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Implementing Learning Analytics-based Feedback in Online Laboratories—using the Example of a Remote Laboratory

Abstract

Laboratory-based learning in practical, lab-based learning environments forms a central pillar of engineering education, as it promotes the practical application of theoretical knowledge and thus supports theory–practice transfer in a particular way. Over the past 15 years, laboratories for use in teaching and research have undergone a rapid transformation. This transformation is primarily reflected in the numerical increase in labs accessible online, such as remote labs, virtual labs, labs supported with augmented reality, or a combination of the aforementioned, which are also known as hybrid, mixed reality, or cross-reality labs. This opens up a wide range of opportunities for data collection, which in turn enables a wide variety of Learning Analytics (LA) applications. The use of LA-based feedback in a remote laboratory-based learning environment will be illustrated using the RFID measurement chamber laboratory at Hochschule für Technik Stuttgart (HFT).

Key Words

Learning Analytics, Laboratory-based Learning, Engineering Education

1 Introduction

When we use online labs in Higher Engineering Education, a large amount of learning process data could be generated and opened up for LA and the resulting feedback processes. Using an LA-based method to support teachers in providing meaningful feedback in online lab environments to students is one of the goals being pursued as part of the DigiLab4U project and the ways to do this are illustrated by the remote laboratory RFID measuring chamber in this paper. In general, the core of the data collection in online laboratory learning environments includes usage data from the online laboratories themselves, i.e. the *experiment operation data (EOD)* such as time, duration, number of experiments or attempts, type of experiments, error reports, results data, process data, and in some cases motion data (VR, AR) (see, e.g., Schardosim Simao, Mellos Carlos, Saliah-Hassane, Da Silva, & Da Mota Alves, 2018, p. 88; Schwandt, Winzker, & Rhode, 2021, p. 121). Laboratory exercises are often accompanied by *learning management systems (LMS)*, which can also supply a wealth of data. The integration of usage data from the LMS provides LA data such as logs, duration, results of quizzes, downloads, reads, access, and usage of learning resources (videos, templates, scripts), activity data (discussions, forums) etc. (see, e.g., Tobarra et al., 2019, p. 2 ; Wuttke, Hamann, & Henke, 2015) In addition, depending on the laboratory and its desired learning outcome, there is also the possibility of using further data sources for LA. like video data on the respective laboratory usage, eye-tracking data or questionnaires (see, e.g., Gonçalves, Alves, Carlos, da Silva, & Alves, 2018a; Ehlenz et al., 2021 ; Heinemann et al., 2020; Heinemann et al., 2022). This promising mix of data and sources, both sensor-based and event-based, enables the use of LA, which generally describes "*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*" (Siemens & Long, 2011, p. 34). According to Duval, who describes LA as the collection of "*traces that learners leave behind*", the DigiLab4U project aims to locate those traces in online lab environments to improve learning and teaching processes (Duval, 2012). To address this concern, the following research questions (RQ) were explored in this contribution.

RQ 1: What ways do LA provide to support feedback in remote labs?

RQ 2: How and at which point in the teaching/learning process should LA be anchored in hybrid learning environments to support feedback processes using the example of the RFID measuring chamber?

In the first step, the purpose of this contribution is to introduce current theoretical insights into the integration of LA in remote labs and to identify what types of feedback are currently provided in remote labs. In the second step, a didactical concept of a remote laboratory-based learning environment is presented and analyzed, with the aim of defining starting points for the use of LA.

2 Supporting Feedback Processes in Online Labs with LA

Feedback is a highly use-oriented and complex communication process in higher education institutions and has been identified as one of the most important factors influencing a student's academic achievement (Hattie, 2015, p. 206). Hattie and Timperley were able to identify four dimensions of feedback commonly used in learning processes, which will serve as an orientation for the provision of LA-based feedback in online labs in this contribution. These dimensions include feedback on tasks, feedback in processes, feedback for self-regulation, and personal feedback (Hattie & Timperley, 2007, p. 90). According to Resch, feedback conducive to learning should be constructive, timely, and future-oriented (Resch, 2019, p. 100).

A classic perspective in higher education describes feedback as a way to provide information that is specific to a task or a learning process and bridges the gap between what has been understood so far and what needs to be understood and thereby helps to identify strengths and weaknesses (Ramaprasad, 1983, p. 4). Feedback in this sense aims to reduce the discrepancy between current understanding and performance on one hand and a learning intention or goal on the other (Hattie, 2015, p. 208). It is assumed that the pure information given via feedback is sufficient to change students' own performance actions and that students receive and understand feedback in the same way as the teacher intended (Boud & Molloy, 2013, p. 701).

In higher education processes, feedback is not a one-way form of communication that informs about a gap between a status quo and possible target states anymore; it is imperative to integrate feedback into dialogical processes to support self-help and self-regulated learning (Hattie, 2009). In contrast to assessment, feedback is intended to show observations, perceptions, and potential for improvement. Furthermore, feedback can address learning needs in a timely manner (Resch, 2019, p. 101). The goal is to use feedback in such a way that students gain confidence and motivation to continue learning. We need evidence that students were affected by the feedback, and it must become clear that they are developing their skills and competence in the desired direction. This means that the feedback loop has been closed only when perceivable effects become apparent (Boud & Molloy, 2013, p. 703). Necessary conditions for feedback are the availability of data providing a reference level for a particular determinant (e. g. learning objective), data on the actual level of achievement of a determinant, and a mechanism for comparing the two to obtain information about the gap between the two levels. There can be no feedback if any of the three (data as a reference level, data on an actual level, and a mechanism for comparison) is not available (Ramaprasad, 1983, p. 6). In order to integrate feedback into the learning process in a meaningful way, learning activities should build upon each other and pursue similar objectives as far as possible. Enough time between two tasks should be given for teachers to prepare the feedback and for students to receive it and to be able to align their own actions with it (Boud & Molloy, 2013, p. 703).

Boud and Molloy name three key features of a sustainable feedback model in higher education (Boud & Molloy, 2013, 706ff). The first one is *the learners and what they bring*. Instructors often experience that students do not take responsibility for their learning process. For this reason, students should experience themselves proactively as learners who can influence their learning process. Feedback in this sense requires active engagement and the feeling of being responsible for their knowledge. When students receive feedback, they have to engage in self-assessment to use this feedback for the improvement of their performance (Nicol, 2009, p. 339). It is essential for students to learn this evaluative capacity. The second one is *the curriculum and what it promotes*. The authors see feedback as a "*key curriculum space for communicating, for knowing, for judging, for acting*" and recommend implementing certain didactical elements to foster feedback, e.g. implementing calibration systems, that enable learners to check knowledge resources or installing learners as both feedback seekers and providers, so that they can practice giving and receiving feedback among other didactical elements (Boud & Molloy, 2013, p. 708). The third feature is *the learning milieu and what that affords*. This considers how the curriculum, with its learning objectives, assessments, and faculty expectations is ultimately implemented because this is reflected in the daily interactions students have with teachers, with their peers, and within the context, in which they operate. This involvement also plays a central role in feedback processes.

In summary, the classic understanding of feedback is more about bridging the gap between what has been understood so far and what needs to be understood in the future and identifying possible individual strengths and weaknesses. This form of feedback can be helpful for less complex tasks and especially for students whose behavior for self-directed learning is still less pronounced (Nicol & Macfarlane-Dick, 2006, p. 7). Feedback processes in Higher Education should not stop here but should increasingly support processes that allow students to self-assess and interpret their performance as well as actively request feedback if required.

What does this mean for the use of LA-based feedback in online labs? Online laboratory learning environments can provide a wide range of data that seems appropriate for sophisticated and data-based feedback processes. Nevertheless, implementing LA-based feedback in remote laboratories poses further challenges from both a technical and a didactical perspective. From a technical perspective, opening up a real laboratory to digital processes, such as remote control and data collection, requires considerable effort to integrate them into a digital infrastructure for learners' access (Adineh et al., 2022). From a didactical point of view, at least two requirements must be met: the activities of learners must be identified in the remote lab exercise for which feedback is to be provided and meaningful indicators must be identified, visualized, and presented (Pardo, Jovanovic, Dawson, Gašević, & Mirriahi, 2019, p. 129).

LA is already widely used for teaching and learning purposes in online labs in Higher Engineering Education. The following section addresses the first research question and provides insight into current scientific studies in which LA is already being used to support feedback processes.

2.1 Results RQ 1

This section focuses on RQ 1: What ways do LA provide to support feedback in remote labs? A look at the research literature shows that the combination of learning LA-based feedback in online labs is rather new and was first mentioned in professional articles in 2014 (see, e.g., Orduña, Almeida, Lopez-de-Ipina, & Garcia-Zubia, 2014; Tibola, Pereira, & Rockenbach Tarouco, 2014). At this point, the most striking results are presented in the following.

In general, it can be stated that some online labs already use LA to provide automated feedback. A typical use of feedback processes facilitated by LA in online laboratories can be seen in the study by Considine et al., in which the authors analyzed the nature and scope of students' mistakes in a remote lab, where they work with an oscilloscope (Considine et al., 2018). Data analysis of their remote lab usage identified a number of common errors, and building on these findings, Considine et al. developed an Intelligent Tutoring System (ITS). The system provides the students with real-time feedback on their mistakes and delivers support when a certain error is detected, i.e. the error is marked with a red flag and if the student is not able to resolve the error using the hints given by the tutoring system, they can contact a human tutor, who offers targeted assistance. This tutor also has insights into the individual results, and they are able to offer help if required (Considine, Nafalski, & Nedic, 2018, p. 2). In their laboratory, Goncalves et al. use a recommender system that provides similar functions for the provision of real-time feedback as the ITS (Gonçalves, Carlos, Alves, & da Silva, 2018b). Students receive automated feedback on errors that happen in the remote lab. Each error is mapped with a corresponding explanation, which is displayed to the students. With the help of LA-based feedback in the form of suggestions and recommendations, the aim is to generate valid recommendations to increase students' performance in their laboratory learning activities. In the remote lab of Wuttke et al., automatic feedback is also generated for students as soon as an error is detected by the system. Based on an error database, the most frequent errors were recorded in advance, analyzed, and matched with corresponding automated feedback (Wuttke et al., 2015). This includes feedback for exercises that were completed by the students in the learning management system (quizzes) as well as tasks that involved the remote lab environment (practical handling of the remote lab). In these studies, data analysis is focused on monitoring the logs, acquiring all requests, remote operations, and responses from the experiments. This data is used to build LA-based feedback such as summarizing and analyzing data and providing the results presented as information that may help both students to improve their performance as well as teachers to better understand their students' performance during remote experimentation activities.

In the virtual lab of Castillo, students work together in groups to program a virtual agent. Every two weeks, they receive LA data-based feedback, which includes key performance indicators such as number of attempts, time elapsed, absolute time elapsed, and number of different solutions generated. The feedback is openly accessible, and the students can compare their results with the anonymized feedback of their fellow students. According to Castillo, this information is primarily valuable for the teacher to guide the learning process. For the students, it can be observed that the feedback presented results in changes in team behavior and improvements in their performance (Castillo, 2016). To what extent and how this is expressed in concrete terms is not further explained in the study. Akhtar et al. primarily use feedback based on LA data to inform teachers about the lab performance of their students. They were able to identify two indicators that correlate with performance in the VR lab they researched: attendance and working in groups. Feedback on this can be retrieved from the instructors (Akhtar, Warburton, & Xu, 2017).

Venant et al. developed a dashboard for different complex feedback processes to enable students to reflect on their lab exercises in a mixed reality (MR) lab. Therefore, a dashboard integrated into the MR lab, first of all, provides a *social awareness tool* that reveals current and general levels of lab performance via progress bars and allows students to compare their own achievements to their peers. Secondly, the authors provide a *reflection-on-action tool* that delivers detailed insights into the lab tasks to make the students deeply analyze both their own completed work and the tasks achieved by their peers in greater detail. The third and last tool they implemented is a *reflection-in-action tool*, a live video player which makes it easy for students to observe what their peers are doing and how they are operating the lab (Vidal, Venant, & Broisin, 2017).

In addition to Venant's already very elaborate results of LA-based feedback, several online labs exist in which LA are used primarily to provide teachers with feedback on their students' online-lab usage, such as date, start, end of the experiment, number of uploads, measurement results, number of operations, and for lab initiatives especially IP addresses, country, or timestamp. The first step here is to collect the data and assess its suitability for further feedback processes. For teachers, this data can already provide interesting feedback about the use of the lab, common errors, and the studying behavior (e.g., cooperation, study regularity, etc.) of their students (see,e.g., García-Zubía et al., 2019 ; Schwandt et al., 2021).

What is missing are findings about whether and how students use the feedback provided for their learning process. Equally lacking is more complex feedback that corresponds to the needs of Higher Education processes, such as fostering processes that stimulate the learners' disposition to seek feedback and take responsibility for their own laboratory-based learning processes. Some approaches seem very promising in this regard; however, no research is yet available on students' reception and concrete usage concerning reflection tools (see, e.g., Vidal et al., 2017). What is not currently clear from the studies, with some exceptions, is the extent to which LA-based feedback is used as the basis for individual, pedagogical interventions or F2F conversations between teachers and students. Are these taken as an opportunity to contact the students involved or is this not feasible due to large study cohorts? Table 1 shows an overview of feedback processes in labs. The structure is oriented on Hattie's recommendation for feedback (Hattie, 2007) The diverse data collection in laboratories offers many opportunities for feedback processes. At this point, the question arises as to what extent more complex dialogical feedback processes can be stimulated with the help of LA in the future. This includes feedback for *self-regulation* and *personal feedback* processes, which are currently underrepresented in laboratory-based learning processes.

Table 1 Feedback in laboratory-based learning processes

Study	Feedback on tasks	Feedback on processes	Feedback for self-regulation	Personal feedback
Wuttke et al., 2015	x	x		
Castillo, 2016	x	x	x	
Akhtar, Warburton, & Xu, 2017	x			x
Vidal, Venant, Broisin, 2017	x	x	x	
Considine et al., 2018	x	x		x
Gonçalves, Carlos, Alves, & da Silva, 2018	x	x		

While learning scenarios mediated via technical systems are often easily outfitted with LA data collection capabilities, real-world F2F learning is more elusive. One way to bridge this gap is by recording learning activities on video and manually annotating them later, using tools such as the one presented by Heinemann et al. (2022). Another way to access hybrid lab environments lies in the use of multimodal learning analytics (MLA). The sources or modalities in MLA include data resources that are easily available, like log-file and learning data from lab environments and learning management systems, but also learning artifacts and natural human signals such as gestures, gaze, speech, or writing. As learning is always a multimodal activity, MLA aims to analyze, understand, and optimize learning by capturing traces of the interactions occurring in each of the relevant modes (Ochoa, 2017). In the future, this opens up the possibility of developing LA-based feedback processes likewise for traditionally non-digital learning scenarios.

3 Example of Implementing LA in an RFID Laboratory

In this chapter, we present the integration of LA as part of feedback using a concrete example. First, we will explain this and then show the first results of the work done so far.

3.1 The lab RFID measuring chamber setting

The RFID measuring chamber at HFT Stuttgart is a test environment for RFID UHF tags. RFID technology is a key technology in logistics, as it makes warehousing and the movement and trafficking of goods transparent. To learn the correct use of the RFID measuring chamber, students are given an industry-specific use case to learn the background knowledge, the practical use of the chamber, and the interpretation of the results. The students work together in small teams and should gain multifaceted experiences which help them to know, remember, and explain the technical use and handling of the measuring instruments and to apply, analyze, and evaluate selected RFID measurement values to optimize the use of RFID for a certain use case.

The laboratory exercise proceeds in different phases, and LA data collected in different phases and partly prototypical scenarios can be checked in terms of its relevance for feedback processes. This is illustrated by the developments for the example of the RFID measurement chamber laboratory exercise and the following table. In addition, the phases of the laboratory exercise in the summer semester of 2021 were examined with the aid of qualitative content analysis to determine which problems and difficulties were encountered particularly frequently.

Table 2 Analysis grid of the laboratory exercise

Lab phases	Lab exercises and activities	Social format	Most common problems	Data acquisition
Introduction	Pre-test	Single	lack of basic knowledge in physics	Test results
	Access to all learning resources via LMS	Single	Learning resources provided are not used,	Login data, access numbers, downloads, forum usage, time
	Preparation task: generating a hypothesis for their practical remote lab exercise	Group	Terminology is used incorrectly, Basic knowledge of laboratory measurements is not known	# of uploads, time with LMS tap inactive (# of unfocused) data about video usage, e.g. # of video starts

Lab phases	Lab exercises and activities	Social format	Most common problems	Data acquisition
Lab experiment	Preparing their remote lab exercise with a VR application of the RFID measuring chamber	Single	-	VR motion profiles; duration; # of performed measurements, non-verbal gestures, gaze, log data, like controller interactions
	Conducting a laboratory exercise with the remote laboratory	Group	Interpretation of measurement results is often incorrect: Graphs are interpreted incorrectly (terms, correlations), the correlation between RFID tag and substrate is not explained correctly, Difference between measurements cannot be explained;	EOD of the remote RFID measuring chamber, # of performed measurements, and video recordings, which will be annotated
Documentation and presentation	Creating a test report	Group	Errors that were already evident during the practical laboratory exercise are reproduced.	Uploads: time, # of uploads, scope
	Post-test	Single	Measurement results are not interpreted correctly (missing terminology, wrong correlations, lack of physical knowledge); partly incorrect terminology;	Test results

3.2 Results RQ 2

RQ 2 is dedicated to the question of how and at which point in the teaching/learning process LA should be anchored in hybrid learning environments to support feedback processes—using the example of the RFID measuring chamber.

The preliminary tests conducted to check the LA visualizations for the Introduction phase were mainly done so with educators. In order to generate testable LA results for this step, we added possible and artificial data in addition to the data accrued. The overall results of the discussions with the educators are in line with Herding (2013) and Martinez-Maldonado et al. (2020), for example, the indicators relating to requests, logins, and learning material access are relevant for educators in digital labs, which was also shown by Dyckhoff et al. (2012) for fully virtual learning environments. Fig.1 shows a visualization related to that content. Our test showed that educators ask for the ability to filter according to the previously achieved e-test score, which could help to get an overview of the current learning situation and the preparation of the students. The result, namely enabling teachers to give students feedback on their own learning situation, is considered to be valuable for the students by the educators questioned.

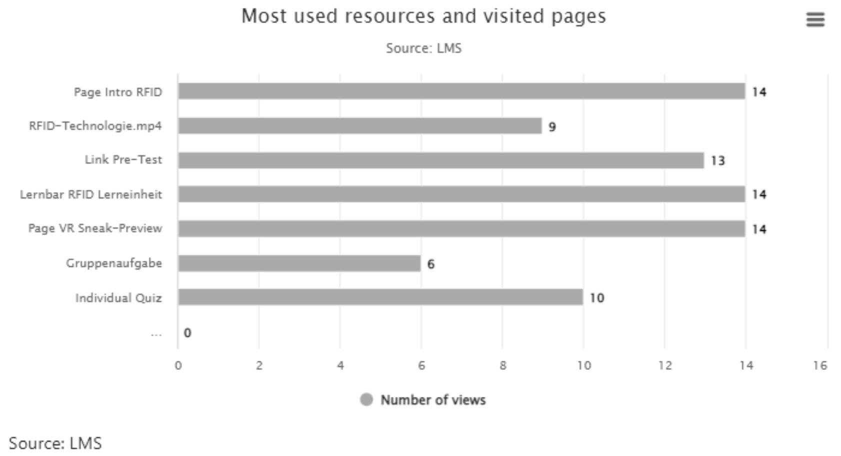

Figure 2 Most used resources and visited pages

The Lab experiment phases provide interesting data for a multimodal view of the learning process. The correct physical explanation of the measurement processes and the interpretation of the data (see Table 2) especially are central problems in the laboratory exercise, which can be reflected with the help of LA feedback. The remote measuring chamber and the VR version provide a wide range of possible indicators. The VR version is guided by a digital avatar that communicates verbally with the learners. To provide feedback about the quality of instructions to the educators, we implemented a data collector that can recognize gestures such as a nod of the head, as this can express understanding. If this data is linked to the learners' interactions, it is not only possible to analyze the learning process. We can also use this data in future versions to give immediate feedback to the learners and be more flexible in responding to prior knowledge. Let's stay with the example of the RFID measuring chamber. If a learner does not respond to an instruction from the robotic assistant, the system could recognize this and offer further assistance, e.g. highlighting the possible interaction spots. The opportunities of multimodal LA in the context of hybrid labs and the technical implementation of the architecture have already been described in Pfeiffer et al. (2020).

LA could be used in the documentation phase in different ways. Following the conceptual model of the tutor-in-the-loop approach, which is described in detail in the dissertation by Herding (2013), it is possible to use logs when students request feedback and to get insights into their course-wide performance. To obtain good support for feedback through LA in the final phase of multifaceted courses such as the HFT measurement chamber, other factors must be considered in addition to a user-centered approach. What prior knowledge do teachers and students have and what ways are there to use the various data streams for a helpful visualization of the course-wide learning process? To work on these questions in more depth, we will continue with a HCLA development process (see Shum et al., 2019).

To answer RQ 2, the evaluation results of the summer term 2021 can also provide first indications of where to anchor the LA-based feedback. For the preparation phase, the *quiz results*, the *time spent on task,* and the *downloads* are, for example, helpful for a first estimation and assessment of who has adequately prepared for the laboratory exercise and who might have knowledge gaps for the subsequent laboratory exercise. These results should be understood as preliminary, as the numbers of participants were too low (N = 37) to obtain meaningful results. Nevertheless, as far as the integration of LA-based feedback is concerned, the evaluation results can provide first indications of where the feedback should be anchored.

To conclude, there are different ways to integrate LA into the learning process and to support it with multimodal feedback. First, answers to the question of how to integrate LA into the feedback process are given, as is an analysis of the different times at which LA can be used.

4 Conclusion

The employment of LA-based feedback, as in many other LA fields, makes it clear that one size does not fit all. To provide LA-based feedback, it is necessary to adapt LA to laboratories and the objectives they pursue as precisely as possible. What is the intended learning outcome of the lab exercise? Where do students exhibit problems? What is the nature of these problems etc.? A detailed look into the implementation and use of LA in an increasing number of online labs makes this observable.

The process described in this paper shows the ways of generating LA-based feedback in a laboratory-based learning environment. The next step will be to exploit the potential of combining digital traces captured by technology mediation via LA in online labs with teacher knowledge and expertise to provide frequent and personalized feedback messages for the students using the remote lab. This will happen in the summer term 2022 when a further evaluation of using LA-based feedback in the remote lab will be conducted.

This research has some limitations: one is that the student cohorts undergoing the RFID laboratory exercise are relatively small for LA investigations and can only reveal developmental trends at this time, if at all. Nevertheless, providing access to the remote lab via a lab network is planned, so that higher numbers of participants can be expected in the future.

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References

Adineh, H., Galli, M., Heinemann, B., Höhner, N., Mezzogori, D., Ehlenz, M., & Uckelmann, D. (2022). Challenges and Solutions to Integrate Remote Laboratories in a Cross-University Network. In M. E. Auer, K. R. Bhimavaram, & X.-G. Yue (eds.), *Springer eBook Collection: vol. 298. Online Engineering and Society 4.0. Proceedings of the 18th International Conference on Remote Engineering and Virtual Instrumentation* (1st ed., pp. 189–202). Cham: Springer International Publishing; Imprint Springer.

Akhtar, S., Warburton, S., & Xu, W. (2017). The use of an online learning and teaching system for monitoring computer aided design student participation and predicting student success. *International Journal of Technology and Design Education, 27*(2), 251–270.

Boud, D., & Molloy, E. (2013). Rethinking models of feedback for learning: the challenge of design. *Assessment & Evaluation in Higher Education, 38*(6), 698–712.

Castillo, L. (2016). A virtual laboratory for multiagent systems: Joining efficacy, learning analytics and student satisfaction. In F. J. García-Peñalvo, A. J. Mendes, & I. S. o. C. in Education (eds.), *Learning analytics technologies. International Symposium on Computers in Education (SIIE): Salamanca, Castilla y León, Spain, September 13–16, 2016* (pp. 1–6). [Piscataway, NJ]: IEEE.

Considine, H., Nafalski, A., & Nedic, Z. (2018). Understanding Common Student Mistakes in the Remote Laboratory NetLab. In M. J. W. Lee (ed.), *Proceedings of 2018 IEEE International Conference on Teaching, Assessment, and Learning for Engineering (TALE). Date and venue, 4–7 December 2018, Novotel Wollongong Northbeach Hotel, Wollongong, NSW, Australia* (pp. 266–271). [Piscataway, New Jersey]: IEEE.

Duval, E. (2012). *Learning Analytics and Educational Data Mining.* Retrieved November 06, 2019, from https://erikduval.wordpress.com/2012/01/30/learning-analytics-and-educational-data-mining/.

Dyckhoff, A. L., Zielke, D., Bültmann, M., Chatti, M. A., & Schroeder, U. (2012). Design and Implementation of a Learning Analytics Toolkit for Teachers. *Educational technology & society*, *15*(3), 58–76.

Ehlenz, M., Heinemann, B., de Groot, R., Kühn, D., Nadenau, C., Quirl, D., & Schroeder, U. (2021). Through the eyes of cooperation at multi-touch tabletop displays. In M. Scheffel, N. Dowell, S. Joksimovic, & G. Siemens (eds.), *Companion Proceedings of the 11th International Conference on Learning Analytics & Knowledge LAK21*. Society for Learning Analytics Research (SoLAR).

Feisel, L. D., & Rosa, A. J. (2005). The Role of the Laboratory in Undergraduate Engineering Education. *Journal of engineering Education*, *94*, 121–130.

García-Zubía, J., Cuadros, J., Serrano, V., Hernández-Jayo, U., Angulo-Martínez, I., Villar, A., et al. (2019). Dashboard for the VISIR remote lab. In *5th Experiment International Conference (exp.at'19)* (pp. 42–46). IEEE.

Gonçalves, A. L., Alves, G. R., Carlos, L. M., da Silva, J. B., & Alves, J. B. d. M. (2018a). Remote Experimentation supported by Learning Analytics and Recommender Systems. In F. J. García-Peñalvo (ed.), *Proceedings — TEEM'18. 800th anniversary of the University of Salamanca* (pp. 313–319). New York, Salamanca: ACM — The Association for computing machinery; University of Salamanca; GRIAL — Research group in interaction and eLearning; IUCE — Research institute for educational sciences.

Gonçalves, A. L., Carlos, L. M., Alves, G. R., & da Silva, J. B. (2018b). Learning Analytics and Recommender Systems toward Remote Experimentation. In *Conference Learning Analytics Summer Institute Spain 2018* (pp. 1–12). Léon / Spain.

Hattie, J. (2015). *Lernen sichtbar machen* (3., erweiterte Auflage mit Index und Glossar). Baltmannsweiler: Schneider Verlag Hohengehren.

Hattie, J., & Timperley, H. (2007). The Power of Feedback. *Review of Educational Research, 77*(1), 81–112. Retrieved May 28, 2021, from http://www.columbia.edu/~mvp19/ETF/Feedback.pdf.

Hattie, J. A. C. (2009). *Visible learning: A synthesis of over 800 meta-analyses relating to achievement* (Reprinted.). London: Routledge.

Heinemann, B., Doveren, J., Usman, M., & Schroeder, U. (2022). Combining Learning Analytics in remote and virtual lab-based learning with real lab experiences with xAPI video annotation. In M. Scheffel, N. Dowell, S. Joksimovic, & G. Siemens (eds.), *Companion Proceedings of the 12th International Conference on Learning Analytics & Knowledge LAK22*. Society for Learning Analytics Research (SoLAR).

Heinemann, B., Ehlenz, M., & Schroeder, Prof. Dr. U. (2020). Eye-Tracking in Educational Multi-Touch Games: Design-Based (interaction) research and great visions. *ACM Symposium on Eye Tracking Research and Applications*, 1–5. https://doi.org/10.1145/3379156.3391838

Heradio, R., La Torre, L. de, & Dormido, S. (2016). Virtual and remote labs in control education: A survey. *Annual Reviews in Control, 42*, 1–10.

Herding, D. C. (2013). *The tutor in the loop model for formative assessment* [Dissertation, RWTH Aachen University]. http://publications.rwth-aachen.de/record/229512

Martinez-Maldonado, R., Echeverria, V., Fernandez Nieto, G., & Buckingham Shum, S. (2020). From Data to Insights: A Layered Storytelling Approach for Multimodal Learning Analytics. *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, 1–15. https://doi.org/10.1145/3313831.3376148

May, D. (2020). Cross Reality Spaces in Engineering Education – Online Laboratories for Supporting International Student Collaboration in Merging Realities. *International Journal of Online Engineering (iJOE), 16*(03), 4. Retrieved August 19, 2021, from https://www.learntechlib.org/p/218004/.

Nicol, D. (2009). Assessment for learner self-regulation: enhancing achievement in the first year using learning technologies. *Assessment & Evaluation in Higher Education, 34*(3), 335–352.

Nicol, D. J., & Macfarlane-Dick, D. (2006). Formative assessment and self-regulated learning: a model and seven principles of good feedback practice. *Studies in Higher Education, 31*(2), 199–218.

Ochoa, X. (2017). Multimodal Learning Analytics. In C. Lang, G. Siemens, A. Wise & D. Gasevic (eds.), Handbook of Learning Analytics (pp. 129–141). Society for Learning Analytics Research (SoLAR). https://doi.org/10.18608/hla17

Orduña, P., Almeida, A., Lopez-de-Ipina, D., & Garcia-Zubia, J. (2014). Learning Analytics on federated remote laboratories: Tips and techniques. In *IEEE Global Engineering Education Conference (EDUCON)* (pp. 299–305). IEEE.

Pardo, A., Jovanovic, J., Dawson, S., Gašević, D., & Mirriahi, N. (2019). Using learning analytics to scale the provision of personalised feedback. *British Journal of Educational Technology, 50*(1), 128–138.

Pfeiffer, A., Lukarov, V., Romagnoli, G., Uckelmann, D., & Schroeder, U. (2020). Experiential Learning in Labs and Multimodal Learning Analytics. In D. Ifenthaler & D. Gibson (eds.), *Adoption of Data Analytics in Higher Education Learning and Teaching* (pp. 349–373). Springer International Publishing. https://doi.org/10.1007/978-3-030-47392-1_18

Ramaprasad, A. (1983). On the definition of feedback. *Behavioral Science, 28*(1), 4–13.

Resch, K. (2019). Feedback in der Hochschule und der Schule – eine Begriffsbestimmung. *jlb (journal für lehrerInnenbildung)*. (01), 98–104.

Schardosim Simao, J. P., Mellos Carlos, L., Saliah-Hassane, H., Da Silva, J. B., & Da Mota Alves, J. B. (2018). Model for Recording Learning Experience Data from Remote Laboratories Using xAPI. In *2018 XIII Latin American Conference on Learning Technologies (LACLO)* (pp. 450–457). IEEE.

Schwandt, A., Winzker, M., & Rhode, M. (2021). Utilizing User Activity and System Response for Learning Analytics in a Remote Lab. In M. E. Auer & D. May (eds.), *Advances in Intelligent Systems and Computing. Cross Reality and Data Science in Engineering* (pp. 63–74). Cham: Springer International Publishing.

Siemens, G., & Long, P. (2011). Penetrating the Fog: Analytics in Learning Education. In P. Long (ed.), *Proceedings of the 1st International Conference on Learning Analytics and Knowledge* (pp. 31–40). New York, NY: ACM.

Shum, S. B., Ferguson, R., & Martinez-Maldonado, R. (2019). Human-Centred Learning Analytics. *Journal of Learning Analytics*, *6*(2), 1-9-1–9. https://doi.org/10.18608/jla.2019.62.1

Tekkaya, A. E., Wilkesmann, U., Terkowsky, C., Pleul, C., Radtke, M., & Maevus, F. (eds.) (2016). *acatech Studie. Das Labor in der ingenieurwissenschaftlichen Ausbildung: Zukunftsorientierte Ansätze aus dem Projekt IngLab: acatech Studie.* München: Herbert Utz Verlag GmbH.

Tibola, L., Pereira, C. E., & Rockenbach Tarouco, L. M. (2014). *Using cockpits to monitor the students' performance in engineering labs.*

Tobarra, L., Robles-Gómez, A., Pastor, R., Hernández, R., Cano, J., & López, D. (2019). Web of Things Platforms for Distance Learning Scenarios in Computer Science Disciplines: A Practical Approach. *Technologies, 7*(1), 17.

Vidal, P., Venant, R., & Broisin, J. (2017). Awareness and Reflection in Virtual and Remote Laboratories: the case of Computer Education. *International Journal of Technology Enhanced Learning, 9*(1/2), 1.

Wuttke, H.-D., Hamann, M., & Henke, K. (2015). Learning Analytics in Online Remote Labs. In E. I. Conference (ed.), *3rd Experiment International Conference. Online Experimentation: June 2nd–4th, 2015, Ponta Delgada, São Miguel Island, Azores, Portugal: exp.at'15* (pp. 255–260). [Piscataway, NJ]: IEEE.

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