Study based analysis of Learning Analytics Dashboard features for teachers conducted at the University of Twente

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This paper presents the results of a study-based analysis of Learning Analytics Dashboard (LAD) features for teachers conducted at the University of Twente. LAD features were collected based on an extensive literature review, after which the perceptions of higher education teachers at the University of Twente on these features were tested by means of an online survey. The survey aimed to assess the teachers' interest in using these features and to determine whether or not teachers assess the various features as an improvement to their workflow. In general, participants were interested in gaining more insight into the workflow of learners, also allowing them to refine their own course materials. However, concern was raised about possible privacy issues when handling and displaying individual learners' data.

Additional Key Words and Phrases: Learning Analytics Dashboard, Learning Management System, Learning Analytics, Online Learning, Artificial Intelligence

1 INTRODUCTION

The digital world is playing an increasingly large role in all environments, and education is no exception. Learning Management Systems (LMSs) facilitate this service by providing an interactive online learning environment and automating a great number of processes for both students and teachers [32]. The concept of an LMS was once an emerging technology, but they have since been widely adopted at educational institutions all around the world [5]. Learning Analytics Dashboards (LADs) are a part of LMSs where different metrics are displayed in an overview, aiming to offer an easily understandable visualization of the learner's progress. Multiple aspects of LMSs and LADs have already been widely researched from a student perspective [14, 15, 19]. However, LADs aimed specifically at teachers have received relatively little attention in scientific literature. Important aspects that the literature lacks are teacher experiences and perceptions. This study aims to enhance the understanding of teacher dashboards by conducting a survey with higher education teachers at the University of Twente (UT). Because usability evaluation is considered one of the main factors in measuring the efficiency of LMSs [31], participants in the survey were asked for the perceived usability of a number of features gained from the literature. In this paper, the terms learner and student are used interchangeably. Both terms relate to learners who have a student role in higher education.

2 RESEARCH QUESTION

The main research question that is to be answered in this paper is: What are the perceptions of teachers at the University of Twente on Learning Analytics Dashboard features for teachers?

This question is supported by the following three sub-questions:

(1) What is the state-of-the-art in Learning Analytics Dashboard features for teachers?
(2) What problems do teachers face that they think can be solved by means of Learning Analytics Dashboard features?
(3) What are teachers' opinions on how Artificial Intelligence can be used to extend Learning Analytics Dashboard features?

3 RELATED WORK

The goal of Learning Analytics (LA) is to use large data in order to track learners' progress as they study, therefore optimizing their learning and learning environment [37]. A Learning Analytics Dashboard is a tool used in LA, where all the data relevant to LA is displayed on one page giving a clear overview of a learner's progress. According to Verbert et al. [33], a LAD's aim consists of three main goals: a learner should gain insight into their learning actions, a teacher should stay aware of subtle interactions in their course, and researchers should be able to discover patterns in large sets of data. LADs can be of high importance in educational environments, as it has been shown that making use of a LAD positively impacts the students' final scores [12]. Multiple LAD designs with different features mostly aimed at students have been conceptually proposed [2, 26]. These student-aimed features include goals set by the learners themselves, seeing an overview of required and actual time spent on studying, suggestive and corrective feedback, and peer performance overviews. Another proposed feature for student LADs is integrated automated feedback, where learners get feedback on their specific learning goals not only at the end of a learning cycle but also during the learning cycle [28]. That type of feedback can be presented to the user of the LAD in numerous forms, including video, text, and audio [25, 29]. However, not only the features themselves are important to the effectiveness of a LAD. As stated by Sedrakyan et al. [27], the use of appropriate visual elements is also an important component of a LAD.

Only a small amount of research has been conducted into LAD features specifically for teachers. Martinez-Maldonado [13] conducted an experiment to research teachers' experience with a handheld LAD aimed at aiding the teacher in giving attention to project groups with the highest need for it. It was highlighted that the eventual success of a LAD depends heavily on how the teacher uses it. If a teacher is of the opinion that the LAD is not useful, they will probably not use it to its maximum capacity [38]. Despite that, according to Rienties et al. [21], teachers generally welcome the interactive and hands-on approach of LADs but are also sceptical about the potential ease of use. When diving deeper into specific LAD features, Dourado et al. [6] conducted a design study for a teacher LAD. Teachers were interviewed and several potential features were extracted. One of the designs included a feature where teachers were able to define a

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learning sequence for their students. Thus allowing them to track how far along the course their learners are, compare this with the expected progress, and intervene if deemed necessary. Additionally, the same dashboard presented a participation level per learner, based on the percentage of days in the course that the learner accessed the LMS. Although participation levels can be solely based on accessing the LMS, it could also be based on participation and interactions with fellow learners or teachers. One such example is CADA, a plug-in for the Canvas LMS which automatically gives teachers an automated analysis of the discussion forum posts and interaction patterns [10]. Other studies propose learners can participate in short online self-assessment quizzes, ranging from indicating where they are on the course schedule to answering multiple content-related questions to automatically gauge how far along the course they are [9, 30]. These self-assessments were subsequently scaled and visualized using colour to give teachers insight into the progress of their students [1].

The existing hype around Artificial Intelligence has also reached the field of Learning Analytics, and educational software companies are starting to incorporate AI into their products [20]. Multiple studies have aimed to outline the potential that AI brings with it. Proposed possibilities include visualizing the behaviours and interactions of teachers, assessing video-based oral presentations through automatic scoring, and exploring levels of engagement using AI methods [23]. However, the same study also highlighted the lack of attention to ethics and data privacy, as few of the reviewed articles mentioned ethics clearance. It is proposed that AI can give learners immediate feedback, predominantly relevant in a remote learning environment, allowing them to continuously improve without the constant need for a teacher [7]. An overview of the potential advantages of AI for teachers is provided by Celik et al. [4]. These include helping with the planning of activities, making the teaching process more interesting, and reducing the teacher workload. A few of these advantages are also applicable to LADs, such as assisting in selecting or adapting the optimum learning activity based on AI feedback [3]. Additionally, AI can assist in automatically scoring students' tests or assignments [11], taking workload off the teacher and allowing them to spend this time on other teaching-related activities.

4 METHODOLOGY

4.1 Literature review

The first step in answering the research question was doing an extensive literature review to review the state-of-the-art in LAD features for teachers. The main goal was to identify previously proposed features as well as known shortcomings of LADs or obstacles teachers are currently facing in their teaching. The main tool used in this review was Google Scholar, primarily searching for the keyword 'Learning Analytics Dashboard' in combination with keywords including but not limited to 'teachers', 'Artificial Intelligence', 'design', and 'features'.

4.2 Survey design

Based on the findings from the literature in Section 3, a survey has been designed reflecting on the main findings. The aim was to receive as many submissions as possible in order to be able to make a useful conclusion. Therefore, the amount of features in the survey was kept relatively small, also considering that participants were asked to participate in the survey without any form of compensation. The five most relevant features were extracted with the aim to reveal, firstly, teacher perceptions of these features found in the literature, and secondly, more features from practical experience of teachers that did not emerge from the literature review. Therefore, the primary part of the survey presents participants with the five previously discovered features. Participants are presented with a title per feature, together with a short description that gives some explanation of what the feature entails. The features with their respective descriptions are as follows:

- *Popular content among students*
  Look at which content is most popular among students based on the most frequently accessed course materials. This helps you gain insights into how far along the course your students are and could indicate the need to make small adjustments in teaching.

- *Participation ratings*
  Per student, see a rating based on how actively they are participating in the course. This can be based on accessing course content, handing in assignments, participating in discussions, and doing quizzes. This helps you gain insights into which students need more attention or guidance.

- *Student self-indicated progress*
  Students get asked weekly to indicate for themselves where they are on the course schedule.

- *AI guidance recommendations*
  Get help from AI to see which students need more attention and guidance in your course, this can either be based on online participation in the course or on real-life participation in the classroom.

- *AI mistake analysis*
  See if multiple students are making the same mistake repeatedly, either in attempted quizzes or in assignments, as well as suggestions from AI on why they may have made that mistake.

The participants were then asked to rate these five features on a seven-point Likert scale, where one represents very useless and seven represents very useful. An odd number of points was chosen to give participants the option to rate a feature neutrally, aiming to not scare them off by having to choose a side. Additionally, seven was selected as size as it was found to be a good balance between having enough points of discrimination without having to maintain too many response options [24]. Before rating any of the features, participants were asked for demographic data. That included their age, the faculty they teach in most regularly, and in what role they teach. Both these demographic questions and the feature ratings were marked as required and participants were not able to submit their responses without answering them all. Besides, these questions

were close-ended with the possibility to fill in a custom answer in an 'Other' option. Furthermore, participants were asked multiple optional open-ended questions for suggestions for LAD features, how they think AI will assist them in gaining insights into learners' progress and for any further remarks on the survey or research at the end of the survey. As participants should not be scared off when they do not have an idea for a new feature, the open-ended questions were not marked as required.

4.3 Data Collection

The target participants of this research were all staff or students who were engaged in a teaching role at the University of Twente. That means that both full-time and part-time teachers as well as teaching assistants were included. Part-time teachers are defined as people who besides their work as teacher, also have a role as researcher. Full-time teachers are not primarily involved in any research and only work on teaching-related activities. The participants' technical background, faculty, or any other demographic characteristic was of no importance to their eligibility to participate in the survey. Potential participants were approached via email with a short explanation of the study and a Google Forms link to participate in the survey. All participants were asked to partake in the survey without any direct incentive. A few potential respondents were proposed by the supervising team, and a small part of potential respondents were found via previous courses of the author. However, most potential respondents were found and selected at random via the online register of University of Twente staff [17]. This method was chosen as it allowed the contact details of a large amount of UT staff to be easily found. Because the website only shows results when entering a search term, the five faculties of the UT were separately entered. As only staff in a teaching role were targeted, people with a listed role of professor, assistant professor, associate professor, or lecturer were randomly selected from the list. As teaching assistants are not listed on the online register, these contacts were only found via previous courses of the author.

5 RESULTS

The survey counted a total of 41 respondents, consisting of teachers or teaching assistants at the University of Twente. The quantitative data collected in the survey was imported into a Python Jupyter Notebook and converted into a Pandas `DataFrame`. The notebook was used to get clear overviews of relevant data, as well as to manipulate the data structure in order to create graphs. The Python libraries `seaborn` [34] and `matplotlib` [8] were used to create graphs, and `ydata_profiling` [36] was used to gain insights into correlations between variables. The open-ended questions have been subject to a qualitative analysis. The responses were coded and categorized to reveal themes and patterns in the answers of the participants [35]. These answers were then used to gain new insights in addition to reinforcing the conclusions of this research.

5.1 Demographics

In the first part of the questionnaire, participants were asked several demographic questions. These included their age, in which faculty they teach, and in what role they teach. Table 1 displays the age groups of all participants.

Table 1. Age of participants

Age	Number of Participants
18-24	3
25-34	8
35-44	14
45-54	8
55-64	8
Over 64	0

As can be seen in Table 1, all expected age groups are represented in the results. An explanation for the lack of participants over 64 could be that they have already retired, or are at least not still active in a teaching role. All three participants in the age group 18-24 stated being active in a teaching assistant role, and not in a full-time or part-time teaching role. Table 2 presents the respondents' faculties.

Table 2. Faculties of participants

Faculty	Number of Participants
Behavioural, Management and Social sciences (BMS)	13
Engineering Technology (ET)	9
Electrical Engineering, Mathematics and Computer Science (EEMCS)	10
Science and Technology (TNW)	10
Geo-Information Science and Earth Observation (ITC)	6

Participants were only able to pick one age group out of the possible options, they were however able to pick multiple faculties. This resulted in six participants selecting two faculties, and one participant selecting three faculties. Thus, the total number of choices for faculties adds up to 48. Participants active in the ITC faculty were only active in one faculty, the other participants who selected multiple faculties were active in a mix of BMS, ET, EEMCS, and TNW.

Table 3. Teaching role of participants

Teaching role	Number of Participants
Full-time teacher	19
Part-time teacher	19
Teaching Assistant	3

In Table 3 the teaching role of participants is displayed. It can be observed that an equal amount of full-time and part-time teachers, as defined in Section 4.3, are represented in the results. Because only three teaching assistants participated in the survey, and, as mentioned previously, the three participants in the age group 18-24 are all TAs, these two groups are identical.

5.2 Ratings

In the second part of the questionnaire, participants were asked to rate each of the five features on a Likert scale of one through seven, based on how useful they think that feature would be to them. A visualization of the results of these questions can be seen in the violin plot in Figure 1, created with the Python library `seaborn`. A box plot is included in the graph to provide insight into the distribution of the ratings.

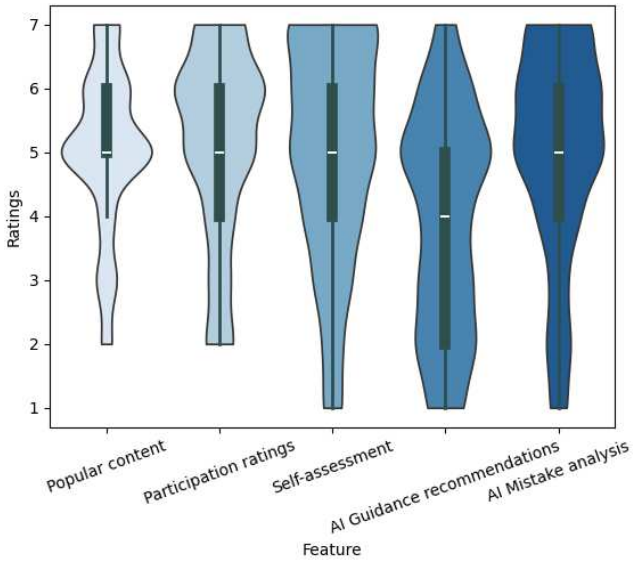

Fig. 1. Violin plot of given ratings

As can be seen, all means of the features are rather equal, and all hover around a round integer. The participation ratings feature is the highest rated out of all the options with a mean of 5.12. The features regarding popular content, self-assessment, and AI mistake analysis all follow with respective scores of 5.05, 5.00, and 5.00. Only the feature for AI guidance recommendations scores lower, with a mean of 3.93, thus scoring slightly below the median possible rating. Although almost all features have similar means, the sample variances are less uniform, as shown in Figure 1. The variance of the popular content feature is relatively low, whereas the variance for the AI guidance recommendations is large, indicating no clear agreement among participants.

5.3 Correlations

The correlation heatmap shown in Figure 2 was created with the help of Python library `ydata_profiling`. Dark blue means there is a strong positive correlation between the variables shown on each side of the axes, and dark red signals a strong negative correlation. White means there is no correlation between the variables. Some of the names of features have been shortened because of sizing issues.

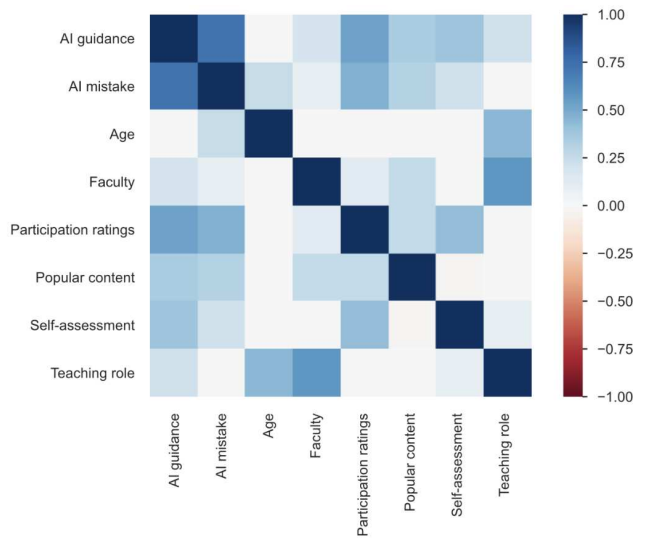

Fig. 2. Correlations between variables

As the heatmap in Figure 2 shows, there are some interesting correlations, as well as some notable lack of correlation.

- A strong positive correlation shows between how participants rated the AI guidance feature and the AI mistake analysis feature.
- The faculty of participants shows a high overall correlation with the teaching role they are active in.
- A high overall correlation was found between how participants rated the AI guidance feature and the participation ratings feature.
- None of the demographic variables showed any strong correlation with any of the five features.
- No negative correlations were found between any of the variables.

5.4 Open Questions

At the end of the questionnaire, participants were presented with multiple optional open-ended questions. Firstly, the option to propose new features that were not already included in the five feature options. Secondly, how they thought AI could help them gain insights into learners' progress via a dashboard. Lastly, they were invited to share any general remarks or comments on the survey or study. Respectively 30%, 47%, and 25% of the total amount of participants answered the open-ended questions.

5.4.1 Other features. Multiple participants suggested new features that were not already in the options or proposed additions to one of the mentioned features. A generalized overview of new suggestions from the participants can be seen in Table 4.

Table 4. Proposed new features by participants

Feature	Number of Suggestions
Time student spent on ...	3
Ask why content is hardly visited	1
See if students work towards ILOs	1

The most popular newly suggested feature is seeing how much time students spend on specific course material, mainly to gain an insight into which material is difficult to understand and needs improvement or where more material is needed. This feature was independently suggested by 23% of participants who left a suggestion. One participant also suggested asking students why hardly visited course material actually is hardly visited. This could give the teacher insights and new ideas as to how to improve the online material, as there can be numerous reasons students do not engage with course content. Additionally, automatically evaluating at regular intervals if students are working towards the course's Intended Learning Outcomes (ILOs) was suggested as a potential new feature.

5.4.2 AI influence in LADs. Participants were given the option to share their opinions on how Artificial Intelligence could assist them in gaining insight into their learners' progress via a dashboard. These answers were analysed and coded, an overview can be found in Table 5.

Table 5. Participants' opinions on AI in LADs

Comment	Number of Suggestions
Provide tips and guidance for students	4
AI should not look at individual cases	4
Only useful for big courses	3
Analyse how students handle course material	3
Prefer personal contact, no AI	2
Developing questions	1
Alert unusual activity	1
Analyse results	1

When not even considering the specific suggestions, participants were evenly split on their opinion if AI would help at all in education. Half of participants indicated AI would be of no use in education, and that it could not help them in their teaching. In total, 14% of participants commented that AI could possibly be of help to them, but only for courses with a large amount of students. When teaching in small groups with more personal contact, respondents indicated AI would not be of added value to them. Additionally, 19% of participants who shared their opinions expressed their concerns with how the privacy of students could be upheld when utilizing AI, also considering the new EU AI Act [16]. Thus, these participants suggested not looking at individual cases of students but letting AI be of service in a more general sense. This could include giving tips to the teacher to inspect some specific course materials more closely or giving the teacher indications of how far along the course the complete group is.

The other half of the participants believed that AI could be of help in their teaching activities. As can be seen in Table 5, this includes developing relevant quiz questions, analysing students' test results, and analysing how students handle course content. This could mean analysing how much time students spend on specific materials or how they click through all available materials. However, 33% of the participants actively mentioned that individual students' evaluation should be kept to the students themselves, and not shared with the teacher. These participants would prefer the dashboard to send out regular updates to the teacher on how the group, for example, is handling the course materials or if there are materials that are opened unusually often. A thought provided by a questionnaire participant was that AI should not be the intelligence of the students, but should enhance the intelligence of the students. Even though this is not strictly linked to teacher LADs, it means letting the students make their mistakes on their own and letting AI assist in their thinking patterns, but never giving the full answer. Participants added that these suggestions coming from an AI should be labelled, so students are invited to not blindly copy the AI's suggestions.

5.4.3 General comments. Additionally, participants were invited to share any final general remarks on the questionnaire and/or research. A selection of relevant comments to the research is summarized in Table 6.

Table 6. General comments of participants

Comment	Number of Suggestions
Sceptical of LADs or LA	3
Sceptical of a feature	3
LAD privacy concerns	1

A few of the participants pointed out being sceptical of LADs or Learning Analytics as a whole. The main reason they gave was that LA focuses on easily measurable metrics, like logins or clicks, and it could be argued whether these are true indicators of a deep, nuanced understanding of the material, especially in predominantly theoretical subjects. Another participant also questioned LADs, arguing that they do not work because most of them do not provide actionable feedback to the user. As also shown in Table 6, one participant indicated their concern about student privacy in LADs and mentioned that as a teacher they did not want any individual data to be collected or shown. Additionally, 27% of the participants commented on a specific feature that was presented to them in the questionnaire. It was pointed out that there was a concern about whether students would truthfully fill in the answer for the self-assessment feature, as otherwise the feature obviously becomes obsolete. Another participant noted that for the popular content feature, the fact that a certain course material is accessed often could mean multiple things. For example, it could indicate that all students are at that stage of the course planning, however, it could also indicate that that specific material or topic is unclear or perceived to be difficult.

6 DISCUSSION

6.1 Features

Of the five features, as can be seen when looking at Figure 1, all features, except for the AI guidance feature, were rated very equally by participants. Of this group, the popular content and participation rating features stand out as their average rating is the highest and their ratings are the least spread out. The AI guidance recommendation feature stands out negatively, as participants in the study rated the feature neutrally, making it not worthwhile to study in more depth. The low number of teaching assistants participating in the study can probably be explained by the relatively low number of TAs that were reached out to, compared to UT staff, in the data collection phase.

Participants actively shared their opinions on possible new features. As can be seen in Tables 4 and 5, more insights into specific student behaviour is a wish. This can be either in the form of analysing how students interact with the course material, giving notifications of unusual behaviour, or analysing the results of assignments that were handed in. However, many of the participants were also either aware of new legislation surrounding AI or thought AI processing individual students' learning data to be ethically questionable. As was shown, a desire to gain more insight into and analysis of individual students' learning progress arose both in participants' suggestions for new LAD features as well as participants' opinions on how AI can be of use in LADs.

6.2 Limitations

This study primarily focused on the theoretical part of a select number of LAD features for teachers. The theoretical and textual outline of the survey may have resulted in participants not having a completely clear image of how a specific feature would function in their daily working environment, resulting in them not being able to correctly anticipate the usefulness of that feature. To resolve this limitation, mock-ups of the features, possibly even a minimal prototype, could be constructed as visualization. Alternatively, the textual explanations of the features could have been elaborated to ensure correct interpretation by participants.

Furthermore, the number of features in this research was very limited, mainly due to the self-imposed constraint to limit the time needed to fill out the questionnaire. As participants did not get any form of compensation for participating in the study, there was a concern that participants would give up halfway through the questionnaire if it took too long. Therefore, in order to be able to give a meaningful answer to the research question, in this study, the possible number of participants was prioritized over the number of features to be included. Eventually, 41 teachers participated in the survey. Even though this is not a small number, it is too small to conclude and generalize for all teachers at the UT. Especially when considering the teaching assistants, of whom only 3 partook in the survey. For that reason, the study would benefit from a greater amount of features as well as a greater number of participants. The three TAs who did participate in the study possibly also biased the results, as their experience with working with LADs may differ vastly from teachers' experience. Additionally, the 18-24 age group existed exclusively of TAs, and vice versa, which could have brought biases to the related variables.

Another limitation originates from the method of contacting potential respondents, as some of the teachers that were contacted to participate in the survey were found via previous courses of the author. These teachers could have been influenced by previous experiences and thus not have been truthful in their answers. Furthermore, as was previously seen in Figure 1, virtually all features in this study were rated similarly by participants. This could be explained by the fact that all participants are from the University of Twente and were possibly biased by their generally identical use of LMSs and LADs. To avoid this possible bias, the target audience could be broadened to outside the UT.

Other limitations come from the design of the questionnaire. Firstly, due to the manner of formulating the questions, it is possible that all participants, when presented with a new LAD feature, deemed this feature to be useful solely because it was new and was presented to them in a positive way. Therefore, the survey could have suffered from acquiescence bias. This bias could have been reduced by avoiding a bipolar scale and providing verbal labels for the midpoint of the scale [18]. Alternatively, questions could have been repeated and asked in a negative form to confirm the opinions of participants. Furthermore, because the features gained from the literature were presented to the participants first, they could have been unknowingly influenced in their answers to the open-ended questions. This could have been avoided if the participants were challenged to reflect on the problems they experienced with LADs first, and presented with possible solutions to these problems afterwards.

7 CONCLUSION

To conclude, the state-of-the-art in Learning Analytics Dashboard features for teachers is a field with many possibilities for further research. There are numerous proposed features in the literature, however, not many have been implemented or tested with actual mock-ups. In the few cases where dashboards were implemented, they were found to aid both teachers and students in their learning process.

At the University of Twente, the teachers who participated in this study are primarily interested in Learning Analytics Dashboard features to gain more insight into their learners' progress. Particularly the features that focus on gaining insight into how learners are engaging with content and how they are engaging with the course as a whole. Participants wanted to know how much time students spend on course materials and additionally, if possible, analyse the differences found. From this information, the teacher can adjust their course materials to better suit the needs of their students. This wish by participants emerged both in the results of the features gained from the literature, where the popular content and participation ratings features scored highly, and in the results of the open questions, where participants independently came up with this same wish.

Due to the design of the survey, the second sub-research question, asking what problems teachers face that they think can be solved by means of LAD features, was not fully answered. Only possible

solutions were presented to participants of the survey, rather than challenging participants to come up with the problems they are facing.

Regarding the third sub-research question about what teachers' opinions are on how AI could be used to extend LAD features, many of the participants from the UT are excited about possible opportunities that AI can bring to the field of education. Most importantly, participants were of the opinion that AI can give more insight into the learning patterns of individual students. With that information, teachers can fine-tune their teaching, or alternatively, AI can give learners personal guidance without the need for an attending teacher. According to the participants, the real power of AI comes to light in large courses with little personal contact, as this often results in students falling into anonymity more easily. Even though AI can be of great service, the educational community should also be warned about possible issues with the privacy of students. Blindly feeding personal learning data to an AI should be avoided, both because it is, possibly, prohibited by EU legislation, as well as ethically questionable. Despite these possible roadblocks to the integration of AI in education, a large number of participants indicated being excited by the possibilities and curious about how AI can help them in their teaching.

In conclusion, participants in the survey were positive about a large number of LAD features but specifically interested in gaining more insight into learners' individual learning progress. Artificial Intelligence can be of great assistance in this, but the educational community should be aware of privacy and ethical issues regarding feeding personal data to an AI.

In future research, it is recommended to develop mock-ups or a minimal prototype in order to test the real-life working experience of teachers with the presented features. Additionally, research into the perceptions of teachers on a larger amount of features is recommended. The different indicators representing students' success, social interaction, participation, and progress presented in a study by Safsouf et al. [22] would be a good starting point. Furthermore, in future research, it is recommended to broaden the target audience to outside the University of Twente, test if there are demographics that do have an influence on participants' rating, or test whether teachers also actively seek the features they rated highly to be added to the LAD in their LMS. As this research only focused on opinions on the expected usefulness of five possible features, perhaps teachers are of the opinion that a specific feature is nice to have but does not actually add value to their LAD.

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