.
	MMLA level of preparedness.	Explains the evaluators’ opinions of the preparedness of the technology that the framework is designed for.
	Implementation of the framework in real-world settings.	Describes the evaluators’ opinions of the challenges related to implementing the framework in real-world settings.
	Enhancing MMLA end-user’s comprehension through application of the framework.	Summarises evaluators’ perspectives on how effectively the framework supports end-users’ understanding of MMLA.
	Reliability of the MMLA research.	Explains the evaluators’ opinions of the reliability of the MMLA research.
	The framework should undergo regular reviews and updates.	Evaluators’ recommendations for the framework to be regularly reviewed and updated.
	GDPR is not universal.	Discusses evaluators’ perspectives on the rationale for adopting the framework.
	Adoption of the framework by various countries.	Describes evaluators’ perspectives on how each country intends to adopt and implement the framework.
	Promoting the use of the framework.	Describes strategies suggested by evaluators to promote the adoption and effective use of the framework.
Comprehensiveness of the framework.	The comprehensiveness of the framework.	Discusses evaluators’ perspectives on how comprehensively the framework addresses each critical issue.
	Framework questions related to the transparency of MMLA systems.	Describes evaluators’ perspectives on the framework's questions concerning the transparency of MMLA systems.
	Framework questions related to the assessment of MMLA’s trustworthiness.	Describes the evaluators’ opinions on the framework questions about a system’s readiness to provide reliable assessments.
	Views on the questions related to using MMLA results for assessment.	Views on the questions related to whether MMLA results should be used for assessments, as perceived by the evaluators.

	Distinguish between data that is gathered intentionally and incidental findings.	Discusses framework questions suggested by evaluators on distinguishing between intentionally gathered data and incidental findings.
	Storage protection measures for multimodal data.	Describes the evaluators' opinions of the framework questions concerning the storage of multimodal data.
	Right to privacy and fairness.	Explains how the evaluators consider student privacy to be more important than fairness in the learning process.
	Privacy versus security.	Describes the evaluators' opinions of the distinction between security and privacy.
	Data that contains sensitive personal information.	Describes the evaluators' opinions of data that contain sensitive personal information.
	Students' awareness of the sensitivity of multimodal data.	Describes the evaluators' opinions of student's awareness of the sensitivity of multimodal data.
	Surveillance concerns with MMLA.	Describes the evaluators' opinions of the surveillance issues with MMLA.
	Institutions' accountability.	Explains how the evaluators viewed the institution's accountability
	Further restrictions on the private sector's use of data.	Explains evaluators' views on why the private sector should be subject to additional data restrictions.
	Strategies to reduce bias in MMLA.	Explains the evaluators' opinions of the strategies used to reduce bias in MMLA.
	Cultural issues affecting the collection of MMD.	Discusses the evaluators' opinions of the cultural issues affecting the collection of multimodal data.
	Informed consent.	Describes the evaluators' opinions of the importance of informed consent for end-users.
	Awareness among students and teachers of the potential risks and benefits associated with MMLA.	Assesses the extent to which students and teachers are aware of the consequences of using MMLA, according to the evaluators.
	Duplicated set of guiding questions.	Identifies the guiding questions that are duplicated
	Trade-off between the advantages and disadvantages of using MMLA.	Describes the evaluators' opinions of the trade-off between the advantages and disadvantages of using MMLA.
	The connection between bioethics and MMLA.	Describes the evaluators' opinions of the connection between bioethics and MMLA.
	The importance of continuous consent	Explains the intrusiveness of continuous consent during the study

Novelty of the MMLA framework.	Novelty of the framework.	Describes the features that distinguish this framework from other frameworks, as discussed by the evaluators.
	The framework's added value.	Refers to the question about how the framework adds value, from the perspective of the evaluators.
	The framework is MMLA driven.	Describes how the framework is MMLA driven from the perspective of the evaluators.
	Articulating the framework for the purpose of MMLA.	Describes the evaluators' opinions of how to articulate the framework for the purpose of MMLA.
Comprehension and clarity of the framework.	Comprehension and clarity of the framework.	Evaluates the clarity of the framework from the perspective of the evaluators.
	Simplified versions of specific words within the MMLA framework.	Refers to the alternative terms suggested by evaluators for specific words.
	Clarity of the framework's content.	Evaluators' perceptions of the degree to which users understand the content presented in the framework and recommendations for future enhancements.
	A different framework for each stakeholder.	Provides an overview of the evaluators' suggestions to design a framework for each stakeholder.
	Presentation and visualisation of the framework.	Presents the evaluators' perceptions of the current condition of the framework and future recommendations for improvements its visibility.
	Clarity of the framework's structure.	Describes the evaluators' opinions about the clarity of the framework's structure and their recommendations for improvements.
	Differentiating objective criteria from guiding questions.	Explains the evaluators' opinions about how objective criteria and guiding questions should be differentiated.
	Similarities between the framework and the evaluation rubrics.	Examines the evaluators' opinions of the similarities between the structure of the evaluation rubric and the framework.
	Similarities between the framework's structure and other ethical guidelines.	Describes the evaluators' opinions of the similarities between the framework's structure and other ethical guidelines.
	The introduction of the MMLA framework.	Explains the feedback provided by the evaluators regarding the introduction to the framework.
	Further concerns as regards the implementation of the framework.	Discusses the evaluators' opinions of the concerns that should be addressed prior to the implementation of the framework.

The following sections present the themes in bold and quotations from the interviewees in italics. Each interviewee's name is anonymised using letters and numbers: (ES) for students, (ET) for educators, (ER) researcher–practitioners and (EP) for policymakers.

5.5.1 Theme 1: Practicality and Usefulness of the MMLA framework

In terms of the framework's usefulness, more than one third of the evaluators (12 out of 27) found the framework useful for raising awareness of the ethical issues surrounding the use of MMLA, as acknowledged by ER20: "*I'm pretty sure this framework will help to increase end-user awareness, because when I'm myself reading it though, I'm doing MMLA research and I have missed some of these objectives*". The framework was deemed particularly beneficial for those who had never used MMLA tools previously. One educator stated: "*For educators who haven't done this kind of thing, it might be an eye opener for them*" **(**ER3).

Similarly, most of the evaluators found the framework to be a practical tool that would increase users' awareness: "*I think there is certainly a practical value in this framework, to help people become more aware of the importance of ethical aspects in multimodal learning analytics*" (ER16). Moreover, as mentioned by ER27, the framework was "e*asy to implement*".

In practice, the framework has proven highly effective in assisting researchers with improving their experiments and maintaining ethical standards: "*I think the framework was effective in helping us improve our experiment and keep it ethical"* (Professor Dominguez). In response to the framework, researchers altered certain aspects of their research methodology. As the framework emphasises that students may withdraw at any time during the experiment., consent has been redefined to include continuous consent:

> *The students have to give consent before starting the experiment, right before registering in the app. The way we had it before, once the students gave consent, that's it. But of course, the framework made us realise that a student should be able to withdraw at any time during the experiment. So, we implemented the functionality that we didn't have before* (Professor Dominguez).

Moreover, given that the framework placed a high level of importance on protecting students' privacy, this made them more aware of this issue:

> *This act of recording in other homes in many cases reveals a lot of personal information about the student. For example, one of the things that is easily revealed is the social economic status of a student and their family. The fact that the framework has a very strong emphasis on protecting the privacy made us realise that we have to be very careful now with the privacy. Therefore, we didn't alter the system, but we altered the methodology experiment. For example, only the professor saw the videos* (Professor Dominguez).

Using the framework also gave researchers a sense of confidence and relief that all ethical considerations were being taken into account:

> *When we submit our research to publish it, the reviewer asked us, do you have an ethical approval of these experiments? And yes, we did have the ethical approval. I believe it was not very difficult to get, because from the beginning of the experiment we had this guidance for the framework. So, we felt that we were doing everything OK on the ethical side and when we send it to the ethical committee, they confirm that, yes, this seems to be OK* (Professor Dominguez).

While most of the evaluators determined that the framework was practical, a few expressed concerns. According to one researcher, the framework was appropriate for extremely mature technologies that have already been tested and whose issues have already been identified: *This framework is best suited for technologies that have already been tested [...]. It is too early to have discussions about, for example, privacy or students' agency or fairness and bias in most cases* (ER11).

Similarly, another point was raised that MMLA systems cannot cover every ethical issue without being implemented in the real world: "*You will not be able to cover all aspects, all of the privacy issues, unless MMLA systems are implemented*" (EP24). Moreover, one researcher found the framework to be more related to research than to its use in a real-world setting: "*I find the framework more related to research than to use*" (ER20). Another expressed a concern that although the framework was not overwhelming, users might find it too long: "*I think it's easy, but it's very long. But, at the same time, umm, I don't think it's overwhelming*" (ER18). Furthermore, a researcher claimed that it was difficult to address all the questions in the framework: "*We were not able to implement some of the dimensions of the framework either because we didn't have the resources. Or quite simply, there was no way of doing this within our institution"* (Professor Dominguez).

Several suggestions were made for how to improve the practicality and usefulness of the framework. The first recommendation was that students should be informed in advance about the ethical implications connected with using MMLA, so they would take it seriously: "*To allow students to take* *this as a serious issue, you have to prepare them before reading this framework, with maybe a graphic or, like, a video about the consequences of using their data*" (ES15).

A second recommendation was that the framework should be updated on a regular basis: "*Because technology keeps on being updated, you need to add a point where you mention the progressiveness of this framework [....]. I would say, ah, it should be updated every six months*" (ET13). A third was to enhance the framework by establishing regulations and procedures to guide its implementation: "*It should be accompanied by regulations and procedures on how to implement this framework, so the framework itself will not be enough. You need a lot of documents helping to implement this policy*" (EP24). Finally, a fourth recommendation related to improving the usability of the framework by developing a user-friendly web page with a series of questions:

> *If you want the framework to be useful, I think that you will need to develop a kind of user interface, something that guides the user. [….]. I can imagine, like, a web page where you can see, like, a quiz to go through questions, and you can answer the questions* (ER26).

5.5.2 Theme 2: Comprehensiveness of the framework

The framework was deemed comprehensive by approximately one third of the evaluators (10 out of 27). A number of the students, teachers, policymakers and ethics experts indicated that the framework provided a comprehensive analysis of all the issues they were concerned about: "*The framework meets my concerns*" (ET6). In addition, the evaluators commented that the framework addressed all the relevant ethical issues that must be considered prior to the start of a MMLA project. For instance, ER16 asserted: "*It pretty much covers, like, a 360 view of the questions I would like to ask in terms of ethics when starting a project that uses MMLA*".

However, a few evaluators also expressed concern regarding the comprehensiveness of the framework's objectives and guiding questions. Based on these concerns, a number of recommendations were made. The first related to the guiding questions related to accountability. One researcher maintained that institutions should clarify the type of risk assessment they conduct: "*If there has been any risk assessment, it is good to see what measures have been taken"* (ER3). The second suggestion underlined the need to clarify which types of information are considered sensitive from the perspective of end-users, given the wide variations in perceptions of what represents sensitive information, in order to protect their privacy. This was emphasised by ES14: "*The understanding of what is sensitive information differs from one person to another depending on the field or area, like, is the name or age or gender sensitive information or not?*".

A third recommendation was to delete the duplicate guiding questions that appear in different objective sections: "*Some of the questions in some of the criteria are repeated in different sections. That could discourage researchers and practitioners*" (ER16). A fourth question was raised regarding the benefits of sharing information, as noted by ER17 who claimed: "*I was wondering whether you could ask a question, like, what's the benefits of sharing the data rather than rerunning it*?". As a fifth recommendation, a policy maker advocated added restrictions on the information collected from the end-users to prevent misuse:

> *We know that the private sector usually is results-oriented and is looking for a profit. So we need to make sure that this collected data will not be misused by the entity to collect more money or selling these data to other organisations*.

The sixth recommendation would be to include a separate objective regarding confidentiality, and to clarify the difference between confidentiality and privacy: "*There's just a distinction between confidentiality and privacy. You should clarify the definitions; confidentiality of data is about data security and disclosure, whereas privacy more broadly encompasses principles like data minimisation*" (ER7).

Seventh, the framework should emphasise the importance of thoroughly training the entire MMLA tool, not just the algorithm itself: "*Emphasis on the separation that the algorithm is trained enough, but also the tools that you're using*" (ER17). The eighth suggestion was to differentiate between data that are deliberately collected and data that are discovered by accident:

> *I would distinguish between the data that is deliberately gathered and the incidental findings, and then possibly have sub-questions for sensitive information and health information. So the first question would be: Will you be gathering any information that could be classified as sensitive personal information? And only deliberately? Or is there any potential for accidental findings? And then underneath that you could have two separate sub-questions, one of which could be around, will this data include health information? Will this information include other sensitive personal information?* (ER7).

An eighth recommendation would be to include a question that underlines the importance of considering both local policy and the framework when it is being implemented.

> *The framework does not take into consideration factors such as the local data privacy law, for example, law that was passed in 2021. Students can only give permission by physically handing*

> *in their consent form, instead of submitting it online. Therefore, the framework could be improved, for example by adding the following question: "Are you taking into account the institution's data confidentiality policies and the relevant national privacy laws?* (Professor Dominguez).

Finally, a suggestion was made regarding an additional guiding question related to whether the MMLA system had been tested for potential issues of bias arising from the design of the training data collection: "*You should discuss fairness due to the research setup*" (ER27).

5.5.3 Theme 3: The Novelty of the MMLA Framework

A significant theme that emerged from the study was the novelty of the designed framework. A number of evaluators (9 out of 27) praised the MMLA framework for its novelty and added value. The framework has a novel aspect in that it is the first to address ethical issues associated with MMLA, as indicated by ER11: "*What I like about this framework is that it tries to address the ethical concerns and issues related to multimodal learning analytics. I haven't seen other attempts*". Despite several previous attempts to incorporate ethical concerns affecting MMLA into research, no existing framework has yet emerged: "*I haven't seen any ethical framework. Actually, it was some notes about what information we need to consider during research. So it's not like this framework. I think this one would be a very original contribution to the field*" (ER4).

Similarly, a number of evaluators expressed their appreciation for the novelty of the framework. Emphasis was placed on the importance of articulating a framework specifically for MMLA: "*The framework is very MMLA driven, although when I zoom out I do realise that it could be used in other areas, like even generally in data analytics*" (ER16). Articulating a framework specifically for MMLA could be achieved, for example, by presenting an MMLA-focused scenario within the framework, as proposed by ER16: "*Maybe you could add that really specific MMLA information in your framework, even more, like about sensors, and give examples, probably*". It could also be achieved by adding additional guiding questions regarding MMLA data, particularly concerning the normalisation, synchronisation and triangulation of MMLA data obtained from various sources, as recommended by ER5:

> *As this is MMLA, you probably need to explain what makes this particular framework unique. Is it about the normalisation techniques concerning data from multiple data sources? How can they be compared? How do they synchronise the data? And if the results need to be validated, that would be another question about triangulation.*

The novelty of the MMLA framework was further confirmed by Professor Domínguez, who found the framework advantageous in providing guidance regarding potential ethical issues, particularly when developing and using the mobile phone version of the RAP system, which was considered to be more of an ethical risk than the traditional version:

> *The framework was exceptionally useful in the sense that we needed guidance on how to approach the ethical issues related to using a mobile phone because we felt that the ethical issues with mobile phones are more evident now than with the traditional systems. The risk of committing an ethical violation appears to be significantly greater now, so we needed some guidance on how to best deal with this concern appropriately"* (Professor Dominguez).

The framework's most prominent feature relates to its guiding questions:

> *The questions are in fact what guide you and, in my experience, using the framework helps. For example, I am already aware that privacy is a concern beforehand. I know that safety is a concern. I knew all these things before. I mean, I don't need a framework for that. But the questions that you put in the framework are really useful because they'll give you the details of what specific aspects of privacy you need to be aware of. What really makes it useful for researchers is the questions* (Professor Dominguez).

5.5.4 Theme 4: Comprehension and Clarity of the Framework

There was agreement among a number of evaluators (9 out of 27) that the framework was simple and transparent. This was specifically noted by ET19, who stated: "*I think that the language is very clear and simple*." While the framework was considered clear and simple, concerns persisted about its clarity, particularly for novice users, such as students and teachers: "*So for me it was clear, but I'm not sure if it's going to be clear for students*" (ET21). This was in accordance with the feedback given by Professor Dominguez—that the framework might not be clear to other users other than MMLA researchers:

> *For me personally, it was not a problem because I am someone who is working in this area. But I know that if I show this to someone who is unfamiliar with MMLA it will be a bit difficult to understand everything instantly* (Professor Dominguez).

It was therefore recommended that a simplified version be created specifically for students and educators, with fewer technical terms and a more concise explanation of what the guiding questions really mean. ER3 noted:

The framework can be divided into two parts, so one is as it is for the researcher and there is another one for educators. Then there might be another column which is explaining some of these questions, like, what do they really mean, if it was for educators. If you target it at educators, probably make it a bit less technical and a bit more, like, straightforward. A simplified version can be made just for educators.

Similarly, Professor Dominguez stressed the importance of simplifying the wording in the framework, inserting images and making the framework more dynamic.

For example, to be more user-friendly, the privacy part can have a picture that quickly identifies that this is about privacy. It can be dynamic. So, you click here and then the questions appears This could be included in some sort of infographics (Professor Dominguez).

Moreover, the addition of a glossary of terms could aid in clarifying any technical terms: *"Usually, policies are accompanied by terms and their meanings. So, you could put a list of terms and what you mean by each term*" (EP24).

5.3 Discussion of the Findings of the Evaluation Process

Evaluations were regarded as an essential step in developing the framework by receiving feedback from a broad range of stakeholders. A number of valuable findings were identified during the evaluation process, including: the framework was easy to read and had a clear structure, and it could assist framework users to understand the importance of ethical issues when using MMLA, particularly those who had never used MMLA tools previously. Nonetheless, several suggestions were made in support of further improvements.

First, although most of the evaluators agreed that the framework was practical, some felt it was more appropriate for use in a research context than in an actual setting. This might be due to the technical terminology employed. For example, a language that appears familiar to researchers may be difficult for other end-users, such as teachers and students, to understand and amend, which may make the application of the framework more challenging. Moreover, this could be due to the lack of practical examples or real-world scenarios. Therefore, a suggestion was made by the evaluators to simplify certain words, provide examples and scenarios in certain situations, and provide examples of best practice to resolve ethical issues. A few also suggested providing educators and students with their own simplified frameworks. This is in accordance with the evaluation of the framework conducted by Chaudhry et al. (2022), where educators confirmed that the language used in the transparency framework should be simplified/explained for ease of access. Additionally, a separate version of the framework should be developed specifically for schools, which describes all the technical terms.

It was extremely beneficial to receive these suggestions as they stimulated the idea of designing a simplified version of the framework. A simplified framework would be useful to allow more users to grasp it without needing to understand the technical terms and without having to undergo special training, thus improving its accessibility and ease of use.

The second recommendation was that students should be sufficiently informed about MMLA and the ethical implications associated with its use in order to be able to seriously consider the framework. This could be achieved by showing a short video about the risks associated with collecting their MMD. This should not, however, be limited to students but should also be available to teachers and the management of any establishment that would be responsible for implementing MMLA or authorising its use. While previous literature, such as the research undertaken by Mangaroska et al. (2021), provided a brief description of the experimental setup upon arrival at the laboratory, a video explaining MMLA and its associated risks is an additional, valuable recommendation.

A third suggestion was to present the framework as a diagram, while others noted that it could be made into an interactive website or application. Developing actionable guidelines in the form of checklists was also recommended, as they would make it easier for framework users to ensure they were covering each of the areas. However, checklists may distract users from fully understanding the framework to merely marking items as completed. Users may prioritise the completion of a task above understanding, perceiving the framework primarily as a series of tasks rather as an instrument for critical reflection and ethical understanding.

Fourth, the framework must be continuously updated as technology continues to evolve. New MMLA tools may generate new ethical concerns and risks that were not previously considered. Therefore, updating the framework on a regular basis may assist with maintaining an effective framework as a guide for ethical decision making.

The fifth suggestion was to clarify that the criteria and objectives outlined in the framework are not limited to MMD; essentially, they can also be applied to learning analytics comprising varying levels of sophistication. However, so as to be comprehensive, they were included in the framework, taking into consideration MMLA. Articulating a framework specifically designed for MMLA was recommended too by including an MMLA-focused scenario and guiding questions regarding MMLA data, including normalisation, synchronisation and triangulation of MMLA data acquired from several sources.

Sixth, the researcher proposed that institutions should clarify what type of risk assessment they conducted. A risk assessment commonly examines privacy, data security and ethical concerns, as well as any potential unintended consequences. Subsequently, an appropriate strategy needs to be developed to eliminate each of these risks.

Seventh, given the considerable differences in opinions regarding the definition of sensitive information in relation to protecting end-users' privacy, evaluators recommended that the types of information considered sensitive from the perspective of end-users should be specified. This may be influenced by particular cultures or religions. For example, recording female faces compared to male faces might be perceived as extremely sensitive in some cultures. In addition, a concern was expressed regarding the possibility of accidental findings. As an example, an unexpected finding might appear to be related to health.

Eighth, a recommendation was put forward that the sharing of student data should be based upon the benefit to the students, and it should be restricted, with the aim of mitigating the risk of data abuse. Genuine challenges arise when data are misused for profit. Inappropriate handling of data can violate students' privacy, integrity and trust when education institutions or developers work with third-party agencies.

Ninth, a key recommendation was to add a separate objective related to confidentiality and to be able to distinguish confidentiality from privacy. Confidentiality should be explicitly addressed rather than assumed under broader privacy concerns. The framework includes confidentiality as a separate objective, emphasising the obligation to prevent unauthorised access.

Finally, it was proposed that a further guiding question be asked regarding the potential bias issues arising from the design of the training data collection process. One of the most significant causes of bias is the fact that the training data are designed specifically for a specific population but are intended to be generically adapted to other populations too. Thus, it is vital that the training dataset be comprehensive enough and that it be trained and tested over a long period. Furthermore, the MMLA tool must be adequately tested in order to confirm its reliability and to ensure that end-users are not exposed to any potentially harmful risks.

Several factors were considered when determining whether to accept the evaluators' recommendations, in addition to the researcher's own judgement. This includes how many times the evaluators made the same suggestion, the background of the evaluator making the suggestion, together with the feasibility of the suggestion.

5.4 Chapter Summary

This chapter has provided a thematic analysis of the data collected through interviews. The results of the analysis revealed four main themes. The combination of these themes, along with the findings of the systematic review presented in Chapter Two and the results of the main data collection analysis in Chapter Four, will enable the development of an ethical framework, which is the subject of the discussion section.

6 Chapter Six: Result and Discussion

6.1 Introduction

This chapter comprises two main sections. Primarily, it presents the final version of the first ethical framework for mitigating the ethical implications associated with using MMLA in higher education. This is followed by an extensive discussion of the results. This study employed a qualitative approach to provide a detailed understanding of the concerns surrounding MMLA, enabling the development of an ethical framework to address these issues. Data were collected from interviews with 60 educational stakeholders, including 39 students in higher education, 12 researchers, eight educators and one representative from an MMLA company. Based on the information obtained, a suitable framework was developed. This was followed by an assessment of the designed framework using data obtained from 27 researcher–practitioners, educators, ethics experts and policymakers, in conjunction with students from HEIs. The purpose of this chapter is to provide answers to the research questions presented at the beginning of the study. It will also discuss the objectives of the study, taking into consideration the opinions, experiences, qualitative analysis and findings of previous researchers. The results of this study were recently published (Alwahaby & Cukurova, 2024).

6.2 Description of the MMLA Ethical Framework

This section describes the main outcome of the study, an ethical MMLA framework, which has been developed and modified in response to the data collection and evaluation process conducted with various stakeholders, as discussed in Chapters Four and Five. Owing to the evaluation process, two versions of the framework were developed: one for researchers and practitioners (see Table 19), along with a simplified version for teachers and students (see Table 20). It is expected that by incorporating the ethical MMLA framework, users will be able to better understand the potential ethical implications of using MMLA tools in higher education.

As outlined in the framework, the objectives represent the main ethical issues that the framework seeks to address, while the criteria explain how the objectives can be achieved. Assuming that ethical procedures differ across countries, we aim to avoid replicating the process of submitting formal ethics applications on account of privacy concerns. Accordingly, the questions regarding privacy are intentionally designed to be general in nature, so that each country can modify them according to its own ethical standards. It should also be noted that the criteria and objectives in the framework are not restricted to multimodal learning environments; fundamentally, they can also be applied to a variety of complicated learning analytics situations. Nonetheless, with the aim of being comprehensive, they are listed here along with several considerations.

We acknowledge that this framework cannot include every conceivable ethical issue. Evidently, we perceive it to be a foundation that should be systematically updated as our understanding of the implications and risks connected with using MMLA systems evolves. As a result of its implementation, our ethical MMLA framework has the potential to strengthen the ethical integrity of systems that are established. Furthermore, the aim is for the developer to continually improve the framework by means of discussions with and recommendations from the community, with educational institutions informed of these updates.

Table 19. The MMLA framework for researchers and practitioners

Objective	Criteria	Main Questions to be Considered
Beneficence The use of MMLA should emphasise the advantages it offers students and teachers.	Establish the benefits that MMLA might provide for both learning and teaching.	• Is there sufficient evidence that a particular MMLA tool is beneficial for learning? • What are the ethical implications associated with not using MMLA?
Privacy Privacy should be considered an important part of research or practice	Ensure that students' privacy is protected.	• Are there any risks in relation to students' privacy? • What proactive measures have been taken to protect students' privacy? • How effective have privacy mitigation strategies been in reducing risk?
	Determine that sensitive student information is protected. The collection of sensitive personal information may occur either deliberately, e.g., due to explicit questioning or by accident, e.g., appearing in processed images.	• Will you be gathering any information that could be classified as sensitive personal information, either deliberately or accidentally? a- Could this information relate to health? b- Could this information include other sensitive personal information? • What steps should be taken if sensitive information (i.e., related to health conditions) is discovered during the analysis of multimodal data? • What information would be considered sensitive from the perspective of the end-user?

	Ensure that the collection, storage and sharing of multimodal data has obvious benefits for students or teachers, e.g., understanding where the student is academically, and ensuring that the data are collected, stored and shared with their consent.	• Why is multimodal data being collected? • What is the purpose of monitoring each modality? • In your opinion, why is this data source considered more significant than other possibly less intrusive ones? • What benefits does the multimodal feature offer? • What is the trade-off/compromise between the benefits and risks associated with using a particular sensor? • If you are collecting data from several sources, how will you triangulate them? • What mechanism is applied to organise the data? • Who could this data be shared with? • What is the benefit of sharing students' data? • Will the students' data be used exclusively for educational purposes? • What procedures have been established to protect the collected data against exploitation by private educational institutions? • How long will the data be stored? • Will the consent information be revised based on future developments and additions to the MMLA system?
	In the event that the MMLA system is employed for surveillance, it is essential that the potential benefits outweigh the potential negative impacts, that this information is clearly delivered to students and that the system does not have a detrimental impact on students.	• If the MMLA system is used for surveillance and assuming that students give informed consent for this, what is the evidence to support the conclusion that the benefits outweigh the potential negative effects? • Is there continuous assessment to provide evidence that the benefits outweigh the negative impacts? • Is consent obtained throughout the entire process? • What level of surveillance should MMLA tools allow? • To what extent is the Hawthorne effect[3] considered when MMLA tools are used?

[3] The Hawthorne effect refers to a situation where individuals alter their behaviour when they know that they are being observed (Parsons, 1974).

Security Protecting the confidentiality, integrity and availability of the MMLA system and the end-users' collected data against cyber-attacks or unauthorised access.	Verify that the MMLA system and the end-users' collected data are protected against cyber-attacks or unauthorised access.	• Are there any internal or external threats to the collected data? • What are the potential online and offline threats to the collected data? • In the event that a third party, e.g., a foreign country, is involved as a data storage point, what precautions have been taken to guarantee data security? • Would you undertake data classification[4] on data that are expected to be stored on a cloud computing facility? • What security features are considered to protect end-users' collected data?
Safety End-users' well-being, as well as their physical and psychological safety, should be assured while using the MMLA system.	Prevent any potential or actual harm, including physical, e.g., headaches or physiological, e.g., anxiety.	• Could the MMLA system cause physical or physiological harm to a stakeholder, including students, teachers or staff, during data collection, analysis or feedback? • What practical measures have been implemented to prevent any physical and/or physiological harm that could occur as a result of the use of the MMLA system?
End-user awareness End-users should be aware of the potential benefits and risks associated with the use of MMLA.	Ensure that end-users, including students and teachers, understand MMLA and why it is used, and are aware of the potential benefits and risks associated with its use.	• Has an introductory session been conducted for teachers and students regarding the practicalities of using sensor technologies, such as MMLA, the importance of MMLA in improving students' learning, and the associated risks, e.g., inaccurate assessments, inappropriate feedback, data leaks, any potential harm, etc.? • What measures have been taken to determine the accessibility of the information presented in the introductory session and that it is appropriate for the participants' backgrounds, including students? For example, visual aids to explain concepts, avoiding jargon, using accessible terminology, etc.

[4] Data classification can be defined as categorising data assets according to the sensitivity of the information (Daneshgar et al., 2020).

Students' agency Empowering students to make their own decisions.	Promote students with agency to make their own decisions.	• To what extent are students able to challenge and modify the results generated by the MMLA system? • Do students have access to a channel whereby they can ask questions regarding the results generated by the MMLA system?
Students' ownership of their data Students should have ownership, control and decision-making authority over their generated or collected information.	Empower students to own their data.	• To what extent do students have control over their data, including access, discussion and deletion? • To what extent do you think students should have control over their collected data, including access, discussion and deletion? • To what extent does the consent form allow students to retain control over their data?
Transparency and explainability End-users should have an obvious understanding of how the system works.	Ensure that MMLA systems have the capability to provide simple explanations of any MMLA decisions.	• Have education stakeholders been provided with accessible information regarding the training dataset,[5] any potential bias in the dataset and how results are generated by the system developers? • Are the explanations provided by the MMLA system understandable to relevant stakeholders at different levels? • What are the implications of transparency for further implementations of the system and learning designs? • Have you noted any instances of 'gaming the system'? How might these be addressed?

[5] A training dataset is a collection of data that is used to train an algorithm to make accurate predictions.

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Fairness and bias Issues associated with system bias.	Guarantee that suppliers provide relevant information to confirm that MMLA systems are developed in such a way that fairness is considered and attempts to mitigate bias are made. For example, systems are trained and tested on a sufficiently broad sample drawn from different populations.	• Has the system been trained and tested on a sufficiently broad and diverse sample that is representative of the student population who will be using the system? • Has the dataset been sufficiently trained to be able to demonstrate its potential generalisation? • Did the system developers implement transparent protocols and algorithm(s)? • Was the MMLA system designed by a diverse team? • Are there any indicators that the MMLA tool might be biased? • To what extent are the algorithm(s) used obvious to each stakeholder?
	Establish that suppliers provide relevant information to confirm that the results of the MMLA analysis have been verified by the relevant stakeholders, e.g., students and teachers, during the production and evaluation stages.	• Have the results of the MMLA been verified by relevant educational stakeholders, e.g., students and teachers, during the production and evaluation stages?
	Ensure that suppliers provide relevant information so that the validity of the MMLA results can be assessed whilst considering different student populations.	• To what extent were diverse student populations, e.g., based on race and religion, considered when validating the results of the MMLA system? • In what way could the results that have been generated by the MMLA system result in discrimination? • To what extent could the results of the MMLA system be generalised to other contexts? • Has the MMLA system been tested for potential bias arising from the design of the collection of the data that is used for training?
Trustworthiness Confidence and trust in the results.	Confirm the trustworthiness of the MMLA results.	• To what extent is the MMLA system capable of providing trustworthy results? • What are the implications of MMLA-driven assessment? • To what extent have the results of the MMLA assessment been validated using other sources of information?

		• Have the results of the system been verified against the explanation(s) provided by experts, such as teachers, researchers, etc? • Does the MMLA system have reliable evidence that it is trusted by end-users, including teachers and students?
Accountability Who should be held responsible when unacceptable behaviour is demonstrated.	Establish that a risk assessment has been conducted prior to the implementation of MMLA.	• Did your institution conduct a risk assessment prior to implementing the MMLA? If yes, what type of risk assessment? • Do you have an action plan in place in the event that any system-related issues arise? • Is there a designated group within your institution, composed of experts in various fields, to provide guidance and support for any potential challenges related to the implementation of MMLA?

The simplified version of the framework is accompanied by a glossary of terms, examples and scenarios borrowed from the paper published by Ochoa et al. (2018), as shown in Tables 20 and 21, respectively. Regarding a specific scenario, we will assume that an MMLA system is being employed on a university course. The system provides automatic feedback to students concerning their oral presentations. As students deliver oral presentations to a virtual audience displayed on a screen in front of them, the MMLA system records utilising a camera and a microphone. The data gathered are collectively referred to as Multimodal Data (MMD). An analysis of the video is performed in order to estimate the direction of the presenter's gaze and body posture based on the position of the skeletal joints in the video. These are classified as correct or incorrect based on the guidelines and models developed with expert advice. Two features are extracted from the audio recordings: voice volume and filled pauses consisting of vocalised hesitations, e.g., eh, uh, uhm, er, etc. These features are also categorised as correct or incorrect based on previous models. Each presentation is scored based on the following four features: posture, gaze, voice volume and filled pauses. After each presentation, the system generates a feedback report for the presenter to evaluate. Additionally, teachers are asked to provide feedback to students via the system. The different dimensions related to this framework will be applied in this context, with scenarios presented in the fourth column of Table 20.

Table 20. Simplified ethical MMLA framework based on a scenario for other users, including students and teachers

Objective	Criteria	Main Questions to be Considered	Contextualised Questions for the Example Scenario (MMLA for Oral Presentations)
Beneficence The use of MMLA should emphasise the advantages it offers students and teachers.	Establish the benefits that MMLA might provide for both learning and teaching.	Is there sufficient evidence that a particular MMLA tool is beneficial for learning?	Is there sufficient evidence that using automated feedback system improve students' oral presentations?
		What are the ethical implications associated with not using MMLA?	What are the ethical concerns related to the institution not agreeing to the use of automated feedback system to improve students' oral presentations?
Privacy Privacy should be considered as an important part of research or practice.	Ensure that students' privacy is protected.	Are there any risks in relation to students' privacy?	What are the risks associated with capturing students on video and audio?
		What proactive measures have been taken to protect students' privacy?	What measures would you take to safeguard the privacy of students' audio and video data?
		How effective have privacy mitigation strategies been in reducing risk?	How much have the privacy mitigation strategies reduced the risks for students and teachers?
	Determine that sensitive student information is protected. The collection of sensitive personal information may occur either deliberately, e.g., due	Will you be gathering any information that could be classified as sensitive personal information, either deliberately or accidentally?	Could the information generated from the analysis of the direction of a student's gaze, pose or voice volume be indicative of their health?

	to explicit questioning or by accident, e.g., appearing in processed images.	a. Could this information relate to health? b. Could this information include other sensitive personal information?	Could the direction of a student's gaze, pose or voice volume include other sensitive personal information?
		What steps should be taken if sensitive information, specifically that related to health conditions, is discovered during the analysis of multimodal data?	What steps should be taken if sensitive information, specifically that related to health conditions, such as ADHD, is discovered during the analysis of students' audio and video data?
		What information would be considered sensitive from the perspective of the end-user?	What information would be considered sensitive from your perspective?
	Ensure that the collection, storage and sharing of multimodal data has obvious benefits for students or teachers, e.g., understanding where the student is academically, and that the data is collected, stored and shared with their consent.	Why is multimodal data being collected?	Why do you think audio and video data should be collected specifically, as opposed to other types of data?
		What is the purpose of monitoring each modality?	Are there any theoretical arguments that demonstrate the connection between the direction of a student's gaze, pose, voice volume and filled pauses, and their oral presentation skills?
		In your opinion, why is this data source considered more significant than other	Why do you believe that students' audio and video data are more important than other potentially

		possibly less intrusive ones?	less intrusive data, such as log data?
		What benefits does the multimodal feature offer?	Why do you think it is advantageous to collect two types of data, i.e., audio and video data, as opposed to simply audio data?
		What is the trade-off/compromise between the benefits and risks associated with using a particular sensor?	What is the comparison between the benefits and the risks of using a video camera to capture the direction of a student's gaze and pose?
		If you are collecting data from several sources, how will you triangulate them?	How will you combine the results of students' posture, gaze, voice volume and filled pauses?
		What mechanism is applied to organise the data?	How do you plan to synchronise students' gaze with their voice volume at a specific moment?
		Who could this data be shared with?	Who would you share the students' video and audio data with?
		What is the benefit of sharing students' data?	What is the benefit of sharing students' video and audio data?
		Will the students' data be used exclusively for educational purposes?	Will the students' video and audio data be used purely for educational purposes?

		What procedures have been established to protect the collected data against exploitation by private educational institutions?	What procedures have been established to safeguard students’ video and audio data against exploitation by private educational institutions?
		How long will the data be stored?	How long will the video and audio data be stored?
		Will the consent information be revised based on future developments and additions the MMLA system?	Will the consent information be updated based on future developments and additions to the oral automated feedback system?
	In the event that the MMLA system is employed for surveillance, it is essential that the potential benefits outweigh the potential negative impacts. The information must be clearly delivered to students and it must be ensured that the system does not have a detrimental impact on students.	If the MMLA system is used for surveillance and assuming that students give informed consent for this, what is the evidence to support the conclusion that the benefits outweigh the potential negative effects?	If a camera is used to capture students’ pose, it might unintentionally allow the monitoring of student behaviour. Assuming that students give informed consent for this, what is the evidence to support the conclusion that the benefits outweigh the potential negative impacts?
		What is the evidence to support the conclusion that the benefits outweigh the potential negative impacts?	Have any attempts been made to provide evidence that the benefits of the oral automated feedback system outweigh the negative effects in the long-term?
		Is consent obtained throughout the entire process?	Are the students provided with regular opportunities to review

			their consent whilst using the MMLA system?
		What level of surveillance should MMLA tools allow?	To what extent should the monitoring of students be allowed through the use of oral automated feedback system?
		To what extent is the Hawthorne effect[6] considered when MMLA tools are used?	What consideration is given to students altering their behaviour in response to being observed by the MMLA system?
Security Protecting the confidentiality, integrity and availability of the MMLA system and the end-users' collected data against cyber-attacks or unauthorised access.	Verify that the MMLA system and the end-users' collected data are protected against cyber-attacks or unauthorised access.	Are there any internal or external threats in relation to the collected data?	Are there any internal or external threats to the students' video and audio data?
		What are the online and offline threats to the collected data?	What are the online and offline threats to the students' video and audio data?
		In the event that a third party, e.g., a foreign country, is involved as a data storage point, what precautions have been taken to guarantee data security?	In the event that a third party, e.g., a foreign country, is included as a data storage point, what precautions have been taken to ensure data security?
		Would you undertake data classification[7] on	If the data collected are stored in a cloud

[6] The Hawthorne effect refers to a situation where individuals alter their behaviour when they know that they are being observed (Parsons, 1974).

[7] Data classification can be defined as categorising data assets according to the sensitivity of the information (Daneshgar et al., 2020).

		data that are expected to be stored in a cloud computing facility?	computing facility, would you categorise the data based on the information's sensitivity level (high, medium or low), such as personally identifiable information or protected health information?
		What security features are considered to protect end-users' collected data?	What security features did you consider to protect students' video and audio data?
Safety End-users' well-being, as well as their physical and psychological safety, should be assured while using the MMLA system.	Prevent any potential or actual harm, including physical, e.g., headaches or physiological, e.g., anxiety.	Could the MMLA system cause physical or physiological harm to any stakeholders, including students, teachers or staff, during data collection, analysis or feedback?	Could the MMLA system cause physical or psychological harm to students or teachers during data collection, analysis, or feedback?
		What practical measures have been taken to prevent any physical and/or physiological harm that could occur as a result of the use of the MMLA system?	What practical measures have you set up to ensure that the MMLA system does not cause any physical and/or psychological harm?
End-users' awareness End-users should be aware of the potential benefits and risks associated with the use of MMLA.	Ensure that end-users, including students and teachers understand MMLA, why it is used, and are aware of the potential benefits and risks associated with its use.	Has an introductory session been conducted for teachers and students regarding the practicalities of using sensor technologies, such as MMLA, the importance of MMLA in improving students' learning, along with the associated risks, e.g., inaccurate assessments,	Have you provided students and teachers with an introductory session concerning the practicalities of using sensor technologies such as MMLA, the importance of MMLA in improving students' learning, together with the associated risks, e.g., the risks related to inaccurate

		inappropriate feedback, data leaks, any potential harm, etc.?	assessments, inappropriate feedback, data leaks, any potential harm, etc.?
		What measures have been taken to determine the accessibility of the information presented in the introductory session and to ensure that it is appropriate in relation to the participants' backgrounds, including students? For example, visual aids to explain concepts, avoiding jargon, using accessible terminology, etc.	What measures have been taken to verify the accessibility of all the information presented in the introductory session, and to ensure that it is appropriate in relation to the students' backgrounds? For instance, visual aids to explain concepts, avoiding jargon, using accessible terminology, etc.
Students' agency Empowering students to make their own decisions.	Promote students' agency to make their own decisions.	To what extent are students able to challenge and modify the results generated by the MMLA system?	To what extent do you think students should be able to challenge and modify the results in the feedback report generated by MMLA system concerning their oral presentation skills?
		Do students have access to a channel where they can ask questions regarding the results generated by the MMLA system?	How can students ask questions about the results generated by the MMLA system?
Students' ownership of their data Students should have ownership, control and decision-making authority over their generated or collected information.	Empower students to own their data.	To what extent do students have control over their data, including access, discussion and deletion?	To what extent do students have control over their collected audio and video data, including access, discussion and deletion?

		To what extent do you think students should have control over their collected audio and video data, including access, discussion and deletion?	To what extent do you think students should have control over their collected audio and video data, including access, discussion and deletion?
		To what extent does the consent form allow students to retain control over their data?	To what extent does the consent form let students control their video and audio data?
Transparency and explainability End-users should have an obvious understanding of how the system works.	Ensure that MMLA systems have the capability to provide simple explanations regarding any MMLA decisions.	Have education stakeholders been provided with accessible information regarding the training dataset,[8] any potential bias in the dataset and how results are generated by the system developers?	Are teachers and students aware of which groups the system was designed, trained and tested on, and whether it demonstrates any bias towards any particular group? How are the results generated?
		Are the explanations provided by the MMLA system understandable to relevant stakeholders at different levels?	Are the feedback reports and explanations about students' oral presentation skills delivered in language that is easy to understand?
		What are the implications of transparency on further system implementations and learning designs?	What are the implications of explaining how the oral automated feedback system operates on further implementations of the system and learning designs?

[8] A training dataset is a collection of data that is used to train an algorithm to make accurate predictions.

		Have you noticed any instances of 'gaming the system'? How might these be addressed?	To what extent do you think students might repeat a certain behaviour during their presentation in order to game the system? How would you address this issue?
Fairness and bias Issues associated with system bias.	Guarantee that suppliers provide relevant information to confirm that MMLA systems are developed in such a way that fairness is considered and attempts to mitigate bias are made. For example, systems are trained and tested on a sufficiently broad sample drawn from different populations.	Has the system been trained and tested on a sufficiently broad and diverse sample that is representative of the student population who will be using the system?	Has the system been tested on a variety of users in terms of their race, gender, age, etc?
		Has the dataset been sufficiently trained to be able to demonstrate its potential generalisation?	Has the data that will be used to train the algorithm or model been sufficiently trained to guarantee that it can accurately predict the outcome variable across different groups of people comprising different genders, ages, etc?
		Did the system developers implement transparent protocols and algorithm(s)?	Can teachers and students understand how the algorithm decides when a student is exhibiting an inappropriate posture during the presentation?
		Was the MMLA system designed by a diverse team?	Was the MMLA system designed by a diverse team or only by the designers?

		Are there any indicators that the MMLA tool might be biased?	Are there any indicators that the MMLA tool might be biased? For example, could the system be biased against the students' skin colour?
		To what extent are the algorithm(s) used obvious to each stakeholder?	To what extent are the algorithm(s) used obvious to each stakeholder?
	Establish that suppliers provide relevant information to confirm that the results of the MMLA analysis are confirmed by the relevant stakeholders, e.g., students and teachers during the production and evaluation stages.	Have the results of the MMLA been verified by relevant educational stakeholders, e.g., students and teachers, during the production and evaluation stages?	Will you compare the feedback report generated by the MMLA system with the teacher's feedback to corroborate the results?
	Ensure that suppliers provide relevant information to confirm that the validity of the MMLA results is assessed whilst considering different student populations.	To what extent were different student populations, e.g., those based on race and religion, considered when validating the results of the MMLA system?	To what extent were different student populations, e.g., those based on race and religion, considered when validating the results of the MMLA system?
		In what way could the results generated by the MMLA system result in discrimination?	In what way could the results generated by the MMLA system result in discrimination? For example, could the MMLA system be biased against certain body types?

		To what extent can the results of the MMLA system be generalised to other contexts?	To what extent can the results of the MMLA system be generalised to other contexts, such as in high schools as opposed to universities?
		Has the MMLA system been tested for potential bias arising from the design of the collection of data that were used for training?	Has the MMLA system been tested for potential bias arising from the design of the collection of data that were used for training? For instance, when students are divided into unequal groups in the classroom?
Trustworthiness Confidence and trust in the results.	Confirm the trustworthiness of the MMLA results.	To what extent is the MMLA system prepared to provide trustworthy results?	To what extent is the MMLA system prepared to provide trustworthy results related to student performance in oral presentations?
		What are the consequences of MMLA-driven assessment?	What is the significance of using MMLA presentation scores for student assessment?
		To what extent have the results of the MMLA assessment been validated using other sources of information?	To what extent have the results of the MMLA assessment been validated using other sources of information? For example, the students' own opinions or peer reviews?
		Have the results of the system been verified against the explanation(s) provided by experts, such as teachers, researchers, etc?	Have the results of the MMLAs assessment of oral presentations been verified against the explanations provided by teachers, researchers,

			etc., over a reasonable period?
		Does the MMLA system have reliable evidence that it is trusted by end-users, including teachers and students?	Does the MMLA assessment system of oral presentations exhibit reliable evidence that it is trusted by teachers and students?
Accountability Who should be held responsible when unacceptable behaviour is demonstrated?	Establish that a risk assessment has been conducted prior to the implementation of MMLA.	Did your institution conduct a risk assessment prior to implementing the MMLA? If yes, what type of risk assessment was undertaken?	Did the university conduct a risk assessment to identify and assess any potential threats prior to implementing the MMLA? If yes, what type of risk assessment was conducted?
		Do you have an action plan prepared in the event that any system-related issues arise?	Does the university have an action plan in the event of a system-related issue?
		Is there a designated group within your institution, composed of experts in various fields, to provide guidance and support for any potential challenges related to the implementation of MMLA?	Is there a designated group within your institution, composed of experts in various fields, to provide guidance and support for any potential challenges related to the implementation of MMLA?

Table 21. Glossary: Table of technical terms used in the framework

Term	Definition
Algorithm	Process or set of rules that a computer adheres to when solving problems or performing calculations (Cormen et al., 2022).
Models	Models are physical, mathematical or logical representations of systems, entities, phenomena or processes. In machine learning and statistics, data can be processed algorithmically to develop models (Alpaydin, 2016).
Predictive models	Models developed using statistical or machine-learning techniques and able to predict future outcomes based on historical and current data (Alpaydin, 2016).
Training dataset	A training dataset is a collection of data that is used to train an algorithm in order to predict an outcome accurately.
Model bias	The term "model bias" refers to a series of errors present in a model that cause it to make repeated incorrect predictions. In the course of training the model, errors may arise due to the choice of training data, the features selected or the algorithm utilised (Alpaydin, 2016).
Algorithmic transparency	Comprises making the factors that influence algorithmic decisions discernible to those who use, control and are impacted by those systems (Diakopoulos, 2020).

6.3 Discussion

The purpose of this section is to provide answers to the main research questions presented by the study. Chapter One outlines three questions which this study aims to address and answer:

1. What are specific examples of MMLA being employed in education and the related ethical concerns mentioned in the literature?
2. What are the opinions of researchers, practitioners and students on the ethical use of MMLA in higher education?
3. How can MMLA be applied in a more ethical way in higher education?

This section will combine and analyse the findings from the data collection in Chapters Four and Five and the review of the literature in Chapter Two, in order to determine how far these research questions have been addressed.

RQ1. What are specific examples of MMLA being employed in education and the related ethical concerns mentioned in the literature?

The first research question aimed to explore the existing research on the use of MMLA in education, underlining the extent to which the ethical considerations related to its use have been tackled in the literature. By conducting a Systematic Literature Review (SLR) as presented in Chapter Two, it was determined that there were no comprehensive discussions concerning the ethical issues associated with MMLA in education. (Part of the resulting review has already been included in a published paper—see Alwahaby et al. (2022). The review was updated in February 2024 for inclusion in this thesis).

Although the SLR identified 42 papers discussing ethical concerns related to the use of MMLA, most of the discussion related to data privacy, consent forms and data management. Owing to this, there was a significant gap in the literature on many of the factors summarised and proposed for debate within Chapter One. While MMLA researchers are beginning to consider the ethics pertaining to transparency, accountability and fairness, there is a paucity of literature on how these ethical problems can be resolved. Similarly, Martinez-Maldonado et al. (2018) have also suggested that further discussion is necessary to address the ethical concerns regarding MMLA. In addition, other researchers have also demanded the development of a MMLA framework and stressed the need for future studies to focus on the ethical factors involved in MMLA (Mangaroska et al., 2021). Hence, it is essential to explore the ethical concerns associated with the use of MMLA in higher education.

RQ2. What are the opinions of researchers, practitioners and students on the ethical use of MMLA in higher education?

RQ3. How can MMLA be applied in a more ethical way in higher education?

Given that the study's second research question was designed to obtain a better understanding of participants' perceptions of how MMLA might be applied in higher education and how this information could be used to develop an ethical MMLA framework, qualitative methods were chosen as the most appropriate, for example individual structured interviews. As Creswell (2018) notes, a qualitative approach seeks to understand what individuals and groups attribute to social or human issues. Similarly, because MMLA is an emerging technology and a new topic, the variables to be examined in terms of its ethical applications are unknown, therefore a qualitative approach was crucial (Creswell, 2018). It should also be mentioned that qualitative research comprises examining descriptions and meanings that cannot always be quantitatively represented.

Upon reviewing the literature in combination with the analysis of the interviews, it became even more evident that there is an urgent need to establish an MMLA ethical framework to protect users, including students and teachers who are using MMLA. This became the primary motivation for this work, as addressed in the third research question, which focuses on promoting the ethical use of MMLA. Interviewees expressed the need for an integrated and overarching code that would ensure minimal harm related to MMLA, but which primarily demonstrates fair treatment and ethical measures regarding users. According to the interviewees, a unified ethical framework would enable the use of MMLAs in education to be more consistent, safe and appropriate. This would be particularly important for MMLA users based in countries other than those currently affected by the GDPR, who in actual fact depend on their own national laws for data protection.

To the best of our knowledge, the framework developed in this study is novel, as it is the first designed to address and mitigate the ethical issues associated with the use of MMLA in higher education. Based on the SLR conducted in Chapter Two, in recent years, researchers have only briefly addressed the magnitude of these emerging issues without providing any extensive analysis or actionable solutions. Additionally, in accordance with our findings, the novelty of the designed framework was one of the principal themes that emerged during the evaluation process. It is worth mentioning that numerous interviewees praised the MMLA framework for its originality and added value. According to the interviewees, the framework is distinctive in that it is the first to investigate the ethical issues pertaining to MMLA. It was also stated that although some previous research had attempted to address a number of the ethical concerns relating to MMLA, a comprehensive framework has yet to be developed. This is in line with the existing literature insisting upon the development of an MMLA framework (Mangaroska, Martinez-Maldonado et al., 2021).

The following is a discussion about each component of the framework and how each part adds value to the current literature.

Beneficence of using MMLA: It is important to mention that although the term 'beneficence' may not have been identified in the literature, numerous previous studies underline the value of employing MMLA to support teaching and learning methods, e.g., Cukurova et al. (2020). This result is consistent with our findings, as it was one of the most significant themes obtained from the interview data. Numerous interviewees including researchers, teachers and students, accentuated the importance of MMLA and underlined the possible consequences of failing to use it. Moreover, many interviewees considered MMLA to be a valuable tool to mitigate classroom bias and favouritism. They believe that it helps educators to recognise differences in learning among students and improves the learning process for those with disabilities, therefore reducing dissatisfaction with teaching and increasing student discipline. MMLA's beneficence objective implies that its application should be guided by the potential benefits to both students and teachers. Including questions concerning beneficence in the framework was valuable, as it aimed to raise user awareness of the possible consequences of not using MMLA, as well as to support the use of MMLA.

Privacy: A key component of the framework stresses the need to consider privacy in research and practice by asking a number of critical questions to increase user awareness of these issues and subsequently mitigate them. Questions regarding privacy were designed to tackle the concerns raised in previous research and those that were mentioned during the interviews. The privacy objective in the framework focused on three specific themes: 1) protecting students' privacy and sensitive information; 2) ensuring that the collecting, storing and sharing of MMD were done on the basis of the benefits provided to students or teachers, and only with their consent; and 3) if the use of the MMLA system is seen as a form of surveillance, there should be evidence that the potential benefits outweigh the potential negative impacts, and that the system is not detrimental to students at all.

Both the previous literature and the results of our interviews identified privacy as the most frequently mentioned ethical concern. The emphasis in the interviews was on the importance of privacy in protecting the user's identity, in addition to personal and sensitive information. Participants considered MMD to be highly sensitive because of the facial recognition and associated data, as well as pictures and videos, which could be used to reveal participants' identities. There were also concerns expressed regarding the misuse of sensor data, such as eye tracking, in non-teaching environments. Similarly, particular sensors might reveal sensitive information, for instance personal emotions and health information. This result is consistent with previous research findings that MMLA may trigger privacy concerns, for the reasons that it collects highly sensitive sensor data (Martinez-Maldonado, Echeverria et al., 2020) and may also reveal details such as daily routines and habits (Kröger, 2018). Therefore, the questions included within the framework were designed to verify that students' privacy and sensitive information are protected, and to clarify that sensitive personal information may be gathered either deliberately, e.g., through explicit questioning, or by accident, e.g., appearing in processed images. Participants made a number of recommendations in this regard.

Among the proposed strategies are sharing students' data only with their explicit consent and when it directly benefits them, implementing differential privacy where group patterns within a dataset are described without revealing individual details, together with introducing noise to large datasets to achieve anonymity. Similar suggestions were made by previous literature to mitigate privacy issues, for example, processing video and audio recordings anonymously (Keskinarkaus et al., 2016), removing data from spatial and audio datasets that could identify individual students (Zhao et al., 2022), using audio data rather than video data to reduce privacy concerns (Donnelly et al., 2016), advising developers to include privacy features, such as a ‘delete/forget’ button and the tokenisation[9] of sensitive information in the data collection system (Dominguez et al., 2021), besides removing all identifying information from the dataset and using colours only to distinguish students while controlling access to prevent any unintended misuse (Zhao et al., 2023). Consequently, the framework questions stress that the collection, storage and sharing of multimodal data has obvious advantages for students or teachers in general, e.g., understanding where the student is academically, but that the data must be collected, stored and shared with their consent.

Moreover, the interviewees believed that MMLA might be too intrusive to comprehensively monitor students’ emotions. Most students reported that being observed by MMLA for a prolonged period could cause anxiety. This is in line with the Hawthorne effect, where people modify a feature of their behaviour when they are aware that they are being observed. This is consistent with an article published by Li et al. (2023) who recommended that researchers and practitioners should consider the possible impact of video surveillance on students’ learning behaviour. In a similar vein, Sinha (2021) recommends that future research should consider the possibility of unintended surveillance when various data sources are employed. Zhao et al. (2023) also highlighted unintended surveillance as a significant ethical concern. To reduce students’ worry about being observed, Sinha (2021) informed students that the results would not be considered as part of their formal evaluation. Similarly, although the position tracker used by Yan et al. (2022) did not place intrusive restrictions on students, the researchers noted that its presence may have caused them to feel as if they were being observed on top of their teachers’ observations. Therefore, our framework underlines that if the use of the MMLA system is likely to become a form of surveillance, there must be evidence that the potential benefits outweigh the potential negative impacts. Likewise, this information must be clearly explained to students and the system must not harm students at all.

These findings obtained from both the interviews and the published literature were applied to determine the privacy guiding questions in the framework. It is important to note that ethical processes differ across countries and it is necessary to avoid replicating the process of filing formal ethics applications for reasons such as privacy. Accordingly, the privacy-related questions are designed to be general in nature, so that they can be customised according to each country’s ethical standards.

Security: While privacy concerns were repeatedly raised in the published literature, security concerns were rarely addressed. The findings pertaining to the SLR in Chapter Two indicate that it was not until

[9] Replacing sensitive data with non-sensitive codes that can be traced back to their original state

2021 that researchers began to address the security issues linked to MMLA and methods to mitigate them. The failure to identify and discuss security as an issue can be explained by the fact that many studies use the term 'privacy' broadly to denote both privacy and security. Nevertheless, security concerns were rarely raised during discussions regarding privacy. As several researchers mentioned in the interviews, this may be because MMLA data do not need to be subject to any additional security safeguards other than those that are ordinarily applied. This is due to the fact that, in their research, MMLA operates as a separate system and does not depend on a web-based server, hence threats linked to unauthorised access to data are prevented. However, this does not justify the lack of additional security measures related to MMD, as the MMLA system can be connected to the Internet at various times or under different circumstances.

The lack of discussion regarding security in the published literature corresponds with the findings obtained by the interview evaluation process which questioned the difference between privacy and security. During the evaluation interview it was recommended that confidentiality should be included as a separate objective, and that the difference between confidentiality and privacy must be clarified. In particular, confidentiality is concerned with data security and disclosure, whereas privacy comprises broader principles, for instance data minimisation. Therefore, it was necessary to highlight security as a critical component of the framework, while also providing an obvious definition of security as it pertains to MMLA data and also presenting questions specifically designed to mitigate security risks.

It is worth noting that although only a few papers identified by the SLR addressed security, the discussions they contained regarding security were useful in providing a better understanding of how to prepare guiding security questions. Among these measures was the use of black boxes, including blurring or pixelation, in publicly shared research documents with the aim of concealing students' facial identities (Li et al., 2023). A different study conducted by Ciordas-Hertel et al. (2021) examined the hashing of re-identifiable sensor data as part of the user-side application by using a secret salt. Salting involves adding a random string of characters to a password before it is hashed, preventing cloud services from analysing the data. Security questions in the designed framework were developed based on the findings obtained from the SLR and the data collection process. These questions were established to safeguard the confidentiality, integrity and availability of the MMLA system and substantiate that the data collected by the end-users were protected from cyber-attacks and unauthorised access.

Safety: A distinguishing characteristic of MMLA tools is that they employ advanced sensing technologies, for example electroencephalography (EEG), wristband sensors and eye-tracking devices. Due to the fact that a number of these sensors may require direct contact between the user and the sensor, several ethical issues surface, for example safety, physical harm and discomfort. Based on the interviews, safety concerns have been identified as a fundamental ethical concern related to the use of MMLA. The use of some sensors with MMLA has been observed to carry the risk of causing harm to the user. The interviewees perceived MMLA data collection to be an invasive technology that may cause some end-users a degree of anxiety.

Various MMLA data collection tools were reported to cause stiffness, which is consistent with previous MMLA studies indicating that students experienced distractions, discomfort, irritability, headaches and reduced mobility (Mangaroska, Martinez-Maldonado et al., 2021).

The level of intrusiveness in relation to MMLA data collection appears to vary according to different stakeholders. Although most participants considered MMLA to be an invasive technology, many researchers believed that the methods used to collect MMLA data were non-invasive. They believed that their opinion was justified, as the sensors are visible and can be touched. It is important to state, however, that the researchers' perceptions were based on their methodology, not on the data themselves. Consequently, researchers need to be more aware of these issues when using MMLA.

Equally, students may experience physiological harm as a result of using the MMLA tools. Also of interest is that specific students may be prevented from using EEG sensors owing to cultural differences, such as wearing head coverings. In a real-life educational setting, it is imperative to take all these issues into consideration when using MMLA, given that they may affect the learners' normal behaviour as well as their learning development. End-user safety is paramount to MMLA and it is important to include a safety objective in the design framework, so as to avoid any potential or actual harm, including physical, e.g., headaches, and physiological, e.g., anxiety.

End-user awareness: The process of obtaining informed consent involves more than simply collecting signatures; it requires an understanding of the scope of the data collection, the characteristics of the technology used, as well as the potential significance of the data collected. Particularly when dealing with sensitive MMLA data obtained from sensors, such as eye-tracking devices or physiological sensors, this issue is exceedingly important. As a result of our interviews, the concept of "data visibility" was introduced as a fundamental factor that affects student awareness. In the opinion of one researcher, students are more likely to participate in data collection if they have the opportunity to observe how the data are collected, for instance by cameras or eye trackers. Nonetheless, regardless of the fact that students may acknowledge and be aware of the collection of data, they often lack a clear understanding of the magnitude and sensitivity of such data. Despite the fact that eye-tracking technology is visible, students may not comprehend how it can be used to gather cognitive processes or emotional states. There is therefore a question as to whether simply allowing data to be visible is sufficient to guarantee informed consent.

The interviewees agreed that students lack adequate understanding of how their data are collected or how sensitive they actually are. Thus, informed consent might not be sufficient for students to understand how sensor data are collected or how algorithms work. It is therefore necessary to provide verbal explanations in addition to consent forms. This is in accordance with research completed by Mangaroska, Sharma et al. (2021), who reported that besides the explanation provided in their consent sheet, students received a brief introduction to the experimental setup upon arrival at the lab, in accordance with Department of Health ethical guidelines.

The interviews revealed that students' understanding of the advantages and disadvantages of MMLA can directly influence their willingness to use it. Students reported a positive correlation between their level of understanding and their willingness to participate. For instance, it was determined that students who are familiar with MMLA and its associated risks are more inclined to utilise it. It is interesting that there appear to be contrasting views between teachers and students in relation to this. As an example, one teacher presented an opposing viewpoint, intimating that increasing learners' understanding may result in a decrease in participation. This finding is in keeping with Beardsley et al. (2020), who ascertained that increasing students' understanding of consent led to a reduction in participation rates. This indicates that a greater awareness of data collection procedures might create reluctance or anxiety amongst students.

Likewise, based on the findings obtained from the interviews, students from particular disciplines, such as law, were less likely to participate due to privacy concerns. This statement contradicts the initial statement that using MMLA would increase student participation if they understood the implications and risks. A crucial ethical question arises from this finding: should the focus be on maximising student participation or increasing their awareness of potential risks? Although increasing student participation is necessary to gather meaningful data, the transparency of consent forms should not be compromised. Consequently, the informed consent protocol needs to be reviewed and applied more comprehensively.

Based on the published literature and interview findings, several recommendations can be made to heighten end-user awareness. Prior to participating, students must be informed through a pre-session or training session that they are participating in a voluntary study and that they have a right to withdraw at any time without any repercussions. Participation in a MMLA module should not be directly related to the results of a summative assessment (Zhou et al., 2023). This is consistent with the interview finding that learners seemed more concerned about whether the data would have an impact on their learning outcomes. According to the interviewees, students are more relaxed if the data will be used to support their learning rather than to provide a grade. Additionally, the use of sensors must not result in physical or psychological harm (Mangaroska, Sharma et al., 2021). Participants' privacy must also be safeguarded by storing MMLA data on an encrypted hard drive and using MMLA data for research purposes only (Yusuf et al., 2024). Likewise, it is crucial to provide transparency regarding what type of data is collected, how it is collected and how long the data will be stored. Considering all of the findings was fundamental to formulating the awareness questions included in the designed framework. To guarantee that students are able to provide their consent in a way that is both ethical and well-informed, it is imperative that researchers and educators deal with these concerns. Consequently, it was believed that it was necessary to concentrate on each of these issues within the design framework.

Students' agency and ownership of their data: The framework was designed to empower students to make their own decisions. According to the results of the interviews, most participants agreed that learners should have control over their learning experiences and personal data. Conversely, opinions differed among participants regarding the extent to which students should have control over their data and agency over their learning. For instance, the students proposed that they should be able to comment on their learning predictions and inform their teachers of any changes they might decide to make. In contrast, teachers were opposed to any changes to the MMD. In their opinion, students' agency over their data and learning may adversely affect their emotional well-being, possibly because they supposed that students may be emotionally affected by their results. However, the researchers reasoned that students should have access to and be able to modify and delete their own information, including incorrect information. This finding is in accordance with Ciordas-Hertel et al. (2021), who allowed participants to download and delete all their data via a web-based interface. Conversely, this may be perceived as data ownership rather than agency. Hence, given the significance of student agency and data ownership, these views were presented as separate objectives and addressed by means of specific questions within the framework.

It is also worth mentioning that during the framework evaluation process, a few researchers reasoned that dealing with concerns such as student agency was premature. They asserted that the proposed framework would be more appropriate for extremely mature technologies that have been tested and had their issues identified. We acknowledge that MMLA has not yet been extensively employed in real-world educational settings. Nonetheless, although we cannot predict all the ethical complications and unforeseen challenges that might arise during the implementation of this technology in the future, we would argue that valuable lessons can be learned from analogous prior technologies regarding the prevention of recognised problems.

Transparency and explainability: MMLA systems have become increasingly influential in developing education, providing data-driven information concerning student learning behaviour and performance. Nevertheless, the transparency and explainability of these systems are paramount. It is vital that end-users, particularly students and teachers, understand how MMLA operates and the process by which decisions are made. Transparency refers to the MMLA's ability to reveal its procedures, data sources and relationships between actions and results. Explainability takes this a step further by not just supporting designers, engineers and developers to understand how decisions are being made, but also providing users with an explanation of how these decisions are made, by means of using more applicable language to make complex algorithms more transparent and understandable.

The interviewees stressed that transparency allows students to reflect on their learning by making quality indicators visible, for instance recognising how specific behaviours influence outcomes and how they can provide students with a detailed understanding of their learning processes. Transparency and explainability are essential factors in developing greater trust in MMLA systems. Several studies have demonstrated that students are more likely to trust systems when they can observe how decisions are made (Kizilcec, 2016). For example, students should be able to understand the system's decision-making process without the need for specialised technical knowledge that may obfuscate the aim of transparency. Robert et al. (2020) underlined that there is frequently a lack of transparency in relation to the algorithms employed to reach decisions. In particular, it is not always clear which datasets or criteria are used by the system. On account of this, users are not always able to determine when or why decision-making criteria are modified. Providing users with clear explanations allows them to challenge the decisions made by systems, resulting in increased learning ownership. In actual fact, most of our interviewees agreed that transparent decision-making generates better learning outcomes. The importance of this is particularly crucial when students receive unexpected results, given that it can help to create trust in the system.

Despite the advantages, the transparency and explainability associated with MMLA present significant challenges, with 'gaming the system' being a significant issue. As an example, a student who is aware of how physical movements influence the MMLA system might modify their behaviour with the aim of achieving a higher score. As one individual highlighted, in a MMLA study aimed at improving students' oral presentations, participants might adjust their posture to follow perceived system preferences rather than focusing on improving their overall performance. Too much transparency can produce manipulation, which undermines the system's goal of promoting genuine learning. It is crucial for there to be a balance between transparency and safeguards to prevent students from gaming the system. A further inconvenience is finding a suitable balance between simplicity and in-depth explanations of how MMLA works. Although transparency is imperative, too much information could confuse rather than inform students. For instance, one respondent stressed that clarifying the complex equations underlying MMLA decisions could be more difficult than explaining the "black box" itself, hence making the explanation ineffective.

The application of categorisation techniques or ML models exacerbates this issue. A participant asserted that while students may not require an understanding of every single technical detail, they should be aware of how a classification system is implemented, as well the potential benefits and limitations. The objective is to deliver explanations that are meaningful without overwhelming or confusing the end-user. The development of the ethical framework tackled each issue related to transparency and explainability by incorporating a set of MMLA-specific questions aimed at heightening user knowledge and mitigating these concerns.

Fairness and bias: The implementation of MMLA may raise significant concerns in relation to fairness and bias. To promote trust in MMLA systems, it is necessary to address these issues, as they bring into question the ability of the system to produce equal and fair results for different populations. Therefore, our ethical framework was designed with the aim of guaranteeing a fair MMLA system while regulating any issues relating to bias. The results of the interviews confirmed that our participants were in agreement that MMLA systems can potentially experience bias issues for several reasons.

First, the MMLA system may well be biased if it was developed and trained for a specific population and subsequently applied to a different population. For instance, the use of MMLA in conjunction with facial recognition to predict emotion may result in bias because of distinctions in appearance, for instance skin colour and facial features. This criticism is repeatedly based on the assumption that MMLA prediction systems are developed and trained using white-skinned males as the target population. Accordingly, to mitigate this issue, researchers such as Sinha (2021) have proposed that the placement of the camera should be initially tested on a small number of students to prevent potential bias in the detection of facial action units. Nonetheless, the interview data indicated that this concern is not limited to physical characteristics, but could also be applied to other aspects, for instance the failure of the system to identify certain accents. Second, MMLA results are likely to be biased if the system lacks information about external environmental factors, such as students' current emotional state, which can only be captured by the human eye, potentially generating incorrect interpretations. Third, an MMLA system may be biased for the reason that it does not allow for factors such as disabilities or cognitive problems, which might affect the validity of the results. Fourth, bias may result from the implicit values of the designers who are responsible for training the system.

MMLA has the potential to introduce bias, but this must be balanced with the fact that these systems may boost educational outcomes. Whether biases are the result of algorithmic design, the data used to train the models, or the implicit values of the system's designers, it is essential to conduct continuous research pertaining to algorithmic fairness, improve transparency in data collection and conduct more rigorous testing of models in diverse populations. It is necessary to address these challenges directly to guarantee that algorithmic systems in education assess students fairly and equitably without maintaining the prevailing inequalities. Consequently, the proposed framework comprises questions to increase users' awareness of these issues, so that they can be addressed in a sensible way.

Trustworthiness: It is not straightforward to establish that the results generated by MMLA systems are accurate and reliable. Accordingly, Martinez-Maldonado et al. (2024) recommend confirming the trustworthiness of these systems. MMLA results must be subjected to rigorous validation procedures to demonstrate their trustworthiness. According to these procedures, it is vital to validate the analytics on a technical level and to continuously validate the data collected. This requires consistently demonstrating the reliability of the results in a variety of contexts over time and under different conditions. This issue is exacerbated by the fact that MMLA systems collect data from a wide range of sources during the learning process, e.g., facial expressions, speech, physiological data, etc. Considering the complexity of the data collected, any errors in the system or bias in analysis may well result in inaccurate results. Therefore, with respect to sensing-based analytics, it is crucial to develop supported learning systems, frameworks and tools that will verify transparency and trustworthiness (Giannakos et al., 2021).

There are several ethical concerns with the way that people automatically trust technology and predictive systems and accept their predictions as fact. Therefore, participants in the interviews recommended exercising caution when they are employed. They stressed throughout the interviews that it is essential that MMLA provides evidence that its results have been validated in the long term and for end-users to confirm that the results are supplemented by human observation. Educational stakeholders have questioned the use of MMLA prediction systems, with most arguing that these systems should be used to provide feedback and support for students rather than for classification or assessment purposes. It is also vital that MMLA systems be fair with the purpose of establishing trust. Therefore, MMLA systems should bear in mind all the potential biases so as to ensure fairness. When developing the MMLA ethical framework, each of these factors was considered.

Accountability: Implementing MMLA in educational settings in particular demands a high level of accountability. Most of our interviewees maintained that accountability is a crucial factor when using MMLA in educational settings. It is extremely challenging to identify who should be held accountable for data management and use in these systems. The inclusion of all the relevant stakeholders in the design and development process is one of the principal recommendations given to increase the accountability of MMLA systems. Moreover, most interviewees agreed that MMLA systems should include students and teachers in their design so as to strengthen accountability and trust. Likewise, end-users, experts and institutional authorities were also mentioned as crucial contributors. From this perspective, accountability must be a shared responsibility between multiple stakeholders, with the aim of incorporating a broad range of viewpoints into the development of the system.

Various studies have raised questions regarding accountability, access to collected data and disclosure. For example, Martinez-Maldonado, Elliott et al. (2020) questioned whether data should be accessible to teachers, students and coordinators. Martinez-Maldonado, Mangaroska et al. (2020) asked a similar question regarding the effect of sharing instructional positioning data with other stakeholders in relation to teachers' accountability. However, there is a paucity of recommendations for how to promote accountability in MMLA research. In light of this, it was necessary to address this particular issue in this study.

During the interviews, it was agreed that educational institutions should be held accountable for any problems associated with MMLA systems. Accordingly, it was proposed that information technology experts should be available within institutions to resolve data-related issues. Although stakeholder participation and institutional responsibility are considered crucial to strengthening the accountability of MMLA, gaps remain with respect to their implementation. Transparency must be prioritised, specifically regarding those who participate in the design process. Furthermore, educational institutions must confront both ethical and technical problems to guarantee that MMLA systems are effective and accountable. Through the developed framework, MMLA users will be required to respond to enquiries on accountability, in order to ensure compliance and responsible use.

During the evaluation process, several recommendations were made to improve the framework. All of these recommendations have been included in the most recent version. These recommendations include the requirement that the framework be reviewed and approved by the entire research community before it can be considered suitably mature and trustworthy. This recommendation was implemented by means of a continuous evaluation process with a variety of stakeholder groups until data saturation had been achieved. A further suggestion was to incorporate real-life scenarios into the framework. This was accomplished by designing a simplified framework based on a specific scenario.

6.4 Chapter Summary

This chapter has provided answers to the research questions found in this study by examining the main contribution of this research; namely the development of an innovative ethical MMLA framework. It has also discussed the components of the framework, whilst clarifying the value it adds.

7 Chapter Seven: Conclusion

7.1 A Critique of the Study

This study has a number of fundamental limitations, several of which have been addressed and improved. These limitations are attributable to the selected design and the methodological choices, which must be acknowledged and considered. Several limitations were discussed in the Methodology Chapter.

7.1.1 Use of Nonprobability Purposive Sampling for the Interviews

In this study, researchers/practitioners, ethics experts and MMLA students were intentionally selected to participate in interviews. The participants were selected based on their experience with MMLA and/or their knowledge of ethics. There are, however, several limitations associated with nonprobability purposive sampling. It is unlikely that a representative sample will be obtained owing to the subjectivity involved in the selection process (Etikan, 2016). Consequently, the results of the interviews may not be generalisable. Nevertheless, because of the nature and purpose of the study, purposive sampling was deemed to be the most convenient and effective method to obtain comprehensive, considered responses from people who are familiar with MMLA and/or ethics.

7.1.2 Issues Related to the Generalisability of the Findings

Researchers can assess the generalisability of their research by determining whether the results are primarily of local importance or if they can be generalised to other subjects and situations (Kvale, 2012, p. 166). Given that this study is based on qualitative research which is not derived from random sampling, it cannot be generalised to a larger population (Niaz, 2007). The relatability and auditability of research can also be more important to practitioners than its generalisability (Cukurova et al., 2018). While the results of this study may not be generalisable to every specific setting in higher education, they remain applicable to similar situations.

7.1.3 Further Limitations

Interviews were conducted with students who were enrolled in higher education, including students working towards their Master's and PhDs. Nonetheless, a current limitation regarding this study is that it did not include students studying for degrees in the sample. Hence, future studies should consider including this specific group. Likewise, K-12 students and contexts may require marginally different ethical considerations, depending on the context.

The ethical MMLA framework developed from the current study should not be regarded as the final version that cannot be improved in the future. In creating the initial version of the framework, we took an approach that entailed generating beneficial information from stakeholders via the interviews. The framework will be further evaluated and improved in future iterations with contributions from various key stakeholders. Future research will include a larger and more diverse sample and a variety of co-design procedures to support the co-design of the framework. These will consist of workshops, participatory design sessions, brainstorming sessions and co-design sessions, all of which can be conducted using different methods where stakeholders can contribute directly to improving the framework.

A further disadvantage of the framework is that, although a group of researchers have adopted and tested it in their research, it has yet to be tested by most of the MMLA research community. Consequently, real-world adoption and evaluation are crucial to understanding its applicability and limitations. Additionally, particular ethical issues may not become obvious until MMLA has been implemented in a genuine educational setting. It is therefore imperative that the ethical considerations pertaining to MMLA be perceived as constantly evolving and revised accordingly.

7.2 Concluding Comments

Although there have been escalating concerns and attempts made by researchers to address the ethical issues associated with the use of MMLA, at present, no systematic process is in place to evaluate, audit and support MMLA research ethics and practice. The primary aim of this research was to develop a framework with an integrated ethical approach to MMLA, so as to permit a safer way to design and utilise this beneficial tool. We have presented the results of our interviews with key stakeholders, including researchers, practitioners, students and teachers, together with a representative from a technology company. In light of the interviews and a review of the literature, we have developed the basic version of a framework pertaining to the ethical use of MMLA. It should be stated that although the concerns and recommendations raised within this framework are not necessarily novel as such, the significance of this study is established in the fact that the concerns and recommendations are discussed within the context of MMLA research and are appropriately adapted to fit its distinctive characteristics. Currently, MMLA research lacks a comprehensive framework that encompasses all the unique and interconnected aspects related to data, AI and analytics ethics, including privacy, accountability, transparency and fairness.

7.3 My PhD Journey: Personal Reflections

This work would not have been possible without the support of my supervisor, Professor Mutlu Cukurova, and the resources and services provided via UCL.

As a lecturer at Princess Nourah Bint Abdulrahman University, I was awarded a scholarship to undertake my PhD. The research I have conducted in the UK has allowed me to make a unique contribution to MMLA ethics in higher education. As a result of weekly meetings with my supervisor, Professor Cukurova, and his constant support, I was able to resolve any obstacles I encountered during my studies. I owe much of my success to his constant belief in me and his endless encouragement.

I learned more about the PhD programme and research expectations during my first meeting with my supervisor. The explanation he provided regarding the research process significantly enhanced my understanding of its impact. My interest in multimodal learning analytics and education led me to pursue a doctoral degree, which will further my career in this particular field. Despite the importance of MMLA in higher education, scant attention has been paid to its ethical implications. Therefore, there was a need to fill the obvious gap. Since I began working in this field, I have gained considerable experience. This is specifically pertinent in terms of the ethical concerns associated with the use of MMLA in higher education. In my role as a lecturer at a university in Saudi Arabia, it is particularly important that I protect my students from any potential harm associated with technology-enhanced learning.

I would also like to mention that my supervisor encouraged me to send weekly email updates. This motivated me to organise a weekly task and develop a daily schedule to ensure that it was completed. My daily work schedule consisted of eight hours of work each day. Although the journey has been challenging, particularly during the pandemic, my supervisor was always available via Zoom and was exceedingly helpful.

During my studies at University College London (UCL), I have had the opportunity to participate in classes and workshops related to research methods, qualitative analysis and academic writing. Additionally, my supervisor encouraged me to attend a number of conferences both within and outside the university. By attending conferences and interacting with colleagues in the field, I was able to present my findings and receive valuable feedback at an early stage in my doctoral programme. As part of my PhD journey and on account of my supervisor’s encouragement, I conducted an SLR, which resulted in the following book chapter: *‘The evidence of impact and ethical considerations of Multimodal Learning Analytics: A Systematic Literature Review In book: The Multimodal Learning*

Analytics Handbook, Publisher: Springer'. The research community's reactions to this article have been very positive, and it has already been cited a significant number of times.

As a result of the systematic review conducted during my first year, I considerably improved my research skills as well as my understanding of my topic. Using this skill, I have been able to share my knowledge with a substantial number of graduate students. In actual fact, I was invited to present a webinar on conducting systematic reviews for the Saudi Cultural Bureau. Furthermore, my supervisor encouraged me to present the findings of my pilot study at the Conference on Learning Analytics & Knowledge (LAK) as a short paper entitled*: 'The ethical implications of using Multimodal Learning Analytics: Towards an ethical research and practice framework'.* Therefore, I was able to receive constructive feedback at an early stage in my research. Likewise, I was able to present a paper at the European Conference on Technology Enhanced Learning (ECTEL), which was my first face-to-face conference during my PhD. This conference provided me with a chance to meet other researchers in person and become involved in valuable discussions regarding my research. Hence, I took the opportunity to invite several researchers to participate in the interview process, given that it was an opportunity that could not be missed. Eventually, with the encouragement of my supervisor, I published the final findings of my study in a chapter in a book titled *'Ethics in Online AI-based Systems',* entitled *'Navigating the ethical landscape of multimodal learning analytics: a guiding framework'.*

For the most part, it was a demanding journey that I would not have been able to complete without the support of my supervisor and the faculty at UCL. On my return to Prince Nourah University as a lecturer, I intend to continue this work by establishing AI ethics in an education centre within the university. It is also my aim to collaborate with The Saudi Data & AI Authority (SDAIA), with the aim of adopting the MMLA designed framework in Saudi HEIs.

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9 APPENDICES

9.1 APPENDIX 1: Final Keyword Searches

WOS

- TS= (("multi*modal data" OR "multi*modal learning analytics" OR "Multi*modal* signal*" OR "multi*channel*" OR "sensing technolog*" OR "Gesture* Recog*" OR "multi*modal information*") AND (learn* OR acqui* OR Teach* OR interact*) AND ("Physical space*" OR "physical place*" OR "physical environment*" OR classroom* OR "physical space*" OR "physical analytics" OR "tangible interaction*") AND (dashboard OR tool* OR technolog*))

Scopus

- TITLE-ABS-KEY (("multimodal data" OR "multimodal learning analytics" OR "Multimodal* signal*" OR "multi*channel*" OR "sensing technolog*" OR "Gesture* Recog*" OR "multimodal information*") AND (learn* OR acqui* OR teach* OR interact*) AND ("Physical spac*" OR "physical plac*" OR "physical environment*" OR classroom* OR "physical analytics" OR "tangible interaction*") AND (dashboard OR tool* OR technolog*))

ACM

- AllField:(("multimodal data" "multi modal data" "multimodal learning analytics" "multi modal learning analytics" "Multimodal signal" "Multi modal signal" multichannel "multi channel" "sensing technology" "sensing technologies" "Gestures Recognition" "multimodal information" "multi modal information")) AND AllField:((learn* acqui* Teach* interact*)) AND AllField:(("Physical space" "physical places" "physical environment" "physical environments" classroom "physical analytics" "tangible interaction")) AND AllField:((dashboard OR tool* OR technolog*))

IEEE

- ((("All Metadata": "multimodal data" OR "multi modal data" OR "multimodal learning analytics" OR "multi modal learning analytics" OR "Multimodal signal" OR "Multimodal signals" OR "Multi modal signals" OR "Multi modal signal" OR "multi channels" OR multichannel OR "multi channel" OR "multi channels" OR "sensing technology" OR "sensing technologies" OR "Gesture Recognition" OR "Gestures Recognition " OR "multimodal information" OR "multi modal information" OR "multi-modal informations" OR "multimodal informations") AND ("All Metadata":learn* OR acqui* OR Teach* OR interact OR interaction) AND ("All Metadata": "Physical space" OR "Physical spaces" OR "physical place" OR "physical places" OR "physical environment" OR "physical environments" OR classroom OR "physical analytics" OR "tangible interaction" OR "tangible interactions") AND ("All Metadata": dashboard OR tool* OR technolog*)))

9.2 APPENDIX 2: Participant Consent Form

Institute of Education

UCL

[The ethical implications of using Multimodal Learning Analytics: Towards a framework for MMLA research and practice]

Participant Consent Form

You are being invited to take part in a research project. Before you decided it is important to understand why the research is being done and what participation will involve, It is important for you to know that you have no obligation to participate and you may decide to terminate your participation at any time.

project's purpose

The focus of this study is on a multimodal learning analytics (MMLA). Considering the recent advances in sensing technology, the collection of multimodal data derived from the physical world, such as eye gaze, heart rate, and body movement are feasible which can provide a significant level of insight into the learning process. However, in real-world educational practices MMLA can present several ethical issues. Therefore, the purpose of this interview is to investigate ethical challenges that might arise with the use of MMLA in order to propose an ethical framework that would facilitate practitioners and researchers to use MMLA more ethically while also allowing end users, including students and teachers, to benefit from what MMLA offers while also protecting them from any potential harm.

Procedures

If you accept to participate, you will be invited to participate in interview answering questions about your previous experiences relating to the development and deployment of MMLA in educational settings. The interview will take about 60 - 80 minutes to complete.

Participant Requirements

Participation in this study is targeting educators, researchers and practitioners who have both limited and advanced prior experience with MMLA in higher education context.

Benefits

Hopefully these investigations will ultimately inform the design of an ethical MMLA framework that is applicable for MMLA researchers. Your contribution is highly appreciated; however, you will receive no compensation after completing the survey.

Risks

Participating in this study does not involve any risks greater than those typically encountered in daily life.

Personal Information: Video or audio data will be collected.

How the collected data will be used

The information provided by the interview will be used primarily to perform the research purposes described earlier. The results of the research will be presented in a research paper and PhD thesis and you will not be able to be identified in either way.

How the collected data will be stored and shared

The collected data will be stored for a period of up to 60 months, and restricted access by other researchers will be allowed.

How to access and control your personal information

The survey dose not collect any personal data therefore there is no way to connect each participant directly to his own data.

Voluntary Participation

Your participation in this research is totally voluntary and you may discontinue your participation at any time during the research activity.

Who is organising and funding the research

The research is part of a PhD student project who is part of The Knowledge Lab, University College London.

Data Protection Privacy Notice:

The controller for this project will be University College London (UCL). The UCL Data Protection Officer provides oversight of UCL activities involving the processing of personal data, and can be contacted at data-protection@ucl.ac.uk

This 'local' privacy notice sets out the information that applies to this particular study. Further information on how UCL uses participant information can be found in our 'general' privacy notice: for participants in research studies, click here

The information that is required to be provided to participants under data protection legislation (GDPR and DPA 2018) is provided across both the 'local' and 'general' privacy notices. The lawful basis that will be used to process your personal data is 'Public task' for personal data.

Your personal data will be processed so long as it is required for the research project. If we are able to anonymise or pseudonymise the personal data you provide we will undertake this and will endeavour to minimise the processing of personal data wherever possible.

If you are concerned about how your personal data is being processed, or if you would like to contact us about your rights, please contact UCL in the first instance at data-protection@ucl.ac.uk

Institute of Education

Contact for further information

For further information please feel free to send your query via email: zczlalw@ucl.ac.uk

If you are happy to participate in this study please complete this consent form by ticking each item, as appropriate, and return to the research team via the contact details below:

1) I confirm that I have read and understood this information sheet, and have had the opportunity to consider the information, ask questions, and have had these questions adequately answered. ☐

2) I understand that my participation is voluntary and that I am free to withdraw at any time, without giving any reason. ☐

3) I know that I can refuse to answer any or all of the questions and that I can withdraw from the interview at any point. ☐

4) I agree for the interview to be audio recorded, and that recordings will be kept secure. I know that all data will be kept under the terms of the General Data Protection Regulation (GDPR). ☐

5) I agree for the interview to be video recorded, and that recordings will be kept secure and. I know that all data will be kept under the terms of the General Data Protection Regulation (GDPR). ☐

6) I agree that small direct quotes may be used in reports (these will be anonymised) ☐

7) In understand that in exceptional circumstances anonymity and confidentiality would have to be broken, for example, if it was felt that practice was putting children at risk, or there were concerns regarding professional misconduct. In these circumstances advice would be sought from a senior manager from another local authority who will advise us as to the appropriate course of action and as to whether we need to inform the authority of what you have told us. ☐

Name: ……….

Signature: ………………………………………………………………………………… Date: ……………………………………

Name of researcher ……..

Signature: ………………………………………………………………………………… Date: ……………………………………

9.3 APPENDIX 3: Main Structured Interview Protocol

Institute of Education

UCL

Structured interview protocol

Introduction

Thank you for agreeing to participate in this interview. As I indicated in the email, this study is focused on a multimodal learning analytics (MMLA). Considering the recent advances in sensing technology, the collection of multimodal data derived from the physical world, such as eye gaze, heart rate, and body movement are feasible which can provide a significant level of insight into the learning process. However, in real-world educational practices MMLA can present several ethical issues. Therefore, the purpose of this interview is to investigate ethical challenges that might arise with the use of MMLA in order to propose an ethical framework that would facilitate practitioners and researchers to use MMLA more ethically while also allowing end users, including students and teachers, to benefit from what MMLA offers while also protecting them from any potential harm. By ethical issue I mean broadly issues related to privacy, accountability, fairness and transparency. By accountability we refer to the institutions responsibility to protect user's personal data and prevent any breach of the system, where's fairness refers to the lack of system bias and providing justification of how the result was generated by the system and finally by transparency we refer to the system ability to provide reasons for an autonomous decision. So, in the interview, I'd like to go through a number of questions to learn more about your experiences with the use and adoption of MMLA in higher education. The interview will take 60 - 80 minutes to complete.

Background demographic information

1. What is your formal training, for example, are you a computer scientist, learning scientist, etc.?
2. What are your years of experience of familiarity with MMLA?
3. If you have teaching experience: What is your experience with teaching and learning, are you actually teaching currently? if not are you an MMLA tools developer or researcher? please specify your current role?

This section provides an in-depth question about the ethical issues related to MMLA mainly: privacy, transparency, accountability, fairness, equity and bias

Data privacy (collection, storing, processing and sharing)

The data collection process in MMLA might involve sensitive data such as participants' personal data therefore, institutions and data collectors should handle these data carefully to protect participants' privacy by taking the highest measures. Using and sharing student data should be a transparent process that is in compliance with the data privacy laws. Who should have access to these data? Where will the data be stored? Who are the other entities that data will be shared with? These are some of the questions that should be raised along with the data collection process.

4. What information do you normally provide to participants?
5. What approach do you take to delivering this information to participants?
6. Who is responsible for deciding what data should be collected: teachers, educators, developers, or the institution?
7. What do you think about the collection of a huge amount of data that is not necessary or that is not directly relevant to your work?
8. How do you think students would feel about their personal information being collected?
9. If you are collecting data using sensors such as EEG, skin sensing, or eye tracking:

9.1 how do you explain this to your participants?

9.2 How will the collected data be processed and stored?

9.3 How would you improve privacy protection when collecting such data compared to more traditional data (e.g., logging of keystrokes, timestamps etc.)?

10. What is your approach to anonymization? As an example, anonymized student IDs by replacing names of students with symbols, such as "*" or "C".
11. What are your recommendations on how to protect the privacy of MMLA data?
12. How do you feel about allowing others access to the data collected?
13. How would you protect the shared data?

Transparency and accountability

Institutional transparency is a really important aspect to consider, which means providing clear information about the data collection, storing, processing, sharing and the transparency of LA technology that involves how the decision is made by the system. Accountability on the other hand means, educational institutions should provide evidence on their system capability to protect user's personal data and prevent any breach of the system

14. What measures should educational institutions take to protect students?
15. Who should be responsible in the event of a breach in the MMLA system (educators, institutions, or developers)?
16. As a means of demonstrating the MMLA system's accountability, what information do you believe should be shared with the end-users?
17. Who should be included in the design process for the MMLA system in order to make the system more accountable?
18. In the event the system generates unexpected results, how would you recommend that learners and teachers be more confident in the result if we provided an explanation of the method by which the result was generated?
19. How will providing all of these details affect the level of end-user accountability?

Fairness, equity and bias

One of the main concerns of using LA systems in education is system bias which might occur for many reasons, for example, an algorithm that has been designed and trained based on a particular dataset might not be applicable to be applied in a different population, that is due to a number of factors such as learner's capabilities, ethnicity, race, religion, gender, and other physical characteristics. Additionally, algorithms bias might occur as a result of the implicit values of people who are responsible for algorithms training.

20. What would you do if you were a teacher who had used the MMLA early failure prediction system on students from different demographic backgrounds (age, gender, race) and then found that the results were totally different between students with the same demographic background and students with different demographic backgrounds? Accept the prediction of the system? 2. refuse to accept the results and raise this issue with the system developer?

20. What are some examples of bias issues that may arise as a result of the MMLA system?
21. Why may algorithmic bias occur?
22. In what ways might the training dataset affect the algorithm's results?
23. What approaches do you propose to prevent inequity issues?
24. What evidence are you suggesting that users should receive regarding the system's efficiency?
25. Considering that the MMLA system predicts learning outcomes differently from a human, which prediction would you prioritize, and why?

MMLA framework

26. Have you followed any special checklist or framework while using MMLA tools?
27. Are you aware of any MMLA framework or checklist?
28. If there is an MMLA framework would you use it?
29. Do you think it should be compulsory?

Closing:

So, before we wrap up, is there any additional comments, suggestion you would like to add about the ethical concerns related to MMLA in education.

Thank you again your participation is really useful. As mentioned in the introduction the aim of the project is to draw an ethical framework for MMLA users in education. And we focused on higher education to help educators and practitioners in dealing with the ethical issues that might emerge with the use of MMLA.

30. I would love to hear from you further so would you be interested in giving feedback on the framework, in the future?
31. Would you refer to someone else who has an experience with MMLA in education?

9.4 APPENDIX 4: Evaluation Interview Protocol

LONDON'S GLOBAL UNIVERSITY

UCL

MMLA ethics framework evaluation

The recent advancements in sensing technology have made it possible to collect multimodal data derived from the physical world, such as eye gaze, heart rate, and body movement, which can provide a significant amount of insight into the learning process. However, in real-world educational practices, MMLA can raise several ethical concerns. Consequently, an ethics framework for MMLA has been developed in order to address this issue by interviewing sixty educational stakeholders concerning their ethical concerns regarding the use of MMLA in higher education, including students, educators, researchers, and representatives of educational technology companies. The purpose of the interviews was to investigate ethical challenges that might arise with the use of MMLA and to propose a framework that would increase the awareness of others. We hope that the framework will facilitate practitioners and researchers to use MMLA more ethically while at the same time protecting end users, including students and teachers, from any potential harm as well as allowing them to benefit from what MMLA offers. Your opinion and feedback regarding the validity, usability, and visibility of this framework would be greatly appreciated.

Would you please answer the following questions concerning the MMLA ethical framework presented below:

Q1:Is there anything you like about this framework and would like to keep it as it is?

Q2:What would you like to change, delete or add to this framework?

Q3:To what extent can this framework be used as a practical guide to increase people's awareness and trust in the use of MMLA?

Q4: To what extent do you believe this framework is clear and easy to use? Is there another way to present the framework that you would suggest?

9.5 APPENDIX 5: Evaluation Protocol for the Implementation of the Framework.

Framework Adoption Structured Interview Protocol

Introduction

Thank you for agreeing to participate in this interview. As I indicated in the email, this study is focused on a multimodal learning analytics (MMLA). Considering the recent advances in sensing technology, the collection of multimodal data derived from the physical world, such as eye gaze, heart rate, and body movement are feasible which can provide a significant level of insight into the learning process. However, in real-world educational practices MMLA can present several ethical issues. As a result, an ethical framework has been developed to mitigate these issues. Therefore, the purpose of this interview is to investigate the researchers' experiences relating to adoption of the developed MMLA ethical framework in their MMLA research. So, in the interview, I'd like to go through a number of questions to learn more about your experience on the adoption of the framework in your research. The interview will take 30 minutes to complete.

Interview questions:

1. Could you please provide a brief description of the MMLA experiment you have conducted where the framework has been adopted?
2. How did you find using the framework in your research?
3. Was your approach altered or modified as a result of the framework?
4. How would you rate the useability and accessibility of the framework? Were there any aspects that you found difficult to understand or apply?
5. What do you consider to be the strongest aspects of the framework? What parts of this framework were the most helpful to your research?

6. Is there any limitation in the framework that you have noticed? Are there any areas that you believe could be improved or expanded?
7. In order to enhance the framework's practicalutility, do you have any specific guidelines or examples that you would like to see included?
8. How effective has the framework been in mitigating ethical issues in your research?
9. What is your assessment of the framework's practicality in real world educational settings?

Closing:

2. Would you consider using this framework in future studies? Would you recommend this framework to other researchers?
3. How likely is it that the framework will become a standard or widely recognized tool within the field of MMLA?

So, before we wrap up, is there any additional comments, suggestion you would like to add

Thank you again your participation is really useful.

9.6 APPENDIX 6: Doctoral Students' Ethics Application Form

Institute of Education

UCL

Doctoral Student Ethics Application Form

Anyone conducting research under the auspices of the Institute of Education (staff, students or visitors) where the research involves human participants or the use of data collected from human participants, is required to gain ethical approval before starting. This includes preliminary and pilot studies. Please answer all relevant questions in simple terms that can be understood by a lay person and note that your form may be returned if incomplete.

Registering your study with the UCL Data Protection Officer as part of the UCL Research Ethics Review Process

If you are proposing to collect personal data i.e., data from which a living individual can be identified **you must be registered with the UCL Data Protection Office before you submit your ethics application for review**. To do this, email the complete ethics form to the UCL Data Protection Office. Once your registration number is received, add it to the form* and submit it to your supervisor for approval. If the Data Protection Office advises you to make changes to the way in which you propose to collect and store the data, this should be reflected in your ethics application form.

Please note that the completion of the UCL GDPR online training is mandatory for all PhD students.

Section 1 – Project details

a. Project title

The ethical implications of using Multimodal Learning Analytics: Significant concerns and potential ways to mitigate them

b.	Student name and ID number (e.g., ABC12345678)	HAIFA ABDULWAHAB S ALWAHABY (19152587)
c.	***UCL Data Protection Registration Number**	**Z6364106/2021/06/210**
	a. Date Issued: 27-06-2021	
d.	Supervisor/Personal Tutor	Dr. Mutlu Cukurova
e.	Department	IOE (Culture, Communication and Media)
f.	Course category (Tick one)	PhD ☒
		EdD ☐
		DEdPsy ☐

g. **If applicable**, state who the funder is and if funding has been confirmed.

h. Intended research start date 1-06-2021

i. Intended research end date 15-09-2025

j. Country fieldwork will be conducted in (**international participants - online**)

k. If research to be conducted abroad, please check the Foreign and Commonwealth Office (FCO) and submit a completed travel risk assessment form (see guidelines). If the FCO advice is against travel this will be required before ethical approval can be granted: *UCL travel advice webpage*

l. Has this project been considered by another (external) Research Ethics Committee?

Yes	☐	External Committee Name:	Enter text
		Date of Approval:	Enter text
No	☒	***go to Section 2***	

If yes:

- Submit a copy of the approval letter with this application.
- Proceed to Section 10 Attachments.

Note: Ensure that you check the guidelines carefully as research with some participants will require ethical approval from a different ethics committee such as the National Research Ethics Service (NRES) or Social Care Research Ethics Committee

(SCREC). In addition, if your research is based in another institution then you may be required to apply to their research ethics committee.

Section 2 - Research methods summary (tick all that apply)

☒ Interviews
☒ Focus Groups
☒ Questionnaires
☐ Action Research
☒ Observation
☐ Literature Review
☐ Controlled trial/other intervention study
☐ Use of personal records
☒ Systematic review **– if only method used go to Section 5**
☐ Secondary data analysis ***– if secondary analysis used go to Section 6***
☐ Advisory/consultation/collaborative groups
☐ Other, give details: Enter text

Please provide an overview of the project, focusing on your methodology. This should include some or all of the following: purpose of the research, aims, main research questions, research design, participants, sampling, data collection (including justifications for methods chosen and description of topics/questions to be asked), reporting and dissemination. Please focus on your methodology; the theory, policy, or literary background of your work can be provided in an attached document (i.e., a full research proposal or case for support document). *Minimum 150 words required.*

Purpose and aim

The focus of this research study will be on exploring the ethical implications, requirements and considerations of using multimodal learning analytics in higher education mainly universities. Only a few studies have been carried out to date with regard to the ethical consideration of using multimodal learning analytics in physical spaces in the context of adult learners and higher education. Based on a systematic review conducted by Alwahaby et al. (2021) focused on the MMLA literature published between 2010 and 2020, only 13 papers were identified to briefly discuss ethical considerations including privacy, consent of participants, data management issues, and ethical clearance from their home institute. However, none of the papers covered in this review specifically addressed the ethical issues or addressed the concerns raised, nor did any of the papers suggest systematic methods of mitigating potential unintended consequences. Instead, they appeared to briefly indicate their possible concerns, the need for ethics, and the fact that future research should be concentrated on the ethical implications of MMLA. This research, therefore, sets out to examine the challenges of practitioners of MMLA with regards to ethics and potential ways of mitigating them by drawing up an ethical MMLA framework as well as providing practical implementation of this framework which would potentially lead to a certain extent the mitigation of the unethical use of MMLA.

Main research questions:

1- What are the current ethical issues of educators and researchers related to the use of MMLA in higher education?

2- What are the potential ways of mitigating negative consequences of MMLA use in higher education?

Research design

It is important to set a specific goal in order to identify the most efficient data gathering methods (Preece et al., 2015). In this study the main goal is to explore the ethical issues related to the use of MMLA. For this research, a mixed method approach will be adopted, in order to gather relevant data, integrating observation, interview and online surveys.

Pre-research observation

The observation process can be defined as the fastest process to obtain direct information from an audience. Observation can be classified into four types: counting, tracking movement, basic observation, and detailed observation. Although the previous types of observation will be useful for collecting observational data, the most convenient observation form for this study will be basic observation to gather in-depth data about the ethical issues related to the use of MMLA which serve the purpose of this study. The observation process will take place while MMLA have been used to investigate to what extent MMLA have been used ethically and how to tackle any ethical issues. Observation will be conducted by taking written and audio notes.

Semi-structured open-ended interviews

Interviews will be conducted either online or in person with at least 30 participants. Interview questions will be simi-structed open-ended to give the participants the ability to express their views and ideas. Questions will be formed to give answers to certain research questions. Furthermore, the interviews will address the participant perceptions with regard to ethical issues of MMLA. The interviews will be conducted online. The structure of the interview will start first by providing a short introduction about the aim of the study and asking Interviewees to declare their affiliation and title, after that the Interviewees will be asked about their opinion and views regarding the ethical issues related to MMLA particularly, fairness, accountability and transparency, and whether they have discussed any of these issues as practitioners before. Interview conversation will be audio or video recorded.

Survey

Online surveys will be conducted with a broader sample of 150 participants to act as quantitative supplement to the interviews. Survey questions will be structured based on the interview findings. The survey will be emailed to direct contacts related to the field of MMLA and will encourage them to pass the survey to other potential participants, additionally the survey will be promoted on social media and online community (e.g., Knowledge Lab, IOE, Kaggle). Qualtrics will be used to conduct the online survey.

Participants

A list of potential participants will be prepared in advance including, researchers, educators, and technology developers.

Data analysis

The qualitative data will comprise notes and transcripts. Thematic analysis will be adopted for the interview data. Data will be transformed into transcripts in order to analyse them using NVIVO. The analysis process will aim to identify a patterns or themes related to the ethical considerations of MMLA. The interview transcripts will be coded by marking the data segments with symbols or words.

Section 3 – research Participants (tick all that apply)

☐ Early years/pre-school
☐ Ages 5-11
☒ Ages 12-16
☐ Young people aged 17-18
☒ Adults please specify below
☐ Unknown – specify below

☐ No participants

Researchers, educators, and technology developers

Note: Ensure that you check the guidelines carefully as research with some participants will require ethical approval from a different ethics committee such as the National Research Ethics Service (NRES) or Social Care Research Ethics Committee (SCREC).

Section 4 - Security-sensitive material (only complete if applicable)

Security sensitive research includes commissioned by the military; commissioned under an EU security call; involves the acquisition of security clearances; concerns terrorist or extreme groups.

a. Will your project consider or encounter security-sensitive material?
   Yes* ☐ No ☒
b. Will you be visiting websites associated with extreme or terrorist organisations?
   Yes* ☐ No ☒
c. Will you be storing or transmitting any materials that could be interpreted as promoting or endorsing terrorist acts?
   Yes* ☐ No ☒

* *Give further details in* ***Section 8 Ethical Issues***

Section 5 – Systematic reviews of research (only complete if applicable)

a. Will you be collecting any new data from participants?
   Yes* ☐ No ☒
b. Will you be analysing any secondary data?
   Yes* ☐ No ☒

* *Give further details in* ***Section 8 Ethical Issues***

If your methods do not involve engagement with participants (e.g., systematic review, literature review) ***and*** *if you have answered* ***No*** *to both questions, please go to* ***Section 8 Attachments.***

Section 6 - Secondary data analysis (only complete if applicable)

a. Name of dataset/s Enter text
b. Owner of dataset/s Enter text
c. Are the data in the public domain?
   Yes ☐ No ☐
   If no, *do you have the owner's permission/license?*
   Yes ☐ No* ☐
d. Are the data special category personal data (i.e., personal data revealing racial or ethnic origin, political opinions, religious or philosophical beliefs, or trade union membership, and the processing of genetic data, biometric data for the purpose of uniquely identifying a natural person, data concerning health or data concerning a natural person's sex life or sexual orientation)?

Yes* ☐ No ☐

e. Will you be conducting analysis within the remit it was originally collected for?
Yes ☐ No* ☐
f. **If no**, was consent gained from participants for subsequent/future analysis?
Yes ☐ No* ☐
g. **If no,** was data collected prior to ethics approval process?
Yes ☐ No* ☐

** Give further details in **Section 8 Ethical Issues***

*If secondary analysis is only method used **and** no answers with asterisks are ticked, go to **Section 9 Attachments.***

Section 7 – Data Storage and Security
Please ensure that you include all hard and electronic data when completing this section.

a. Data subjects - Who will the data be collected from?
researchers, educators, and technology developers

b. What data will be collected? Please provide details of the type of personal data to be collected
Video and audio of interview with participants

Is the data anonymised? Yes ☒ No* ☐
Do you plan to anonymise the data? Yes* ☒ No ☐
Do you plan to use individual level data? Yes* ☐ No ☒
Do you plan to pseudonymise the data?Yes* ☐ No ☒

** Give further details in **Section 8 Ethical Issues***

c. **Disclosure** – Who will the results of your project be disclosed to?

Results will be published in academic outputs and disseminated in non-academic media channels as appropriate always citing the academic outputs.

Disclosure – Will personal data be disclosed as part of your project?
Enter text NO

d. Data storage – Please provide details on how and where the data will be stored i.e., UCL network, encrypted USB stick**, encrypted laptop** etc. Data will be stored on an encrypted USB stick and encrypted laptop only accessible by the researcher and the supervisor.

*** Advanced Encryption Standard 256-bit encryption which has been made a security standard within the NHS*

e. **Data Safe Haven (Identifiable Data Handling Solution)** – Will the personal identifiable data collected and processed as part of this research be stored in the UCL Data Safe Haven (mainly used by SLMS divisions, institutes and departments)?
Yes ☒ No ☐

f. How long will the data and records be kept for and in what format?
5 years, anonymised audio and video recordings of participants.

Will personal data be processed or be sent outside the European Economic Area? (If yes, please confirm that there are adequate levels of protections in compliance with GDPR and state what these arrangements are)
No.

Will data be archived for use by other researchers? (If yes, please provide details.)

Yes, the collected data will be stored for a period of up to 60 months in data Safe Haven, and restricted access by other researchers will be allowed for further data analysis.

g. If personal data is used as part of your project, describe what measures you have in place to ensure that the data is only used for the research purpose e.g., pseudonymization and short retention period of data'.

Enter text

** Give further details in **Section 8 Ethical Issues***

Section 8 – Ethical Issues
Please state clearly the ethical issues which may arise in the course of this research and how will they be addressed.

All issues that may apply should be addressed. Some examples are given below, further information can be found in the guidelines. *Minimum 150 words required.*

- Methods
- Sampling
- Recruitment
- Gatekeepers
- Informed consent
- Potentially vulnerable participants
- Safeguarding/child protection
- Sensitive topics
- International research
- Risks to participants and/or researchers
- Confidentiality/Anonymity
- Disclosures/limits to confidentiality
- Data storage and security both during and after the research (including transfer, sharing, encryption, protection)
- Reporting
- Dissemination and use of findings

According to the General Data Protection Regulation (GDPR) participants' approval should be obtained in advance, therefore, consent sheet should be signed by the participants before the interview recorded ad survey collected as a legal basis for processing personal data. All the data will be saved anonymously and tagged with advanced assigned variables. Since my data is formed of three type of data: notes, audio and video, I will categorize my data according to date. This research is individually based. All the data will be saved in N drive, Back-up copies will be saved in external storage in save place. The data will be kept for 5 years after the end of the project for any further study. Interview and survey questions have been designed to target a wild group of participants ranged from low to high MMLA experience, therefore, questions have been combined with definition of unfamiliar terms with examples and explanations as needed. No sensitive topics have been included in the Interview and survey questions neither any questions that might harm the participants in any way. To put the participant in a comfortable position and make them feel welcomed during the interview, the interview will be simi structured and it would be presented in friendly and informal way. Even though results will be published in academic outputs and disseminated in non-academic media channels as appropriate always citing the academic outputs, participants will not be recognised. The research does not involve children or any vulnerable participants as they are mainly researchers, educators, and technology developers.

Please confirm that the processing of the data is not likely to cause substantial damage or distress to an individual

Yes ☒

Section 9 – Attachments. ***Please attach the following items to this form, or explain if not attached***

a. Information sheets, consent forms and other materials to be used to inform potential participants about the research (List attachments below)

   Yes ☒ No ☐

   Consent and information sheets for participants

b. Approval letter from external Research Ethics Committee Yes ☐
c. The proposal ('case for support') for the project Yes ☐
d. Full risk assessment Yes ☐

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Section 10 – Declaration
I confirm that to the best of my knowledge the information in this form is correct and that this is a full description of the ethical issues that may arise in the course of this project.

I have discussed the ethical issues relating to my research with my supervisor.
Yes ☒ No ☐

I have attended the appropriate ethics training provided by my course.
Yes ☒ No ☐

I confirm that to the best of my knowledge:

The above information is correct and that this is a full description of the ethics issues that may arise in the course of this project.

Name Haifa Alwahaby

Date 20-5-2021

Please submit your completed ethics forms to your supervisor for review.

Notes and references

Professional code of ethics
You should read and understand relevant ethics guidelines, for example:
British Psychological Society (2018) *Code of Ethics and Conduct*
Or
British Educational Research Association (2018) *Ethical Guidelines*
Or
British Sociological Association (2017) *Statement of Ethical Practice*
Please see the respective websites for these or later versions; direct links to the latest versions are available on the Institute of Education Research Ethics website.

Disclosure and Barring Service checks

If you are planning to carry out research in regulated Education environments such as Schools, or if your research will bring you into contact with children and young people (under the age of 18), you will need to have a Disclosure and Barring Service (DBS) CHECK, before you start. The DBS was previously known as the Criminal Records Bureau (CRB). If you do not already hold a current DBS check, and have not registered with the DBS update service, you will need to obtain one through at IOE.

Ensure that you apply for the DBS check in plenty of time as will take around 4 weeks, though can take longer depending on the circumstances.

Further references

The www.ethicsguidebook.ac.uk website is very useful for assisting you to think through the ethical issues arising from your project.

Institute of Education

Robson, Colin (2011). *Real world research: a resource for social scientists and practitioner researchers* (3rd edition). Oxford: Blackwell.
This text has a helpful section on ethical considerations.

Alderson, P. and Morrow, V. (2011) *The Ethics of Research with Children and Young People: A Practical Handbook.* London: Sage.
This text has useful suggestions if you are conducting research with children and young people.

Wiles, R. (2013) What are Qualitative Research Ethics? Bloomsbury.
A useful and short text covering areas including informed consent, approaches to research ethics including examples of ethical dilemmas.

Departmental use	
If a project raises particularly challenging ethics issues, or a more detailed review would be appropriate, the supervisor must refer the application to the Research Development Administrator via email so that it can be submitted to the IOE Research Ethics Committee for consideration. A departmental research ethics coordinator or representative can advise you, either to support your review process, or help decide whether an application should be referred to the REC. If unsure please refer to the guidelines explaining when to refer the ethics application to the IOE Research Ethics Committee, posted on the committee's website.	
Student name	HAIFA ABDULWAHAB S ALWAHABY
Student department	IOE (Culture, Communication and Media)
Course	(Culture, Communication and Media)
Project title	The ethical implications of using Multimodal Learning Analytics: Significant concerns and potential ways to mitigate them
Reviewer 1	
Supervisor/first reviewer name	Dr Mutlu Cukurova
Do you foresee any ethical difficulties with this research?	I do not foresee any ethical difficulties with this research.
Supervisor/first reviewer signature	[redacted]
Date	20.05.2021
Reviewer 2	
Second reviewer name	Pof. Rose Luckin
Do you foresee any ethical difficulties with this research?	I do not
Supervisor/second reviewer signature	[redacted]
Date	24 May, 2021
Decision on behalf of reviews	

Decision	Approved	☐
	Approved subject to the following additional measures	☐
	Not approved for the reasons given below	☐
	Referred to REC for review	☐
Points to be noted by other reviewers and in report to REC		
Comments from reviewers for the applicant		

Once it is approved by both reviewers, students should submit their ethics application form to the Centre for Doctoral Education team: IOE.CDE@ucl.ac.uk.