Review Article

Multimodal Learning Analytics (MMLA) In Education – A Game Changer for Educators

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Abstract

Multimodal Learning Analytics (Hereafter MMLA) has developed as a potential educational strategy, utilising several data modalities to get deeper insights into students' learning experiences. This article thoroughly examines MMLA techniques and their use in educational settings. MMLA provides a comprehensive knowledge of learners' behaviours, interactions, and cognitive processes by combining different data sources such as video, audio, gesture, and physiological data. The article opens with a quick introduction to learning analytics and its growing importance in learning environments. It goes over how to use multimodal data, including gaze, facial expressions, body language, and activity, to get insight into student engagement and collaboration patterns. Wearable gadgets and sensors enhance MMLA by collecting physiological data and providing insights into students' emotional moods, cognitive load, and physical involvement. Moreover, the article explores the use of Kinect sensors for body language tracking. The study findings concluded on the feasibility of using MMLA through a learning analytics model for higher education. Educators can receive meaningful insights from MMLA by leveraging its power to optimise teaching practises, develop personalised learning experiences, and identify students who may require more support. Integrating different data modalities enables educators and researchers to make better-informed decisions, paving the path for a more successful and learner-centred education system.

Keywords: Multimodal learning analytics, Learning analytics, multimodal data, Microsoft Kinect

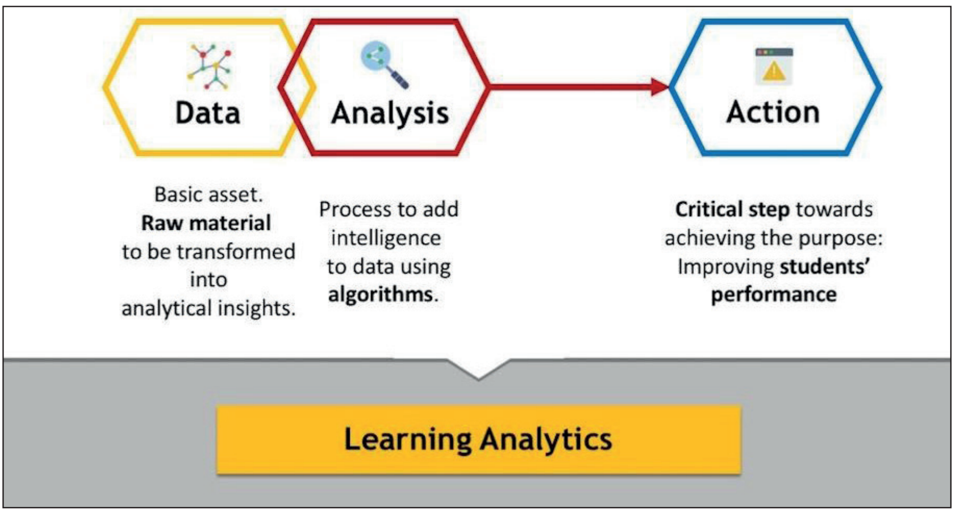
Introduction

Technology has significantly impacted the way learning is assessed in classrooms. Online tests, interactive whiteboards, and educational apps have replaced conventional teaching methods. This has made it possible for teachers to evaluate their students in an engaging and effective way. Technology integration has improved assessments by making them faster, more adaptive, and more personalised. Generally speaking, technology has transformed the assessment process, giving teachers more precise insights into student learning and assisting students in realising their full potential. Teachers can use the recently popular learning analytics tools to examine student data, identify learning gaps, and alter instruction.

Learning Analytics (Hereafter LA) refers to the measurement, collection, analysis, and reporting of data about learners and their learning contexts for understanding and optimizing learning and the environment in which it occurs (Siemens & Baker, 2012). In simpler terms, LA combines student data with intelligent analysis to improve student performance. Learning analytics seeks to comprehend and enhance learning (Ochoa & Worsley, 2016). Past learning analytics research has produced practical data-driven strategies that help educators understand and assess their efforts and innovations in designing learning activities (Lockyer & Dawson, 2012).

Most studies on learning analytics and educational data mining (EDA) have focused on cognitive tutors and online courses. These systems are highly structured and can only be used through interactions that take place on a computer (Perveen, 2018). Cognitive tutors are computer programs that offer personalized guidance to students based on their progress (Guo et al., 2021), while educational data mining refers to analysing educational data to understand learning patterns (Alvarez-Garcia et al., 2024; Sarker et al., 2024). Since many institutions of higher learning use LA, it has been regarded as an emerging field of study that merits more investigation (Guzmán-Valenzuela et al., 2021). Research studies have shown that online learners who frequently interacted with the learning analytics dashboard demonstrated greater academic performance (Kokoç & Kara, 2021). Learning Analytics can transform how we support learning processes, enhancing learning practises and leading to a deeper understanding of students' learning experiences (Viberg et al., 2018). Figure 1 shows the basic architecture of the learning analytics process.

Figure-1: Basic architecture of a Learning Analytics process (Corner, 2022).



Academic achievement, student engagement, and behavioural data are just a few of the data types that LA uses to pinpoint learning patterns, monitor student progress, and direct instructional decisions. By incorporating information from various sources, such as text, images, audio, and video, multimodal learning analytics broadens the possibility of this idea. Multimodal learning analytics (MMLA), as a new trend in learning analytics, leverages advances in multimodal data (e.g., speech, eye gaze, heart rate, and body movement data) to capture and mine learning processes and to address the challenges of investigating multiple, complex learning-relevant constructs in learning scenarios (Xu et al., 2023b). MMLA may be defined as a set of techniques employing multiple sources of data (video, logs, text, artefacts, audio, gestures, biosensors) to examine learning in realistic, ecologically valid, social, mixed-media learning environments (Mangaroska et al., 2020). The main goal of multimodal learning analytics (MMLA) is to combine these various sources of learning traces into a single analysis (Ochoa, 2017). MMLA is a subdomain that aims to integrate various learning traces into LA research and practice by emphasising understanding and optimising learning in digital and real-life circumstances where actions are not always facilitated over a computer or digital device. In MMLA, learning evidence is gathered from various sources, including log files, electronic documents, audio and video recordings, pen movements, position tracking apparatus, biosensors, and other modalities useful for analysing or measuring learning. A more complete picture of the learner's actions and internal state is presented by combining various modalities (Blikstein, 2013).

This paper discusses the theoretical aspects of Learning Analytics, its contributing factors, Multimodal Learning Analytics, and the modalities and their application in education.

Background

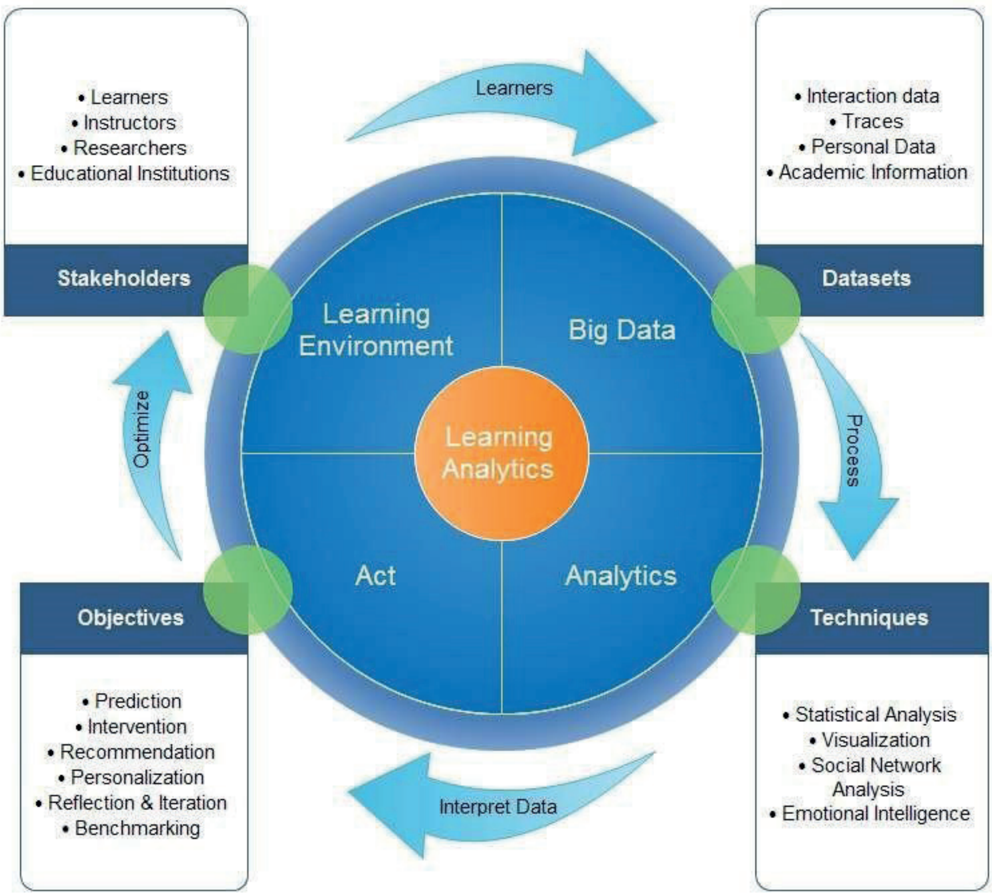
Learning Analytics (LA)

People have studied the teaching and learning processes for a very long time, kept track of pupil outcomes, looked over educational or professional data, made assessments, and used data to strengthen teaching and learning. Building on these well-established fields, learning analytics uses computational analysis methods from data science and artificial intelligence (AI) to take advantage of the fresh possibilities presented by the collection of new types of digital data from students' learning activities. 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 (What Is Learning Analytics? - Society for Learning Analytics Research (SoLAR), n.d.). This broad definition of learning analytics was developed at the inaugural global meeting on Learning Analytics and knowledge (LAK'11) of the Society for Learning Analytics and Research (SoLAR).

Learning analytics employs data analysis techniques to comprehend students' performance, engagement, and learning habits. Then, decisions are made with these insights in mind and educational practices are enhanced. The whole process is typically illustrated using Clow's (2013) learning analytic cycle: understanding learning and learners, collecting data, defining metrics, and deriving interventions aimed to optimizing the educational processes (Nistor & Hernández-Garcíac, 2018). Let's see how a traditional LA operate in a university context.

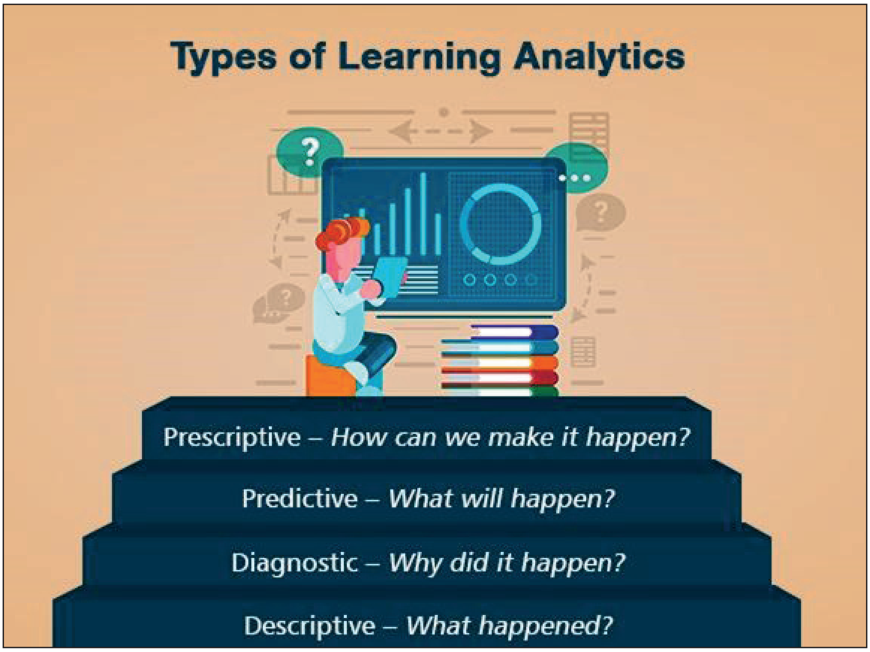
A university, for instance, wants to raise student retention rates and pinpoint the elements that influence student achievement. They implement learning analytics by gathering information from various sources, such as student grades, course attendance, online interactions, and library usage. The university learns from data analysis that students who regularly attend classes, participate in online discussions, and use library resources typically have better grades and higher retention rates. They also discover a link between lower overall student performance and courses with low student satisfaction ratings. The university makes several decisions in light of these revelations. They start by implementing targeted interventions, like sending tailored notifications to students who frequently miss class, giving struggling students extra support, and enticing students to participate in online discussions. These interventions are designed to boost student engagement, attendance, and learning outcomes. Second, the university reviews the teaching strategies and curriculum for the courses with low student satisfaction. To increase student engagement and satisfaction, they take feedback from the students into account, alter the course material, and add more interactive learning activities. The university can identify trends and patterns in student behaviour and performance using learning analytics. This enables them to take proactive measures, tailor the educational experience, and make decisions based on the best information available to increase student success and the calibre of education. A summary of the above example is illustrated in Figure 2.

Figure-2: Learning Analytics Cycle (Khalil, M; Ebner, 2015)



In order to understand the past, present, future, and potential outcomes, LA employs the methodologies of descriptive analytics, diagnostic analytics, predictive analytics, and prescriptive analytics (Figure 3).

Figure-3: Types of Learning Analytics (Athmika, 2019)



There are numerous benefits of having LA in education, like identifying target courses, curriculum improvement, determining student learning outcomes and keys for improvement, as well as personalised learning. The main issue with using LA is that it only processes traditional data like log files and click stream data, where the computer is a key component in the process. As learning is not exclusively a computer-mediated process, analysis of these unimodal data will not give a complete picture of the learning trajectory. However, this gap is filled by taking multiple data modalities into consideration. Thus, the infusion of different types of modalities in LA research gave rise to a new dimension called Multimodal Learning Analytics (MMLA). Before examining the specifics of what MMLA entails, let's take a broad look at multimodal data and the ways these are collected. In order to address the prospective growth of this emerging discipline, the following research questions were deeply studied to come up with certain valid conclusions in this area.

Research Questions

The thematic research on Learning Analytics tries to address the following research questions

1. What are the different factors contributing to developing the construct learning analytics theoretically?
2. How does learning analytics utilize the different modalities of data for predicting learner performance?

Method

This review adopts a systematic approach to identify and synthesize the theories that contribute to the development of learning analytics, focusing on how different modes of data collection can be leveraged to optimise learning outcomes. By systematically analysing the literature, this review highlights the theoretical underpinnings that have shaped learning analytics research, particularly in multimodal learning analytics (MMLA). The primary objective is to explore the contributing factors that help develop domain learning analytics. The paper then addresses the role of learning analytics in utilising the different modalities of data and how multimodal learning analytics applies to learning environments.

The review emphasizes theoretical contributions and frameworks from prior research to better understand the evolution of learning analytics as a field, particularly how data-driven insights have been applied to enhance personalized learning and improve educational outcomes.

Data Sources and Search Strategy

To ensure a comprehensive understanding of the theoretical aspects of learning analytics, a systematic search was conducted across two major academic databases: Scopus and Google Scholar. These databases were chosen due to their extensive multidisciplinary research coverage and relevance to educational technology and analytics studies. The search was limited to peer-reviewed journal articles and conference papers published between 2010 and 2022 to capture the field's most relevant advancements and theoretical developments during this period.

A broad range of keywords and search terms were employed to encompass various aspects of learning analytics, including the use of multimodal data. The key search terms used were: "Multimodal learning analytics", "K-12 classrooms", "Learning analytics tools", "Data collection methods in learning analytics", "Educational data mining", and "Theoretical models in learning analytics". These terms were combined using Boolean operators (AND, OR) to refine the search results and ensure coverage of different perspectives and approaches to learning analytics. For example, "multimodal learning analytics" AND "K-12 classrooms" was used to specifically target studies related to the K-12 educational context, while "learning analytics tools" OR "educational data mining" was used to broaden the scope of tools and methods used to collect and analyse student data. The search strategy ensured that both specific and general learning analytics models were captured to provide a holistic view of the theoretical landscape.

Inclusion and Exclusion Criteria

The inclusion and exclusion criteria were applied to filter relevant studies for the review. Studies were selected based on the following:

Inclusion Criteria

1. Studies focused on theoretical or conceptual development in learning analytics or multimodal learning analytics.
2. Peer-reviewed journal articles and conference papers published between 2010 and 2022.
3. Research that addressed the use of learning analytics in K-12 classrooms.
4. Articles that discussed various modes of data collection (e.g., gaze, body language, facial expression, etc.) and their application in optimizing learning outcomes.
5. Studies that included models, frameworks, or theories relevant to learning analytics or data integration.

Exclusion Criteria

1. Articles not directly addressing theoretical aspects of learning analytics.
2. Studies focusing exclusively on higher education or adult learning environments unrelated to K-12 settings.

3. Non-peer-reviewed sources, including reports, book chapters, or editorials.
4. Papers that did not provide substantial contributions to the development of theoretical constructs in learning analytics.

A systematic search was conducted across multiple academic databases, including Scopus and Google Scholar. The search was limited to journal articles and conference papers published between 2010 and 2022. Keywords and search terms such as "multimodal learning analytics, K-12 classrooms, learning analytics tools" were combined with Boolean operators (from the Scopus database) to capture a broad range of relevant studies.

Data Synthesis and Analysis

A narrative synthesis approach was adopted to integrate the findings of the selected studies. The focus was on identifying recurring theoretical themes, such as how learning analytics frameworks have evolved to incorporate multimodal data and how these developments have impacted learning outcomes. Studies were grouped based on the following themes:

1. Theoretical models of learning analytics.
2. The role of different data types (gaze, body language, facial expression) in enhancing learning outcomes.
3. Theoretical frameworks that support integrating learning analytics tools in K-12 classrooms.

Where applicable, the review highlights how including multimodal data has contributed to more personalized and adaptive learning experiences, particularly through continuously monitoring students' learning processes.

Development of Learning Analytics: Contributing Factors

Due to the growing accessibility of enormous databases of student learning data, LA can be extensively used to track and analyse student learning in greater detail and depth than ever before. Following the pandemic, there has also been a worldwide rise in interest in individualised learning. The emergence of novel educational technologies like Learning Management Systems (LMS) and Virtual Learning Environments (VLEs) have widened the avenues for data collection through Learning Analytics. Besides, the following are five distinctive areas depicted by the 'Learning Analytics in Higher Education Adoption Model' that have contributed to the theoretical framework of LA in higher education (Lester et al., 2017a).

1. Organizational Theory
2. Technology Alignment and Adoption
3. Faculty/Advisor Beliefs and Behaviours
4. Student Use and Action
5. Ethics and Privacy

Organizational Theory

Learning Analytics is a juncture where man and machines intersect, so a good structure in the organization is required. Even though LA can do wonders in the educational field, organizations do face some difficulties in adopting this latest technology. These hurdles include a lack of interest, time, money, training, incentives etc. (Lester et al., 2017). Organizational theory in the LA context suggests the significance of having good institutional preparation and an institutional commitment.

Technology Alignment and Adoption

The most popular technology adoption models that are relevant to LA are the Technology Adoption Model (TAM) (Venkatesh & Davis, 2000) and the Unified Theory of Acceptance and Use of Technology (UTAUT). According to the UTAUT (Venkatesh et al., 2003) theoretical model, behavioural intention influences how technology is actually used. The direct impact of four main constructs, including performance expectancy, effort expectancy, social influence, and facilitating conditions, determines the anticipated likelihood of adopting the technology. Age, gender, experience, and voluntariness of use all act as moderators of the influence of predictors (Lester et al., 2017b; Venkatesh et al., 2003). Though educational institutions strive to get higher ranks through improved academic outcomes for their students, they are less enthusiastic about imbibing this latest technology. The sooner the institutions align with LA, the better the outcomes.

Faculty/Advisor Beliefs and Behaviours

Today, LA allows teachers to effectively scaffold and support students' digital learning. For that, teachers must be highly proficient in digital technology and have mastered the communication, cooperation, creativity, and problem-solving abilities necessary for 21st-century learning to succeed. However, teachers need help understanding the linked digital pedagogical practises and subject-matter expertise and how the technological components might be utilised to promote learning (Sheffield et al., 2018). Therefore, education professionals' decisions to incorporate novel practises, like LA, into their pedagogical practises are heavily influenced by their professional beliefs and the behaviours that go along with them (Lester et al., 2017a).

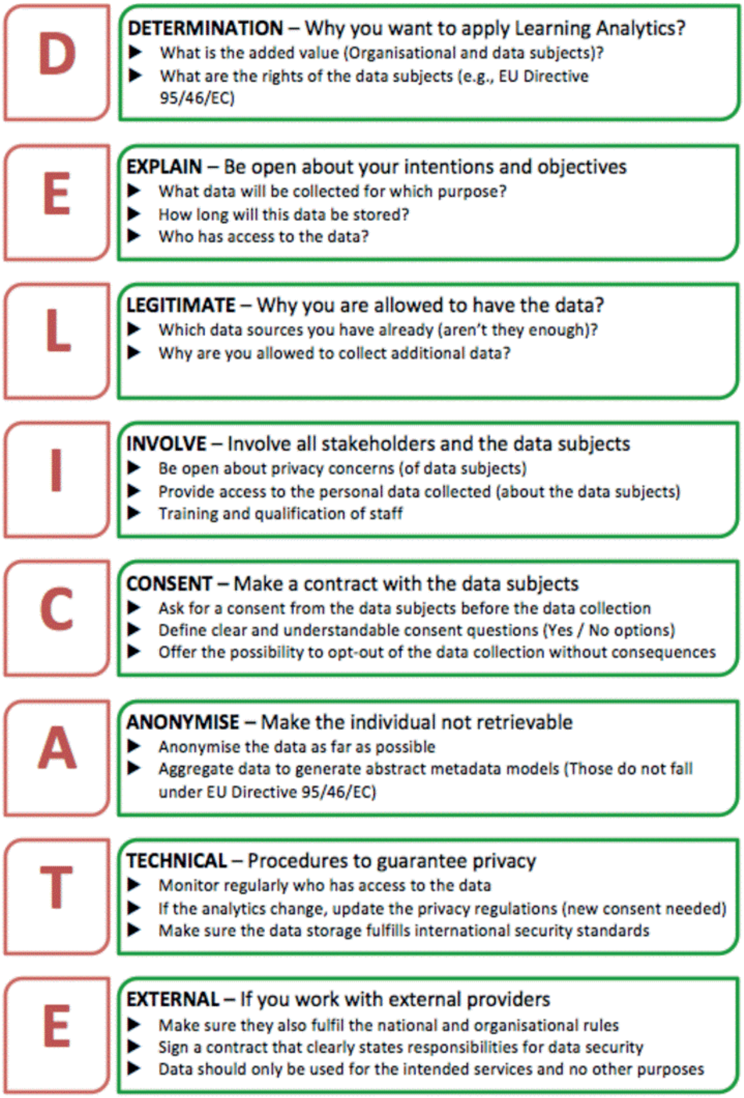
Student Use and Action

The major beneficiaries of any teaching-learning process are the learners. Though LA tools greatly help instructors, the major advantage is what they offer to students. LA provides learners with real-time feedback while interacting with a personalized learning dashboard (Arnold & Pistilli, 2012). This helps students understand their learning progress comprehensively (Lester et al., 2017b).

Ethics and Privacy

Following worries from governments, stakeholders, and civil rights organisations about privacy and the ethics involved in the handling of personal data, the widespread adoption of Learning Analytics (LA) and Educational Data Mining (EDM) has recently slowed down and, in some notable cases, even been reversed (Drachsler & Greller, 2016). The Learning Analytics Community Exchange (LACE) has developed an 8-item checklist named as DELICATE checklist that operationalizes essential ideas and inquiries for privacy and ethics in learning analytics (Ferguson et al., 2016). The DELICATE checklist assists in identifying potential barriers to the adoption of learning analytics and the implementation of reliable learning analytics for higher education (see Figure 4).

Figure-4: DELICATE checklist for Trusted Learning Analytics (Drachsler & Greller, 2016)



Multimodal Data

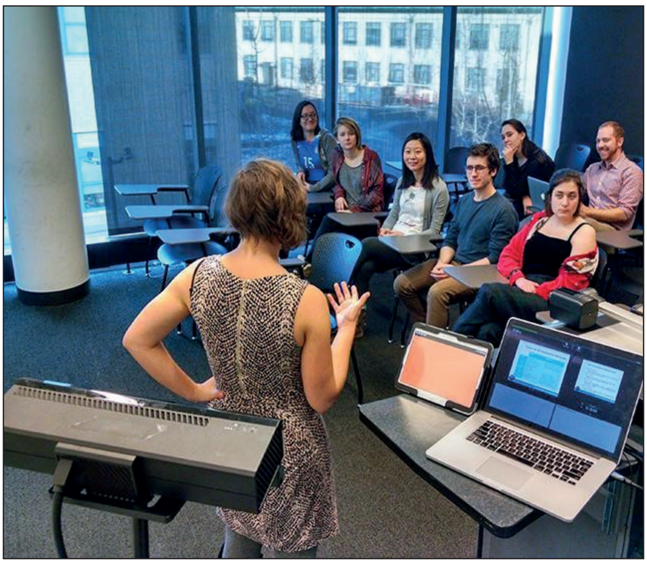
Traditional learning analytics typically use unidimensional data (Schwendimann et al., 2017), out of which most learning management systems utilising click stream data have their own limitations. Real learning is complex, so the learner's behaviour, cognition, and learning contexts are equally important. Digital data, physical data, physiological data, psychometric data, and environment data are the categories under which the data in MMLA fall (Mu et al., 2020). For instance, audio, video, electrodermal activity data, eye-tracking, user logs, and click-stream data are typical examples of such multimodal data (Blikstein & Worsley, 2016). Following are some of the different modes of data that are relevant for learning, though the list is incomplete.

Gaze

Gaze means to look at something steadily and intently, especially something that arouses curiosity and attention, which is a necessary component of learning. The attention level can be assessed using an eye tracker, just like a teacher assessing the students during a demonstration or a lecture. The main methods for recording gaze are monitor-mounted eye-trackers and special eye-tracking glasses, which are invasive and too expensive to be extensively used in educational settings. Past research used video recordings for gaze capturing in MMLA (Raca & Dillenbourg, 2013). They created a multi-camera system to record teacher actions and student reactions during class. A portable eye tracker worn by the instructor, a quantitative feedback form, and detailed conversations with students about how the lessons they took and their participation affected them were used to supplement the data. A camera, or a collection of cameras, was assigned to record the subject(s)' head and eyes. The gaze direction information is extracted from the video recording using computer vision techniques. Recently, online gaze recording software has made tasks much easier and more economical in terms of cost.

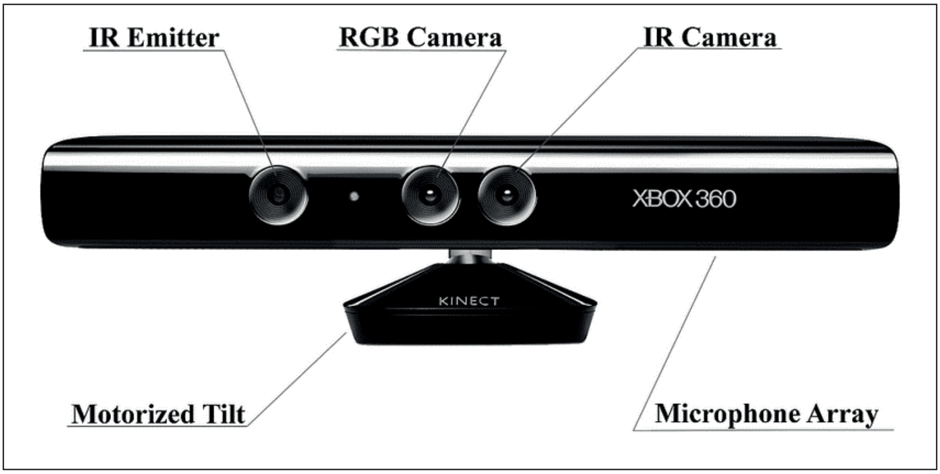
Body Language (Gesture, posture and body movements)

Figure-5: Tracking body language using a sensor



In an educational setting, body language is the non-verbal form of communication that involves gestures, posture, body movements, physical clues, etc., between a learner and the learning material, between the learners, and between the learner and the teacher. Figure 5 shows the tracking of students' body language in a classroom. Because of the reasonable ease of taking video in real-life surroundings, as well as the accessibility of affordable 2-D and 3-D sensors and efficient computer vision algorithms for feature mining, posture, gesticulations, and motion, have been the modes most frequently studied in MMLA (figure 2). The most common device used for automatic extraction of human motion is the Microsoft Kinect (Zhang, 2012). Through a mixture of video and depth capture, Kinect (figure 6) can provide researchers with a reconstructed skeleton of the subject for each captured frame, which is ideal for capturing body postures and gestures ("Handbook of Learning Analytics," 2017). Newer versions of the Kinect sensor can also extract hand gestures (Andres Vasquez et al., 2015).

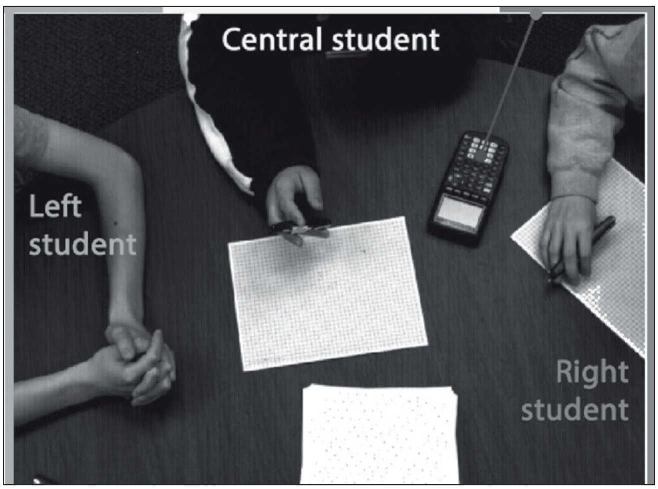
Figure-6: Microsoft Kinect device and its sensors



Action

The primary application of action footage and investigation in MMLA is expertise assessment. For example, the analysis of hand and wrist movement can determine the level of expertise in an engineering building activity (Blikstein, 2014). The percentage of time a learner uses a calculator when solving mathematical problems can be measured (Ochoa et al., 2013). In problem-solving sessions, (Ochoa et al., 2013) tracked the position and angle of the calculator (Figure 7). The student using the calculator at that specific frame in the video was then inferred from the position and angle of the calculator ("Handbook of Learning Analytics," 2017).

Figure-7: Determination of calculator use for expertise estimation (Ochoa et al., 2013)



Facial expression

Facial expressions are also a form of nonverbal communication that conveys a learner's immediate thoughts and emotions about a learning experience. In an educational environment, facial expression tracking is the process of capturing and analysing students' facial expressions during learning activities to acquire insights into their emotional states, engagement levels, and cognitive processes. In this context, facial expression tracking entails detecting and analysing student facial movements, muscle contractions, and expressions using technology such as cameras or specialised facial recognition software. These technologies can recognise a variety of facial expressions, such as happiness, sadness, surprise, rage, and others.

Multimodal Learning Analytics tries to identify how students respond to learning materials, interactions with classmates, or instructional tactics by tracking facial expressions. It can reveal important information regarding students' emotional engagement, degrees of interest or boredom, and potential sources of confusion or frustration. Data from facial expression monitoring can be integrated with other modalities, such as audio analysis, gaze tracking, or interaction patterns, to provide a more complete understanding of students' learning experiences. Tracking facial expressions using a video camera is the most economical way of doing it in a real classroom.

Multimodal Learning Analytics (MMLA) In Education

By its very nature, learning is frequently multimodal. Learning can be achieved through any form of interaction between people where considerably complicated data can be encoded, including studying a text, attending a lecture, observing an event via electronic or physical tools, and other modes of human interaction ("Handbook of Learning Analytics," 2017). A student gesticulating in agreement when a teacher asks if the lesson has been grasped or the instructor highlighting a point during an explanation are just two examples of feedback loops that are used in the learning process. Although they typically encode less complex information, these feedback modes are crucial to the process. Traces of interactions occurring in each relevant mode should be obtained if learning is to be analysed, understood, and optimised (Ochoa, 2017).

Multimodal learning analytics (MMLA), as a new trend in learning analytics, leverages advances in multimodal data (e.g., speech, eye gaze, heart rate, body movement data) to capture and mining learning processes and address the challenges of investigating multiple, complex learning-relevant constructs in learning scenarios (Xu et al., 2023a). MMLA may be defined as a set of techniques employing multiple sources of data (video, logs, text, artefacts, audio, gestures, gaze, biosensors) to examine learning in realistic, ecologically valid, social, mixed-media learning environments (Mangaroska et al., 2020; Ochoa, 2017). It emphasizes extracting these data from various modes of communication, irrespective of the medium on which they are encoded or recorded (Ochoa, 2017).

A promising method has been described as the combination of physiological information from the central nervous system (e.g., electroencephalography, or EEG) and external behaviours (e.g., eye movements) (Zheng et al., 2019). Recent research has demonstrated that combining multimodal data streams significantly improves accuracy and yields more user experience insights (Zheng et al., 2019). For context-aware environments, for instance, brain and eye movement signals convey significant information about users' social and emotional information (Lee & Anderson, 2017). So, one research challenge is to use data-driven insights and multimodal user data to design skills that back human learning. Whether an action is finished, the user creates rich information frequently overlooked when developing learning-supporting technologies (e.g., facial expression, eye movement, and brain activity). The term 'multimodality' might have been used since learners use various approaches to construct their knowledge.

Multimodal Learning Analytics can be used to realize how successfully learners practice the prospects aimed at learning. Multimodal data from wearables and online courses, on the one hand, enables more precise statements about the specific learning scenario, and, on the other, it increases students' personal perceptions of emotional states (Andrade et al., 2016), their perception of stress, and their sense of well-being or energy (Ciolacu & Svasta, 2021). This method offers educators more opportunities for individualised instruction and student support while enabling a more thorough understanding of student learning. Integrating learning analytics and multimodal learning analytics can revolutionise education by enabling teachers to make data-based decisions and improve student learning outcomes.

MMLA emphasises group projects, hands-on activities, and face-to-face interactions while downplaying the computer screen as the primary object of the interface. Though the role of computers cannot be completely removed, the advantage of having compact, innovative computational devices like wearables, microcomputers, etc., is that they may be easily integrated with any complex learning environment.

Results & Discussion

In this paper we have identified certain contributing factors for the theoretical development of Learning Analytics in higher education. They are Organizational Theory, Technology Alignment and Adoption, Faculty/ Advisor Beliefs and Behaviours, Student Use and action, Ethics and privacy. This is on par with what Lester et al. (2017a) have described as the main areas of LA in the higher education model. Apart from the aforesaid technical components, Ethics and Privacy should also be given due concern while dealing with student data. Drachsler & Greller (2016). The second research question was to analyse how learning analytics utilizes the different modalities of data for predicting learner performance. The use of multimodal data, including gaze, facial expressions, body language, and activity, can give insight into student engagement and collaboration patterns. Blikstein and Worsley (2016) list audio, video, electrodermal activity data, eye-tracking, user logs, and click-stream data as typical examples of multimodal data. Wearable gadgets and sensors enhance MMLA by collecting physiological data and providing insights into students' emotional moods, cognitive load, and physical involvement.

Conclusion

At present, Multimodal Learning Analytics is the most modern and potential form of Learning Analytics because it allows for the analysis of natural means of learning and interaction patterns during learning activities that are individual-based or group-based. It utilises all available sources for data (motion, conversation, gestures, writing, online logs, etc.) for enhanced comprehension of the learning process, offline or online. The introduction of sensors allows for the micro-level refinement of the physical data collected, like the angle of head movement and finger movement on the display. Educators and researchers can use this multimodal method to investigate the relationships between facial expressions and various learning outcomes, instructional tactics, or pedagogical interventions. It has the potential to assist educators in improved understanding of pupils' learning pathways as well as cognitive functioning, even in compound and open-ended educational settings. Multimodal Learning Analytics data can inform instructional decision-making, allowing educators to alter their teaching strategies, provide personalised feedback, or identify students needing further support. Meanwhile, when tracking various data in educational contexts, it is critical to keep ethical factors such as student privacy and informed consent in mind.

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