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Information Sources and their Potential for Multimodal Learning Analytics in Laboratory-based Learning

Abstract

Multimodal learning analytics offer opportunities to understand learning processes more precisely and to use these insights to improve or even individualize learning environments for everyone.

Educational lab environments are usually shared spaces: Learners come and go at regular intervals, engage with prescribed learning activities, and—hopefully—gain practical knowledge on the way to add real-world relevance to the theoretical knowledge they have obtained in traditional lecture halls. Digital means can help to transform those shared spaces into personal learning environments catering to individual needs in the learning process. This contribution aims to explore the potential of various enhancements to laboratories as data sources for these improvement cycles. It introduces several approaches and device categories and provides experiences and guidelines on real-world integration for the early integration of sustainable data collection and usage in lab-based research projects.

Keywords

Lab-based Learning, Learning Analytics, Data Sources

1 Introduction

The key to successful adaptiveness in learning experiences is a deep, thorough understanding of the underlying cognitive and social processes. Based on this fundamental knowledge, prototypes can be designed and tested, further hypotheses formulated and evaluated, and additional insights generated. The discipline dedicated to the generation of the required data and the investigation of it as well as its analysis and transfer into workable guidelines and recommendations is Learning Analytics. Since traditional Learning Analytics usually focuses on personal knowledge construction processes happening in similar traditional methods of operation and institutional settings, the field of Multi-Modal Learning Analytics (MMLA) evolved. MMLA strives for an even more complete understanding of learning by incorporating data from a broad range of additional data sources (Chejara, 2020 ; Kitto et al., 2015).

Worsley, 2018 provides an overview of the current state of research in this respect but does not yet address specific learning settings. Laboratory learning environments seem a natural fit for MMLA, as existing equipment might be facilitated as a data source for learning analytics and the environment usually offers a suitable infrastructure to add additional means of observation.

Still, a thorough reflection on possible data sources and their potential field of application in the research process of lab-based learning is mandatory, as are pre-planned strategies for sustainable data acquisition, storage, and processing.

2 MMLA in Lab Environments

Laboratory-based learning offers an ideal breeding ground to apply the set of MMLA tools to a holistic analysis of the educational processes happening there. The defined environment provides two major benefits over traditional learning in general:

First, the actual objects of interest themselves can be considered a reliable source of data if sufficiently integrated. Second, the laboratory environment, be it physical or virtual, can be augmented with sensors and other IoT capabilities to provide additional information to account for previously hidden variables in the learning process.

2.1 The domain-specific learning process

The former benefit, the "connected" subject of the students learning process, is of utmost relevance from a plethora of perspectives, as it provides insights into the usability of the tools employed, the didactical approach of teaching the matter, and the students' method of operation regarding a certain object of interest.

An example could be the comparison of various RFID chips within a measuring chamber. The learning process here includes the operation of the equipment, the handling of the chips, and the proper documentation of the measurement's results (Pfeiffer et al., 2020).

The actual behavior of the students within the lab can be employed to evaluate the student's understanding of the matter. The occurring interaction can be mapped to an idealized expected sequence of events. A matching pattern can indicate a deep understanding, proper preparation, or (in some cases) just a solid imitation of previously observed behavior—which might suffice depending on the context. Deviations from the intended sequence can be interpreted by a skilled tutor in multiple ways (Herding, 2013): Any differences can be either unintentional, indicating a lack of understanding and proper preparation, or intentional, which could be caused either by malice or scientific curiosity. While the differentiation of such nuances often requires classification by trained observation staff, the "human-in-the-loop" approach comes with three significant downsides:

a. It binds a serious share of resources, which could be deployed elsewhere in the learning process. Full observation processes, if done correctly, require at least one observer per participant. Furthermore, this work cannot be assigned to untrained auxiliaries. Often, several aspects must be regarded in parallel and documented accordingly, requiring both experience in scientific observation as well as deep knowledge of the experiment conducted to produce the necessary anticipated results.

b. Relying mainly on personnel in supervision and observation is prone to human error. I.e., in security-aware experimental contexts and lab environments, human intervention might prove too slow to avoid dangers to life, health, or expensive equipment.

c. Technical systems can be superior in terms of pattern detection and allow for downstream analysis.

Still, there might be edge cases where different strategies employed by the learner might lead to the intended result. But usually, when it comes to handling lab equipment, there is a set of prescribed rules and protocols to follow. So often, deviation from protocol is not intended, as it might invalidate the results even if the outcome is similar. A thorough approach to data collection still provides the means for post-factum discussion of such processes: MMLA is explicitly not intended as a replacement for (human) supervision but as a means of deeper inspection of the learning process.

2.2 Environmental conditions

Beyond the previously explained specifics of content-related process definition and supervision, the second benefit is often neglected, as it is much harder to achieve generalizable results from the laboratory in its entirety than to work out success factors in a specific setting. The controlled environment of laboratory learning may provide many insights that, if analyzed and reported, can have a sustainable impact on teaching and learning.

To provide examples for this category as well: Groups of students within a lab will communicate with each other, both verbally and non-verbally. Even a total lack of communication can be considered a special form of communication and thereby interpreted (Breazeal et al., 2005). Students have certain physiological reactions, i.e. to stress, which might be recorded via electrodermal activity, pulse, or close observation of eye movements (Fadeev et al., 2020 ; Moacdieh & Sarter, 2017). While many such factors might play a role, lab-based analytics offer better possibilities in this regard than other domains of application for MMLA such as mobile learning, where there are far more potentially undetected dependent variables like background noise (learning in a train) or significant temperature differences might, for example, impact concentration and thereby alter observed behavior. Thus, a controlled environment ensures, to some degree, comparability between subjects (Field & Hole, 2003).

As a content-related approach is usually highly domain-specific and requires conception and analysis by didactical researchers from the respective field, the remainder of this publication focuses on these more generic aspects: What data can be collected in most lab-based learning environments, what hardware and software requirements does this mandate, and what should be considered in terms of maintaining good scientific practice?

3 Possibilities & Potential of Lab-Based Learning

This contribution focuses on the overarching possibilities of multimodal learning analytics in lab-based learning: data sources for a holistic understanding of collaborative learning processes in controlled environments. Thus, different approaches are examined and analyzed.

3.1 Observing Group Behaviour

For example, learning in groups in such settings is, in contrast to purely online scenarios, not purely mediated by digital systems: Verbal communication as well as non-verbal communication play an important role and are hard to capture (Sturm et al., 2007), (Echeverria et al., 2019), (Martínez et al., 2011). The usage of microphone arrays empowers researchers to determine the individual shares in conversations on a purely technical level, which thereby delivers an important indicator of the productivity of the group.

Furthermore, the same data can be analyzed on a semantic level and provide information on role distribution, on-topic vs. off-topic discussions, and work attitudes. Such microphone arrays can be obtained relatively inexpensively and coupled with an open-source software stack like the ReSpeaker product line or as proprietary solutions by various vendors, all of which come with specific pros and cons, but can be fitted to nearly every lab environment.

The same is true for "visual data sources": A broad range of possible solutions cater to the needs of every potential use case. Even the most basic approach of placing a cheap webcam in a corner will open the option of later post-processing and qualitative analysis, i.e., of a sequence of interactions. Using action cams or other wide-angle equipment will enhance the level of information packed into a single data stream, but the real leap might come—depending on the use case—by obtaining additional depth information by using Kinect systems or Intel's RealSense devices.

Still, recent developments in machine learning have significantly improved the potential gain in this respect, even from different hardware solutions. Modern open-source software enables researchers to extract information like posture, body language, and group formations from recorded video streams (Schneider et al., 2021). Some approaches even raise expectations of reliable detection of facial expressions or stress levels from those recordings[1] (Hassan et al., 2021). Advancements in hardware promote the idea of even integrating those approaches into real-time feedback processes instead of only using them for post-processing.

3.2 The Individual in Focus

Those somehow generic data sources just scratch the surface of what multimodal learning analytics can deliver as a foundation for a deep understanding of educational endeavors (Worsley, 2018). Beyond that, a lot of media provide additional information beyond the obvious for the respective application. For example, VR headsets provide movement data of participants, which can enhance the research process in the emerging area of virtual and hybrid labs (Wiepke et al., 2021), touch surfaces deliver information on traces or concurrency, and additional sensors like electrodermal activity wristbands or heartbeat monitors let the researcher draw conclusions on stress levels and, thereby, introduced cognitive load, for example (Huang et al., 2021).

1 https://lit.gse.harvard.edu/ez-mmla-toolkit

The challenge of multimodal learning analytics is the farsighted extent to which data sources might be of value in the retrospective analysis of learning situations, the construction of a comprehensive understanding of the behavior observed, and the meaningful combination of those sources. Often, many single streams of data generate less valuable information than thought through combinations of two thoroughly selected sources. This contribution aims to guide researchers in the process of planning lab-based learning research: It sheds light on its potential, forewarns potential caveats, and advises on strategies for information collection, e.g., synchronization.

3.3 Contextual Factors

The data sources described so far merely help to record user behavior, i.e., human reactions to external stimuli. To fully understand learning and to optimize the process, it is essential to try to find and record as many of those stimuli as possible. Beyond the obvious impulses provided by experiments and accompanying instruction and documentation, there are a vast number of other impacts on human behavior. Not all of those can always be fully accounted for, like the proband skipping breakfast that day, but others are well within the control of the researcher. It is open to discussion if and which of those factors might contribute and be worth recording. But for some of them, it usually suffices to eliminate change as much as possible, so differences in behavior can be attributed to the intended variations in the setup, e.g., different instruction sets or tools, instead of a hidden variable such as a forgotten open window. Those environmental factors might include temperature or ambient light, and even the weather. While in most lab-based setups, it is possible to keep those constant, as regards others, like background noise and its effects on attention, it might be worth recording, if the opportunity arises. Furthermore, the research methods selected might mandate close monitoring of environmental factors, as variations in temperature for example might tamper with the results of EDA recordings.

There are more possibilities related to factors and corresponding sensors than can be accounted for in this contribution. As mentioned, usually it suffices to keep the factors constant, but if that is not possible, there are different ways to collect the data. They can either be sampled and recorded in fixed intervals of time, added as metadata to (interaction) events as they occur, or be monitored and recorded either in terms of change or when passing certain (pre-defined) thresholds.

4 Lab-based MMLA in practice

As presented before, there is a broad variety of potential data sources and a lot of reasons to record them. Still, just acquiring the respective sensors or logging all user interactions within the system is often not enough to enable a sense-making post-processing analysis.

4.1 Considering fundamental decisions

There are several intriguing, practical questions each researcher planning to employ MMLA within their laboratory learning processes should ask themselves to avoid trouble at later stages:

1. Do I need to synchronize the data streams to be able to draw any retrospective conclusions? If so, which resolution is required?
   For example, if eye tracking is involved, reactions to stimuli occur almost immediately, but often last only for a short period, calling for a resolution in a millisecond scale, while vocal interaction in a multilateral communication process can often be assessed when recorded to the second. Electrodermal activity is even slower, given that the body usually takes minutes to produce this reaction to elongated periods of cognitive stress.
   If synchronization is required, the question of how remains. Using individual, source-specific tools, a simultaneous, multimodal trigger event can mark a common timestamp, and orchestration tools can assist in a timed start of recording. Using a centralized instance like a learning record store omits the problem completely but requires thorough planning to incorporate all the data in a common format like xAPI.
2. Is there any benefit to making the data available in real-time?
   Providing real-time data is a challenge and usually requires a larger effort. Curiosity should not be the sole justification. But there are reasons: Building adaptive systems, monitoring expensive equipment, or coordinating remote collaboration are just some to mention. If the decision for real-time transmission is made, the circumstances usually dictate the follow-up questions: Where to stream the data, how, and using which media? Is a proprietary system the way to go or are open, extensible solutions available? Is data to be streamed just locally? If so, serial interfaces might be an option, otherwise, an internet connection is usually the way to go. Here, various follow-up questions arise beyond the boundaries of this paper, e.g. as discussed in Adineh et al., 2022. Which protocol fits best? Is acknowledged receival or low latency more important?

Didactically, whether the teacher aims for process assessment with the support of learning analytics or whether the students should learn in an ungraded space is also an interesting question.

3. Most of those questions can also be applied to the next aspect: Where, when, and how to record. A modern setup in a lab should not require the researcher to manually collect recorded data with a flash drive from individual machines after the participants have left. So, the data should be automatically transferred, but this can be done in time (synchronous or asynchronous) or be buffered and flushed in batches as the opportunity arises. Potential factors to be considered are resources (storage, memory, CPU) and bandwidth.
4. Finally, it should be considered early on which disciplines are involved. Traditionally, Learning Analytics unites multiple domains, such as computer science, pedagogy, and psychology among others. Thus, the data captured is of interest to all of them, even though some of them not as tech-savvy as the engineering disciplines. A valid precaution is that proper planning and prepared data processing strategies will save time and effort and prevent miscommunication between all the scientists involved. They encourage more autonomous and self-dependent execution of the experiments and enable long-term cooperation.

Fortunately, researchers interested in implementing multimodal learning analytics methods within their educational lab environment do not have to be concerned too much about starting from scratch, as there are previous works to build upon, to use to get accustomed to the topic and to kickstart their projects, as referenced in section 4.3.

4.2 Maintaining Good Scientific Practice

Data collection is usually a necessary evil for many practicing scientists, as it often feels like a dangerous balancing act. Privacy by design is a principle that demands being as scarce in data collection as possible, while researchers always dread the situation in which the analysis shows that the data collected is insufficient. To stay within the boundaries set by policies like GDPR as well as community conventions usually referred to as “Good Scientific Practice” , transparency is key and of utmost importance: Participants must be asked for their informed consent, with the researcher stating clearly what data is recorded and why. Furthermore, privacy by design also mandates the use of means of anonymization and pseudonymization as often as possible, admittedly a challenging task when it comes to learning analytics. Lastly, the Open Science community provides great tools and guidelines. Participating in Open Data might, in the long term, enhance the quality of research, published metadata will help to understand related work, and open-source tools make the research process accessible, transparent, and reproducible.

4.3 Open-Source Approaches

There are different approaches and tools for multimodal learning analytics in laboratory environments, and a thorough discussion would be beyond the scope of this contribution. There are two projects focusing on different stages of the process to be mentioned here as examples and vantage points for explorations of this area: First, there is the set of tools implemented by Ehlenz et al., 2017 and 2021, used in research projects concerning collaborative learning with interactive tabletop displays. While there has been no explicit publication on the tools, they are available open-source and focus mainly on the orchestration of multi-device setups in lab-based learning, including camera recordings and screen captures.

The efforts presented by Praharaj et al., 2018 aim at the data-receiving end of the research pipeline: The identification of possible data sources, the aggregation of said data, and approaches to holistic analysis are discussed in great detail.

Both projects are works in progress and might well be interfaced with each other at some point in the future.

5 Conclusion & Outlook

This paper provided a brief, structured introduction to the field of multimodal learning analytics and its application in the context of laboratory-based learning. As shown, there is great potential in this discipline to enhance learning across many scientific domains and in various areas of institutional learning. Some reviews already show the huge potential of learning analytics, e.g. (Worsley, 2018) and (Samuelsen et al., 2019). They show the most frequent modalities, but alone are not a solution to the task of integrating learning analytics into complex settings like lab-based learning.

By structuring and categorizing that potential and those fields of use, and by introducing a set of further considerations to be taken, experts from other disciplines are guided to a possible starting point to try and incorporate MMLA into their teaching strategy. Technical challenges in this respect are described by Shankar et al., 2018, Mu et al., 2020, and Adineh et al., 2022.

Furthermore, the first glimpse into scientific practice and existing open-source solutions can guide the way to both improving scientific processes as well as enhancing these works by leveraging future contributions.

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