Fostering Lab-Based Learning with Learning Analytics – A Literature Review

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Anke Pfeiffer(✉), Dieter Uckelmann
University of Applied Sciences Stuttgart, Stuttgart, Germany
anke.pfeiffer@hft-stuttgart.de

Abstract—Digital learning environments, such as online laboratories offer many opportunities for collecting data for Learning Analytics (LA). This article presents a systematic literature review for LA in laboratory based learning environments for Higher Engineering Education, which yielded 23 key references. The focus of the study was formed by the following research questions (RQ): What types of data are currently collected in online laboratories (RQ 1)? How is LA used to support learning and teaching processes as well as the design of the online-laboratory environment (RQ 2)? What design recommendations for the use of LA in laboratory-based learning environments can be derived (RQ 3)? The gained results show that LA can be used to provide feedback for simple as well as for complex learning processes in online laboratories. Moreover, it assists data-informed decision making for teaching and learning processes as well as for the design of the lab environment. Implications for future research projects were derived based on the findings and should contribute to the advancement of research on LA in online laboratories.

Keywords—higher engineering education, learning analytics, online laboratories

1 Introduction

Laboratory-based learning environments form a central pillar for engineering education, as it promotes the practical application of theoretical knowledge and thus supports the transfer of theory into practice in a particular way [1]. With the use of laboratory-based learning environments, the goal is pursued to enable students to handle practical equipment in a technically and methodologically targeted manner in order to apply their theoretical knowledge and to gain authentic, practice-relevant experience [2].

Laboratories in higher engineering education are traditionally complex learning and teaching environments allowing students to experiment, observe, and practice in an area of study, addressing and meeting current and future learning needs [3]. In addition to the real, physical hands-on laboratories, remotely operable and virtual laboratories have become increasingly established for teaching and learning purposes in the last fifteen years, which also include simulations and Augmented Reality (AR) [4–8].

AR applications have the possibility to expand real experiments with Virtual Reality (VR) objects and enrich the learning environment with supportive information about the experiment [9]. Laboratories at universities which enable students to conduct laboratory investigations with the help of web and information technology are referred to as online laboratories [10]. Online laboratories provide access to a laboratory experience and they can be defined as *"interactive experiments that are provided over the internet"* [11]. Maier et al. divide online labs into two main groups, firstly software simulations, which include for example virtual lab environments and secondly labs, that provide remotely access to real hardware equipment. Whilst the former are based on computer programs that imitate the functions and behavior of actual physical phenomena, the latter refers to online controlling of real experiments equipped with different elements such as: sensors, actuators and controllers adapted to be manipulated remotely and observed via cameras and monitors [12].

With the advent of online laboratories in Higher Engineering Education, the integration of LA becomes increasingly interesting for laboratory-based learning. Furthermore, online labs enable access to lab resources independent of location and time thus making them suitable for integration into lab networks such as Open Digital Lab 4You [13]. LA can provide useful information and guidance for the development of cross-institutional laboratory learning environments [14].

Moreover, it can be observed, that the digital change is currently having a strong dynamic effect on all areas of engineering, which is particularly evident in the increasing shift of value creation from the physical to the digital world based on information and communication technology in the context of Industry 4.0 and the Internet of Things [15, 16]. It can be assumed, that online laboratories and thus the recording of LA in engineering education will continue to gain importance, hence the use of LA in laboratory-based teaching and learning processes is evident, as extensive data on the learning process can be collected in these learning environments [17].

A number of studies have already proven, that LA is increasingly implemented in laboratory-based scenarios. For example, one of the first successful attempts of implementing LA in lab-based learning scenarios was conducted at the Technical University of Ilmenau (Germany), where they collected learning process data during the interaction of students with an online laboratory, which was coupled with an LMS-assessment tool, that provided automated feedback [18].

A study of Hawlitschek et al. 2019 introduces the collection of LA to analyze dropout factors in a remote laboratory, while Venant et al. focus on students' awareness of their learning performance to engage learners in deep learning processes [19, 20]. Networks such as Go-Lab and LabsLand have also been working for several years on the systematic integration with LA on their platforms [21, 22]. The growing number of studies focusing on this topic show that there is a high diversity in regards to which interactions are being considered or which concrete results were derived from LA.

The goals and the results of implementing LA in the studies, which were identified for the literature analysis vary widely, and in this regard, a detailed analysis is required to determine the added value that LA can have for laboratory-based learning. What is missing so far, is a survey of LA according to the type of online-laboratory (remote, virtual, simulation), that are used for engineering education. Therefore, a systematic literature analysis has been carried out in this paper with the following aims: Firstly, to give an overview of LA implemented in laboratory-based learning processes in the engineering education (type of lab, LA-methods, LA-tools, gathered data), secondly, to systematically record which educational intentions and goals are pursued by the respective study with the use of LA in a certain lab and thirdly to investigate whether and to what extent design criteria for implementing LA in laboratory based learning environments can be derived from the studies.

With this in mind, the paper pursues the following research questions (RQ).

RQ 1: What types of data are collected in the examined online laboratories for the use of LA?
RQ 2: How is LA specifically used to support learning- and teaching-processes as well as the design of the online-laboratory environment?
RQ 3: What design recommendations for the use of LA in laboratory-based learning environments can be derived from the literature?

The article is structured as follows: in chapter 2 the topic of learning analytics is introduced with reference to the potentials that LA could develop for lab-based learning processes and environments. The methodological approach and the research procedure is explained in details in chapter 3. Subsequently, the results of the literature review are presented in chapter 4, based on the theoretical considerations at the beginning. The article concludes with a discussion of the results and an outlook on future research perspectives in chapter 5 and 6.

2 LA in laboratory-based learning environments

Laboratories in engineering education are traditionally complex teaching and learning environments allowing students to experiment, observe, and practice in an area of study, addressing and meeting current and future learning needs [1, 3, 23]. In the course of digitization particularly, new technical possibilities are opening up for laboratories in engineering education [15, 24]. In this context, LA has been identified as an important trend in the educational context with potential for digitized learning environments [25]. It is to be expected that LA will be increasingly widely-used in higher education and thus in engineering sciences [26, 27].

LA is defined by the Society for Learning Analytics Research (SOLAR) as *"the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs"* [28]. LA can be used to dynamically generate data from learners, teachers and learning environments, with the aim of optimizing learning and teaching processes as well as the design of learning environments [29–31]. It contains the collection of educational data, such as static data, including learners demographics, background, perception, environmental characteristics and dynamic data, like student engagement, student performance and behavior [32]. The data collected can be useful in providing students with feedback on their learning process, helping teachers to make informed decisions and to adapt the design of learning environments as necessary [33].

Learning is increasingly taking place independently of time and space and is in higher education often mediated by digital tools, which enable the collection of data for LA [34]. Including for example *"data traces that learners leave behind"* while using an online learning environment [35]. These can deliver valuable insights into their learning activities especially in online laboratories, which can be collected, prepared and visualized to positively affect their future performance. Clow describes the Learning Analytics Cycle of turning data into informed action in four steps: Learners generate data during multifaceted learning processes (a), the data is captured, collected, and stored in a certain infrastructure (b), the collected data is analyzed (c) the data is visualized for the stakeholders, such as learners and teachers (d) [36].

When integrating LA into learning environments the demand is frequently emphasized – not without reason – that pedagogical considerations and intentions should guide the use of LA [31, 37]. But it is also important to analyze the interdependencies of factors that constitute learning under the conditions of implementing a technology like LA, because data-based analysis of learner activities can provide insights into the learning process formerly hidden from teachers and learners due to a lack of options. These options must be opened up, and occasionally they can go beyond the originally intended goals. The possibility of doing this should not be excluded by a too strict focusing on the originally targeted pedagogical intentions. Online labs seem particularly suited to this more exploratory approach, as they still offer much untapped potential.

Mainly, the collection of data for the use of LA in higher education is currently not considered appropriate for higher order research and communication skills [38]. Even though, the literature review will indicate, that there is definitely potential to foster the acquisition of sophisticated competencies. Furthermore, depending on the intentions and pedagogical objectives, which are aimed at with the use of LA for teaching and learning purposes, four types of data analytics can be distinguished, see Figure 1.

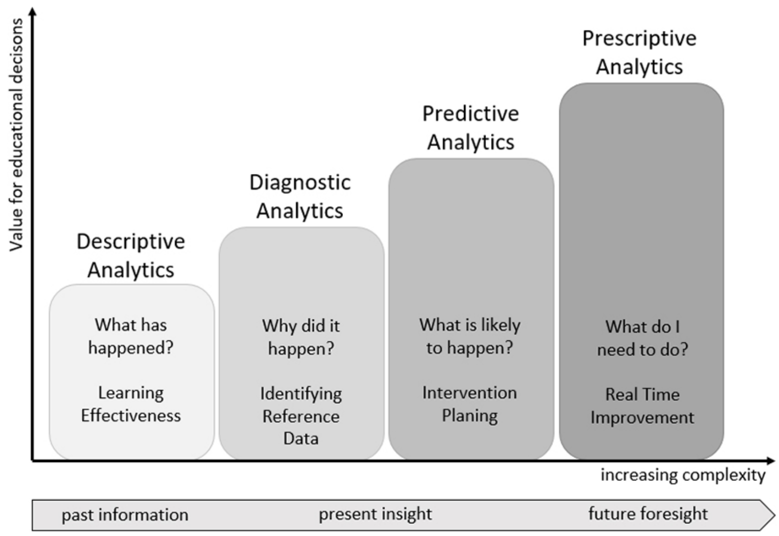

Fig. 1. Types of data collection for learning analytics (based on [39, 40])

Descriptive analytics uses data mining to provide insights into the past. It focuses on learning effectiveness with the goal of analyzing learning content use, extracting learning patterns, and visualizing interactions. Diagnostic analytics examines data or content to answer the question "Why" something happened. Compared to the other types of analysis, this is mostly done in the form of qualitative data analysis. Predictive analytics uses statistical models to detect insights into future developments. It covers intervention planning and includes the identification of students at risk, deviation from suggested learning paths or certain groupings of students. Prescriptive analytics uses optimization and simulation algorithms to advice on possible outcomes and it is directed to improvements in real time. This includes the recommendation of personalized learning paths, the identification of ideal learning strategies or the tracking of corrective processes as well as the enhancement of learning systems [40]. Current studies on LA can be assigned to these types of analyses and they will be applied for the literature review to cluster the use of LA in lab-based learning scenarios for the RQ 1 and 2.

The researched literature has also been analyzed specifically with regard to its use of LA according to the potential for the fields of application: supporting learning processes, teaching processes and/or the design of the learning environment. The fields of application of LA are to be considered specifically with regard to the data collected and the objectives of the respective study. The goal is to determine which laboratory-based data are currently being collected for which areas of application and what specific goal is being pursued with them.

3 Method

The methodological procedure of the systematic literature review will be outlined according to the approach of Döring et al. [41]. The literature review was conducted within the research Project Open Digital Lab 4 You (DigiLab4U), which is funded by the German Federal Ministry of Education and Research. It includes a comprehensible search strategy with in- and exclusion criteria to answer the research questions in the context of using LA in online laboratories in Higher Engineering Education. The period chosen for the study was 2011 till August 2021. The starting point is corresponding to the First Conference on Learning Analytics and Knowledge in 2011.

Table 1 shows the English search terms used for each topic. The search terms were also translated in German in order to be able to extend the search to German scientific contributions in this field accordingly.

Table 1. Search terms

Topic	Search Terms English
Lab-based learning	"Lab-based learning" OR "laboratory-based learning"
AND	
Online Laboratory	"online lab" OR "remote lab" OR "virtual lab" OR "hybrid lab"
AND	
Learning Analytics	"learning analytics"
AND	
Engineering Education	"engineering education" OR "Engineering studies" OR "Engineering study program" OR "Higher Engineering Education" OR "engineering sciences"

The following list shows the six data bases that were chosen and searched from July 2021 to August 2021:

- IEEE Xplore: This is a technical-oriented library and database with access to journals, articles, conference proceedings, technical standards and related materials.
- SpringerLink: The Springer online collection provides access to scientific, technological and educational journals and books.
- ResearchGate: This European social networking website provides access to a large database of scientific and peer-reviewed publications.
- The International Conference on Remote Engineering and Virtual Instrumentation (REV): The REV is of the main conferences with a focus on lab-based learning in Higher Engineering Education.
- Learning Analytics and Knowledge Conference (LAK): LAK is one of the main conferences on LA and covers a wide range of research questions and application areas.
- Google Scholar: Google Scholar is a freely accessible Internet search engine that indexes the full text or metadata of scientific literature in a variety of publication formats and disciplines.

Google Scholar was used for the metasearch. The articles found here were assigned to one of the other original databases subsequently, if they have not already been found via one of the scientific databases beforehand. The inclusion and exclusion criteria that were established for the literature review can be seen in Table 2.

Table 2. Inclusion and exclusion criteria for the literature review

Inclusion Criteria	Exclusion Criteria
• peer-reviewed and published journal articles • conference proceedings and book chapters • written in English or German language • reporting empirical research results of LA in labs • includes LA in online-laboratories in higher engineering education	• literature reviews • posters • not peer-reviewed articles • full text not available to authors

An initial search returned a total of 2040 hits. The large number of results showed that further adjustment of the search criteria was needed to match the desired target. A refinement of the boolean operators was made by adding "higher education" and a screening of the results based on the inclusion and exclusion search-criteria led to 256 results: "online-laboratory" OR "remote laboratory" OR "virtual laboratory" OR "laboratory-based learning" AND "engineering education" AND "learning analytics" AND "higher education".

For these results, a keyword search of the abstracts was performed, leading to 101 references. In a next step, the articles were checked in order to determine whether LA was specifically used in online labs in the context of engineering-oriented degree programs with corresponding results or whether LA was only mentioned once, for example to refer to future research projects. The latter led to the exclusion of the specific resource. In some cases, additional prove had to be done, as some search terms were not explicitly named, but could be determined via a context based follow-up search, for example "engineering education" was not mentioned, but from the name of the lab a clear engineering orientation could be concluded. In addition, duplicate references or references from an author or author team that addressed the same topic without significant new insights into the topic were removed. In these cases, the most recent contributions were adopted.

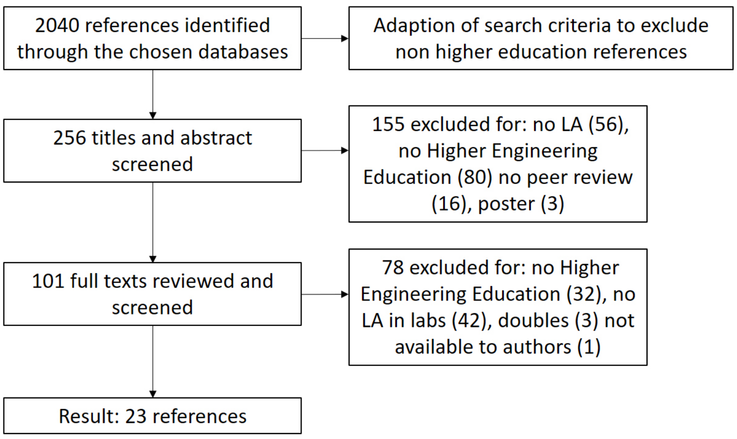

Fig. 2. Literature review flowchart

This procedure led to a result of 23 references (see Figure 2) and a detailed review of the references ultimately revealed 15 different authors (groups of authors) and lab initiatives specifically dealing with LA in online labs for Higher Engineering Education.

Table 3. Number of selected references from the investigated databases

Data Base	Number of Contributions
IEEE Xplore	10
LAK	1
Researchgate	6
REV	1
SpringerLink	5
Total	23

The majority of the studies are from 2018 (8 studies) and it seems surprising that no studies could be assigned in 2020, as an increase in publications can be expected for this topic due to the current developments (Table 3).

To answer the research questions a comprehensive coding system was developed and applied to extract the relevant data. It included the publication type, the source and repository, title, year, author, aim of the contribution and lab-type and technical implementation, gathered data, type of data analysis, as well as didactical aspects like learning objectives, field of application, applied didactical methods and results of the study. In the following section the results of the literature review are presented.

4 Results

4.1 RQ 1 on LA data collection in online laboratories

The first research question addressed the question what types of data are collected in the examined online laboratories for the use of LA. The studies show that currently data collection in laboratories is predominantly in the field of descriptive analytics and diagnostic analytics. 19 references of the 23 examined references could be assigned to these types of analytics. This is not surprising, since this form of data collection builds the basis for further analytics such as predictive and prescriptive analytics, which can already be observed in six references [42–47].

The first step was to determine what data can be collected in general for the use of LA in laboratory-based learning environments. It can be stated that all studies presently use two different data resources for the provision of LA: data from a Learning Management System (LMS) and Experiment Operation Data (EOD) from the laboratory. These data sources deliver a plethora of data for LA. Data from the LMS include data on the frequency of usage, duration, and use of the laboratory-based learning resources provided (e. g. downloaded, viewed), time spent on tasks, number of exercises completed, tests failed or passed, submitted files or interaction data (e. g. usage of forums, chats). The EOD can for example contain the number of experiments conducted, number of trials, number of errors, classification of errors, frequency of usage, time on experiment, submitted control commands, configuration information and interactions with the online-lab-environment (e. g. dialog boxes) etc. [48, 49]. Depending on the interest of the laboratory provider, other data may also be collected, such as user-identifier, laboratory-identifier, timestamps, IP address (location information), accessed labs etc. [22].

To store all the relevant data for LA, 35% of the studies use a Learning Record Store (LRS) for the data management. The LRS is a cloud-based service which provides storage for any relevant learning information and their retrieval. Studies, which use the LRS, also use Experience API (xAPI) for capturing data in a consistent format about learner activities from several technologies [50]. That makes xAPI especially interesting for hybrid learning scenarios such as remote lab-based learning environments, where learning system data (LMS and EOD data) needs to be analyzed. xAPI is an e-learning software specification that allows learning systems to communicate with each other in order to record and track the learning experiences [51]. It records learning activities as follows: the application sends secure statements in the form of "actor verb object" or "learner started experiment" to the LRS for storage. With this communication specification among the used applications all numerical and textual information captured in the LRS stay defined. The dashboard available in the LRS can format the data in various types of charts, visual and audible alerts and traffic lights, for example, to improve the monitoring of the learning process. For example, the reference [52] use the combination of xAPI and LRS to track the interactions of learners with the course materials and with their peers and teachers.

In addition to the data collection with LRS and xAPI, [44] implemented a WEKA tool (Waikato environment for knowledge analysis) which contains a collection of visualization tools and algorithms for data analytics and predictive modelling, together with graphical user interfaces which support easy access to these functions [46]. The tool provides statistics for teachers about the strengths and weaknesses of users and user-groups in an overview or for a certain lecture and in addition it provides feedback on the usage of learning resources.

Moreover, other analysis methods are in use by [45] with similar goals being pursued. They collect and analyze the data generated from the interactions of the students with a specific remote experimentation environment. Their system logs all acquiring requests and responses from the experiments and summarizes those results to deliver graphical or text based feedback about student's difficulties and deficiencies. To visualize LA data a certain dashboard is used, for teachers in order to support informed decisions and for leaners to raise their awareness and activate reflection of their learning activities and behavior by [53]. [42] et al. developed a dashboard called SurreyConnect to collect information with the aim to provide teachers and learners during a lab session with learning process data. Certain indicators deliver hints when to make an intervention with a learning activity and especially for teacher they provide insights into each individual student performance. For laboratory-based learning, this tool offers a special feature, it offers a "One-to-One mode", that enables remote controlled guidance, when students struggle with lab tasks [42]. Two similar dashboard versions, used in the studies by [54] and [53], enable students to monitor their laboratory progress and compare it with their fellow students.

The study of [55] takes another approach of data collection for LA. They collect specific data for a social network analysis to detect students' cooperation and collaboration while conducting lab experiments. A particular difficulty is that the authors focus on offline interactions of lab users since online interactions are not available. To determine offline interactions, the results of the laboratory experiment such as uploaded exercises are examined in more detail. This includes temporal relations, location information, basic user information, contextual information (e. g. accessed from a mobile device) and similarity of uploaded exercises to detect the social dynamics of the lab courses [55].

Table 4 provides an overview of the applied methods of data analysis and the associated didactical intentions that were connected with the respective laboratory. A more detailed view of the latter is provided in the next section on RQ 2.

Table 4. Overview data analysis and didactic intention

Reference	Type of Lab	Data Analytics Method				Didactical Intention
		Descriptive Analytics	**Diagnostic Analytics**	**Predictive Analytics**	**Prescriptive Analytics**	
[42]	VL			X		Predicting students' performance by monitoring and analyzing their actions in the VL
[49]	VL	X	X			Evaluating students' lab performance and usage (to collect data for automated feedback in the future)
[56]	VL	X	X			Using students' performance to support learning processes, provide instructors with timely information and help optimize the pedagogic design of the VL
[19]	RL		X	X		Identify the needs of users and detecting students at risk on the basis of behavior patterns
[57]	VL	X				Providing a dashboard for students and teachers in order to support exploratory analysis of the recorded data
[58]	RL	X				Detecting students action to identify behavior patterns for further research
[59]	RL	X				Collecting data to analyze the lab usage and students activities for adjusting the RL and learning resources
[60]	VL		X	X	X	Implementing a cockpit to visualize students actions and to trigger consequences if needed
[44]	RL	X	X			Testing the understanding and application of knowledge in a predefined lab setting
[12]	VL			X	X	Providing assessment data and real time feedback to all involved actors
Author teams						
[47, 48]	RL				X	Implementing an intelligent tutoring system to supplement personalized data-informed feedback
[45, 46, 61]	RL	X	X		X	Analyzing the students' data to deliver insights for the lab provider and provide suggestions for operating students
[62, 63]	MR Lab		X			Identifying successful lab usage and foster students awareness and reflection to self-regulate
[22, 55, 64, 65]	RL	X	X			Detecting students' actions and progress to improve the lab environment, redesign teaching processes, support self-assessment and apply SNA in lab networks
[20, 53]	RL	X	X	X		Supporting students' awareness and reflection to support data-informed decision-making

Notes: RL = Remote Lab; VL = Virtual Lab; MR = Mixed Reality Lab.

4.2 RQ 2 on LA usage in learning- and teaching processes

The second research matter will be concentrated on the question how LA is specifically used to support learning- and teaching-processes as well as the design of the online-laboratory environment. For learning processes in particular, the focus will be on laboratory-based competencies and objectives that can be supported with the help of LA. The presentation of the results for RQ2 is structured according to the purpose for which the LA data was gathered, whether they were collected specifically for learning processes, teaching processes, or for improving the learning environment.

LA in online labs – advantages for learning processes. LA helps to monitor the performance subsequently or while it is happening. Students can profit likewise from LA, because LA can support maximizing their academic performance and can enhance the overall experience of attending a study program in a university. It delivers them information on how they are progressing and what they need to do to meet their educational goals [66]. By receiving continual process-guided feedback, they can gain the ability to understand how they learn to make good use of this knowledge as they progress through their studies. Based on data about student's aptitude and performance, adaptive learning systems can be designed to help students develop skills and knowledge in a more personalized way [67]. Assessment and feedback supports (self-) assessment and reflection on the effectiveness of their own learning process and gained learning outcomes [68]. In addition, it can be stated that the potential of LA for students can be differentiated by learning process and learning outcome.

In accordance with these demands, most studies of the literature review aim to collect and evaluate students' data to increase the efficiency of the learning process in a broad sense. The types of learning processes, which should be supported with LA, vary depending on the study and laboratory experiment. Initially, it can be observed that most of the studies collect data in an exploratory manner to generate insights into what learning activities can be made visible in the first place, how students interact with the system and/or with their peers and/or to establish initial correlations where it is possible [59]. In this sense, the data is used for statistics analyzing student's patterns in the laboratory. For example, the study of [48] focusses on the question of how students use the system and what can be derived from it. The study illustrates how data are first collected during the laboratory experiment, how they are analyzed in terms of learning process patterns, and how conclusions are drawn about the learning process and finally which pedagogical consequences are derived.

Reference [52] aims to raise learner awareness for their learning activities such as using the course material and interaction with peers and teachers as well as skills and knowledge acquired. In the first place, it is also about recognizing and visualizing usage patterns to foster in-depth and hands-on educational experience.

Supporting learner awareness to foster self-regulated learning is the goal of implementing LA in the virtual lab in the reference [49]. The author introduces key performance indicators such as number of trials, time elapsed or number of different solutions and competitive indicators like quickest team, early bird or most efficient student team. The performance indicators of every team are public so that a team is aware of the progress of the remaining teams. According to [49] this leads to changes in the behavior and fosters the improvement of the team performance.

Students' self-exploration is supported in the simulation-lab of [56]. The authors collect LMS data and combine these with LRS data of the simulation experiment, including mouse and touch event, actions on viewed elements and actions on the simulation model itself in real time to visualize for students the current state of their simulation.

In two further studies, [47, 48] analysed the nature and scope of students' mistakes in a remote lab working with an oscilloscope. A data analysis identified several common errors. Building on these findings, they developed an intelligent Tutoring system (ITS). The system provides the students support when a certain error is detected. The error is marked in the system with a red flag and if the student is not able so solve the error with the help of the tutoring system, a human tutor can offer targeted assistance. In this way, the tutor model guides students while operating the remote lab from known mistakes to correct reasoning.

A similar purpose is pursued by [45, 61], they developed a recommender system for their remote experimentation, that supports the performance of the students and the reflection of occurred errors within the remote lab. Based on activity tracks of students they developed an ontology of errors as knowledge base to clearly typify the errors, that occur while using the remote lab. Their ontology provides an initial visualization of how errors can be made available for reflection.

Building on test and task data [44] developed quality indicators, which provide automatic feedback to the students and help them to adapt their lab results before sending them in for grading. For LA, both LMS data and student EOD are analyzed and processed appropriately for feedback processes. The LMS data is additionally subdivided into the following categories "acquisition of knowledge" and "usage of knowledge" and clustered according to Blooms Taxonomy.

Support reflection on their own learning process is the intention which [63] aims to achieve by using LA in their remote laboratory experiment. They found out, that visualizations showing the status of participants in a same class helped students to observe and reflect their personal progress and based on this feedback, they were able to adjust their laboratory procedures to attain their learning goals.

The review clarifies, learning objectives and competences associated with the use of LA in online labs enable a wide range of applications. A more detailed analysis of which competencies and objectives could specifically be addressed need to be examined in more detail in further studies.

LA in online labs – advantages for teaching processes. Teachers can benefit from LA in higher education in many ways. Monitoring and analyzing learners progress are among the main areas of application for LA. The collected data can be used for predicting and intervention concerning learning performance, dropout and retention [29]. By merging information known about individuals in advance, such as their prior qualifications, with data accumulated about their educational progress, learners likely to withdraw can be identified earlier than in the past [38]. Personalized interventions like weekly performance feedback can then be taken to retain students at risk [69]. In this way, LA can deliver very domain specific orientation by providing tutoring and mentoring [68].

The results of the literature review show, that the main interest for teachers using LA in laboratory-based learning environments is to gain insights into students' lab performance. In general, the value for teachers of implementing LA in online labs can be exemplary summarized as follows:

- support a better understanding of how students use the lab [59, 64]
- provide teachers with timely information about the current state of their lab performance [59]
- log and detect most common errors and difficulties [61, 70]
- deliver information for the improvement of online labs [45]

Since the integration of LA in laboratory-based learning environments is very specific, the possibilities to access LA data and to use them productively in the teaching-learning process vary.

To visualize the diverse data that can be generated in the online laboratories, seven studies present corresponding dashboards for teachers. These assist teachers to get an overview of the lab-usage done by students, provides access to individual students' performance and enable insights into common difficulties and errors [44, 47, 64]. The visualization, that are delivered in the dashboard can support teachers to identify students that need individual support, since errors and the places where they happen become visible and discussable [64]. The summarized data provides information that could help teachers to better understand the students' performance during remote experimentation activities and delivers real time feedback, clarifies where students are struggling and where they perform well [56].

LA data enable teachers to analyze the causes of deficiency in specific subjects, to correlate main errors with executed lab experiments and to guide them in actions of revision or pedagogical improvements in the theoretical and hands-on laboratory phases [61].

The implementation of LA in the VR-lab environment of Castillo makes also patterns of success and failure visible to teachers. Castillo describes usage data as "footprint" of how students solved the lab exercises and, in this sense, these data can provide valuable guidance for the learning experience support. Based on these findings, a virtual assistant is planned, that should guide and support student learning processes in a similar way as already mentioned in section 4.2.1 [49].

Reference [42] aim to provide teachers during a lab session with learning process data. They match learning outcomes of the virtual lab with learner records like interim and final results to detect meaningful trends and indicators of lab-based learning progress. The identified indicators such as attendance and working in groups deliver hints for possible pedagogical interventions. Building on these trends they developed a first version of an early warning systems to catch students at risk of failure.

The references show that LA data can offer a great potential for personal feedback between the actors involved in the learning process as well as for data driven decision making. Based on the collected data, pedagogical interventions can be derived and justified [52].

LA in online labs – advantages for the design of the learning environment. Moreover, LA can deliver information on the use and quality of the educational content and the provided activities and can thus support the improvement of the learning environment [71]. In this context, the use of LA enables the design of adaptive learning environments and learning processes accordingly. Personalized learning environments enable recommendations to support highly learner centric and self-directed learning as well as reflection on the effectiveness of the own learning process [68].

Collecting LA data in online labs can provide valuable insights for the design of online lab environments. Concerning this, LA data can provide insights into general usage and learning paths. Furthermore, they contribute to further developments of the laboratory because they visualize learner activities that are difficult or impossible to capture in hands-on lab exercises.

In general, some laboratories describe using the data to optimize the online laboratory environment. How and to what extent is often not specified [12, 54, 56].

To record cooperative and collaborative processes and to further evaluate them on their platform [55] conducted a Social Network Analysis (SNA). The SNA represents an analysis method that captures and analyses social relationships and social networks and these informations are used to further develop the online lab environment and platform. The authors team focus less on teaching and learning processes, but rather on the interactions between users in a networked learning environment, that monitors real data and creates a network topology based on this data. For example, basic usage information (user identifier course identifier, laboratory identifier) are matched with location and context information (IP address, time on task etc.), laboratory control commands submitted by students and their usage of the learning environment. Since the lab-platform does not allow interaction among students, the connection between students was created based on the submitted exercises and the comparison of these. It showed that some of them had identical content, the same file name and an identical timestamp of the complied files. SNA serves here more as a tool for instructors to gain insight into course dynamics of the learning communities that build around students and to detect those students, that take a more active part in these courses.

The developed ontology of [45] can also be used to enhance the lab environment and further develop the remote experiments. Frequently occurring errors can for example indicate a fault in the system and can thus be investigated specifically.

[64] follow a similar approach to detect errors, the data analysis displays for example when students produce frequently wrong circuits in the remote lab. This provides a reason to examine the laboratory environment to check if technical improvements or didactical assistance is required.

The remote lab environment builds the focus of the LA integration in the study of [19]. The author team was able to determine a correlation between the prior knowledge of students and the higher possibility of error streaks. A correlation between error streaks and extraneous cognitive load could not be statistically proven, but seems likely. Analysis of the data in the remote lab led the authors to the conclusion of incorporating more adaptivity to meet the different needs of their learners. In the course of their research they argued for adaptivity of online labs, in order to meet the different learning needs of students. Since students use online labs in a more self-directed way, an adaptive lab environment could accompany the laboratory experience.

4.3 RQ 3 on design recommendations for LA in lab-based learning

This section addresses the question what design recommendations for the use of LA in laboratory-based learning environments can be derived from the literature.

In many areas where LA has been integrated, the laboratory-based learning environments shows that individual implementations of LA need to consider domain knowledge, the intended purpose, visualizations for different lab requirements as well as user groups and their needs (e. g. student, teacher, online lab designer). Finding this balance will continue to be a challenge in the future. Table 5 shows examples of design recommendations for the implementation of LA in online laboratories. The recommendations were derived from the requirements and features that were mentioned in the selected studies.

Table 5. Design recommendations for LA in online labs

Requirements and Features	Design Recommendation
Dashboard for different user groups [56]	Presenting analyses in a way that is appropriate for the target group
Find suitable indicators for lab performance [42, 49]	Develop templates for different learning occasions and make them available for online labs
Collect, combine and analyse data from different sources relevant to the online lab experience [58]	Using LRS and xAPI or similar systems that enable data collection and analytics from different sources
Establish LA as feedback tool [59]	Develop didactical concepts to use the feedback productively for lab-based learning processes
Use LA to provide a recommender System for students [47]	Detect common errors and typical student behaviour in the laboratory to provide students with action guidance and reflection
Analyse the interaction of students with the online lab in detail [45]	Recommendations, educational guidance, and provision of analytics must be tailored to the specific laboratory
Performance of heterogeneous student groups should be considered when accessing online labs [19]	Take the development of adaptive processes in online labs into account to consider the needs of different target groups
Laboratory experiences include theoretical and practical knowledge [44]	Collect data from practical tasks and theoretical preparation and assessment to gain a holistic impression of the lab performance

The design recommendations listed in the table are specific to online labs, but there already exits a large number of helpful design recommendations for LA in higher education such as a list of expectations of students or General Data Protection Regulation (GDPR) guidelines that must be complied with [72, 73].

5 Discussion and implications

To legitimate the implementation of LA in laboratory-based learning processes, the effects and improvements of LA interventions on learning- /teaching processes and the learning environments must be clearly defined and empirically proven. The studies presented provide a solid basis for further research in this area and to generate more meaningful results for the use of LA in laboratory-based learning environments.

Systematically assessing laboratory-based learning environments in higher engineering education with LA poses quite a challenge for the collection of data. While LA focuses mainly on learning outcomes, this seems not always sufficient for more process-oriented experimentation and open-ended learning environments, which also encompasses laboratory-based learning [74]. Already 48% of the references show useful and supportive approaches to integrate and guide process orientation in the online labs. With Intelligent Tutoring Systems (ITS), recommender systems or access to a certain dashboard, students have the chance to reflect on their lab work or receive support during the lab exercise.

In the studies, it can be observed that data acquisition beyond LMS data and EOD is presently not common. Online laboratories and especially mixed reality (MR) laboratories, where physical and digital lab-equipment is combined, may provide additional data sources for LA such as video- and audio files or for example concerning VR-labs and AR-labs also position tracking devices, eye tracking and speeches that could be useful to understand or measure the learning process [9, 75, 76]. Those MR scenarios are currently not reflected in online laboratories, but they seem to offer a plethora of opportunities to foster lab-based learning processes. With the emerging technical possibilities in this area, e. g. video- and audio-data can become accessible and this will open up opportunities for Multimodal Learning Analytics (MLA). In MLA, the traces extracted from different data sources are combined to provide a more comprehensive view of the actions and the individual performance status of the learner. In addition, these upcoming possibilities can be useful for cross-university, co-located collaborations or lab networks, that include mixed reality scenarios and combine real and virtual reality in laboratory environments [9, 76, 77].

Data analysis in online labs is complex and seems to be getting more extensive as technical capabilities grow. In order to find the right answers to pedagogical questions, a good analysis is needed in advance. The study of Hawlitschek et al. shows how this can be achieved. Concrete areas were clearly operationalized by the authors against the background of learning theory assumptions in order to generate most concrete results [19].

In general, the handling of the presented data requires the competence of all actors to be able to interpret the data accordingly. Models of data interpretation cannot be transferred untested from one online laboratory to another. It is important to check, for example, whether the data collected, key indicators given and data analyses provided are equally suitable and meaningful for a new laboratory, or whether other framework conditions also require different analytics. For example, working in groups and time on task can lead to meaningful findings in one lab, while this is not the case in other labs, where the focus is more on individual work and offline tasks that cannot be captured in time. This seems obvious, but can happen quickly if systems offer standardized LA on online lab environments. To prevent this, Kim et al. recommend the approach of linking quantitative indicators with qualitative aspects of learning to generate meaningful findings [78]. The extent to which this is feasible for online labs will be an upcoming research task.

6 Conclusion and outlook

The literature review shows various pedagogical cases for which LA can be used. All of them focus on improving either the learning process, the teaching process or the learning environment. It makes sense to further empirically evaluate whether LA efforts indeed have done so, by measuring effects of LA interventions in online labs on these particular aspects directly. Therefore, future research in this field should include whether and to what extent the studies achieve the goals they intended with the implementation of LA, such as promoting self-directed learning or self-exploration.

The basis for the integration of LA in laboratories is descriptive analytics, since this will provide a solid database for further developments in the field of predictive and prescriptive analytics. Moreover, the connection of pedagogical concerns and the use of LA should be given a stronger attention in the further development of online labs in the field to prevent data misuse in the future.

In the initial phase of the literature review, some studies had to be excluded from the literature analysis due to the fact that a concrete LA integration had yet not taken place, although it was planned, or it was even just mentioned in the outlook. Against this background, it can be assumed that LA will become a permanent feature in online laboratories. Whether and to what extent LA templates for specific didactic scenarios can be expected remains open. A few labs present promising approaches for the successful didactic integration of LA, for example by incorporating a learning taxonomy, consistent alignment with educational theories and concrete learning goals to be achieved [19, 44, 49]. This could provide a basis for future research on LA templates for certain fields of application.

Furthermore, some research is still missing. LA is already being used to provide feedback, but in how far this feedback contributes to the improvement of personal learning processes or teaching processes or the design of a laboratory environments has not yet been conclusively clarified. The underlying didactical concepts often remain unclear. To look more closely at the possibilities of feedback means it is essential to incorporate the underlying pedagogical concepts more rigorously into the design of the online labs in order to be able to better illustrate possible effects. In addition, the next research step could be to determine which types of feedback can be supported for which learning processes in online laboratories effectively and at which points data-based feedback reaches its limits.

A key point that was given little or no consideration in the studies were ethical aspects and data protection. If LA becomes increasingly important in online laboratories, which is to be expected, this aspect must be given more attention in order to ensure data protection and privacy.

Data analytics can be further improved through the usage of Artificial Intelligence (AI). A current German funding initiative on "AI in Higher Education" with 54 funded projects starting from December 2021 will uncover AI-potentials in university education. Some of the results will also be transferable to improved LA for online lab scenarios [79].

In conclusion, the literature review revealed possibilities as well as future research opportunities for LA in online labs. Using the combination of these technologies in learning, teaching and design processes will contribute to improve the quality and effectiveness of online laboratories in higher engineering education.

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9 Authors

Anke Pfeiffer is head of the Service Centre for Learning & Teaching at the University of Applied Sciences Stuttgart, Schellingstraße 24, 70174 Stuttgart. She worked from 2018 until 2022 as a researcher for the project Open Digital Lab 4 You (DigiLab4U), where she supported the didactical implementation of hybrid learning environments in Higher Engineering Education.

Dieter Uckelmann studied Mechanical Engineering at TU Braunschweig and received his doctorate at the University of Bremen in the Faculty of Production Engineering. Between 2005 and 2012, he has established and managed the LogDynamics Lab at the University of Bremen. Since 2012, he is a professor for Information Logistics at University of Applied Sciences Stuttgart, Schellingstraße 24, 70174 Stuttgart. The focus of his research work is in the field of the Internet of Things, Industry 4.0, and Smart Buildings, the value of information, as well as on lab-based research and education. From 2018 to 2022, he coordinated the project DigiLab4U. Furthermore, he is co-editor of the "International Journal of RF-Technologies: Research and Applications". Prior to his academic career, he has been working in different management positions for several IT companies.

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