Enhancing Learning Management Systems: A Novel Approach to Improve Usability through Learning Analytics

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Fig. 1. Three popular Learning Management Systems. From left to right: D2L Brightspace, Canvas, Moodle.

Learning Management Systems (LMSs), such as Canvas, Brightspace, and Blackboard, serve a vital role in modern education by centralising first-party learning materials, assignments, and grades. Despite their significance, current LMSs often fall short in meeting user expectations, as highlighted by students and educators alike.

This study reviews literature and collects student perceptions through an online questionnaire to identify preferred features for LMSs. By analysing this data, the research aims to provide insights into students' preferences and offer actionable recommendations to LMS developers, ultimately facilitating the enhancement of LMS usability.

CCS Concepts: • **Applied computing → Learning management systems**; *Interactive learning environments.*

Additional Key Words and Phrases: Learning Analytics, Online Learning Environment, Digital Learning Environment, Learning Management System, Canvas, Brightspace, Blackboard, Learning Material Organisation

1 INTRODUCTION

Learning Management Systems (LMS) such as Canvas, Brightspace and Blackboard are important platforms that facilitate much of how modern education functions [Turnbull et al. 2020]. Improving these systems can have great benefits, as it has been shown that the perceived usability of an LMS affects the learning effectiveness and experience of students [Orfanou et al. 2015].

Current LMSs often fall short of expectations, as is expressed by students and teachers alike [Tevekeli 2022] [Blecken et al. 2010; Orfanou et al. 2015]. Many users find these systems poorly designed and lacking in functionality to actually improve usability.

While several studies have explored learning analytics features, empirical evaluation with end-users remains notably scarce. With human-centric design trends prioritising learners in technology design, the co-creation of learning analytics features is increasingly crucial. This study examines prominent learning analytics features through a literature review and assesses their usability using a survey method, alongside gathering perceptions through open-ended comments. We also investigate correlations with end-users' characteristics, including age, gender, role, and study programme. Our findings contribute to advancing understanding in learning analytics and inform the development of more user-centred technology design approaches. By bridging theoretical knowledge with practical application, we aim to address the gap between theory and practice in the field. As part of this, some key features that are set to most improve the perceived usability of LMSs will be suggested, while also discussing how these features could be implemented. Additionally, exploring correlations with demographic and educational factors provides insights into diverse learner needs and preferences. Ultimately, this study supports the creation of more effective educational technologies benefiting learners and educators alike.

The main research question being answered is as follows: *What learning analytics features can be added to Learning Management Systems to improve perceived usability by students?*

This question is supported by means of the following sub-questions:

(1) What is the state of the art in learning analytics for students?
(2) What promising novel learning analytics features can be identified?
(3) What are student perceptions about these features?
(4) What type of data is needed for the integration of these novel features?

2 LITERATURE REVIEW

The goal of this research is to accumulate a number of novel LA features and provide a ranking on their perceived usability. Consequently, it is a vital step to explore related works and discover what LA features have already been presented by others. Additionally,

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it is important to note why such features are presented, as the rationale behind them is often of importance when introducing new features.

2.1 Literature Search

The primary method of finding related literature was through use of Google Scholar. Additionally the built-in search functionality was used on the ACM Digital Library and Springer Link. The following keywords were most used during this systematic search:

- Learning Analytics
- Learning Management Systems
- Online Learning Environments
- Massive Open Online Course
- Learning Analytics Dashboard
- Learning Analytics Components
- Learning Management Systems Usability
- Learning Material Organisation
- Learning Behaviours
- Learning Theories
- Canvas Education
- Brightspace
- Blackboard
- Moodle

Additionally, though to a lesser extent, interesting references found within papers located through use of web search were also used. The total number of papers accessed using these methods reaches almost one hundred, however most of them were not quite relevant for this study.

The relevance of papers was mostly determined by whether it explicitly listed potential Learning Analytics features that are not yet found in common LMSs. Many papers went into much detail of various theories on learning behaviour and regulation, but described little to no context as to which specific features could help solve some of their identified issues.

2.2 Themes and Concepts

Many research papers have been written about Learning Analytics since its rise in the 1990s [Ye 2022] [Verbert et al. 2020]. Much of this research is focused specifically on the use of Learning Analytics Dashboards (LADs) [Sahin and Ifenthaler 2021]. These dashboards are often an app in which Learning Analytics features are all combined into a single overview. These dashboards are usually developed as standalone applications as part of studies [Verbert et al. 2020], and as a result might therefore not actually be implemented and used in practice often.

Much research is performed into learning behaviours and theories such as regulated learning, feedback theory and group learning. These theories are subsequently linked to Learning Analytics features to support why these features could help stimulate learners. [Sedrakyan et al. 2020] As part of this effort, LA features are often further sub-categorised, such as into the descriptive, predictive and prescriptive analytics capabilities [Susnjak et al. 2022].

The goals of student learning are described, as such two different types of goals have been identified. The difference between performance oriented and mastery oriented learning design is often presented. In education, the desire is often for students to be mastery oriented [Shakarian 1995]. This mastery orientation refers to the fact that students learn to master skills. This is in contrast to performance orientation, in which students are learning to perform well in school, in relation to achieving higher grades [Zhuang and Sun 2001]. These different types of goals are identified to support development of the desired type of LA features, that engage mastery oriented mindsets more than that of performance orientation.

Another theme is the design and usability of Learning Management Systems and the courses created in them. Various best practices for structuring online courses within LMSs are presented by [Cobb et al. 2018]. Such ideas can be integrated within LMSs to encourage applying these practices. The perceived usability of current LMSs has been evaluated on multiple occasions as well [Blecken et al. 2010; Orfanou et al. 2015].

2.3 Gaps in the literature

The usability of Canvas in particular has been studied specifically for teachers [Chen et al. 2021], no such specific and extensive research has been found for students, however. Furthermore, there are large numbers of research papers on learning theories and learning analytics, but a relatively small number of them actually present concrete feature suggestions based on their findings.

Additionally, LA features are often presented in isolation, or in a Learning Analytics Dashboard (LAD) application that is completely separate from LMSs. This hinders adoption of use, and more research could be performed on how best to integrate these features into real LMSs.

2.4 State of the Art

There is a broad range of novel input in the area of Learning Analytics, with a wide variety of suggestions. Ranging from simple visualisations based on obtained grades, to visualising effects of emotions on learning [Derick et al. 2017]. Currently with Artificial Intelligence (AI) quickly developing and making it into almost every mainstream product, the realm of possibilities within Learning Analytics has never been so big. A primary goal of Learning Analytics is to automatically adapt to specific courses, as well as the specific needs and wishes of a student, and the current advancements in AI can drastically help to bring this level of personalisation to every student [Aljohani et al. 2019; Ouyang et al. 2023; Salas-Pilco et al. 2022].

2.5 Discovered Features

Many features have been presented in various research papers over the past couple of decades. Below a number of interesting features are discussed.

As part of what is categorised as *Supportive Intervention* by [Sahin and Yurdugül 2022], the feature of being able to compare one self's progress and actions to that of peers is proposed. This information could help the student predict their achievements based on their and peers' interactions with the system [Sahin and Yurdugül 2022][Susnjak et al. 2022].

More primitive features such as an assignment planning view are suggested. Such components can make it more quickly apparent which tasks have to be done by when, but such features are in at least some way present in most current LMSs. However, it is additionally proposed that this feature can also display how important each of the assignments is based on their weight on the final grade, which is not as prevalent in current systems [Kia et al. 2020].

A component where viewed files are listed in a bar chart is also presented by [Kia et al. 2020]. Such feature would allow students to see which files others have opened most, and which files oneself has not opened yet. Based on the number of times a file has been opened, it could be deduced whether a file is important or not.

Allowing students to rate learning materials based on difficulty and helpfulness has been presented as an option to help students better identify time required for content. The aggregated ratings on these materials would then be visible to other students as well as the teacher, allowing the students to better plan their work, and supporting the teacher in improving their materials [Schumacher and Ifenthaler 2018].

Another proposed feature is that learning materials display the expected time required to complete that material, based on the time other students have taken. This time can be automatically adjusted based on whether the student is generally faster or slower than the raw average [Schumacher and Ifenthaler 2018].

It is proposed that current learning content is linked to previous content if it builds on top of previously learned skills. This allows students to easily revise said topics [Schumacher and Ifenthaler 2018].

A feature in which students can customise their deadline reminders has also been suggested [Schumacher and Ifenthaler 2018]. This could also be extended with autonomously personalised notifications, in combination with nudge theory to positively influence when students work on their assignments [Feild 2015].

3 METHODOLOGY

The first and foremost step of this study was to perform systematic literature review. The primary goal of this review was to discover a list of interesting and novel LA components, as well as find previously determined shortcomings or issues in usability and quality of Learning Management Systems for students. These two types of information could then be combined to determine what features are actually novel and could be most promising to introduce to actual LMSs to actually improve the usability of these systems.

The six most promising features of those listed in the Literature Review section were then selected to be included in the questionnaire targeted at people actively engaging with LMSs in higher education. The features have been slightly altered and simplified for easier comprehension.

3.1 Research Design

The questionnaire aims to answer what features students would find most useful in their use of LMSs while studying. As such, the primary section of the questionnaire provides the participants with 6 novel LA features, as can be found in 1. The participants are prompted with the title and short description as can be found in this table, as well as an image with a sample visualisation of what the feature could look like. This is done to be able to quickly convey the feature and its benefits to the participant. They are then asked to rate each feature on a scale of one through ten, based on how useful it seems to them. After rating each feature individually, they are asked to select which of the six features they would like to see added to their LMS, in a question where they can select anywhere between zero and all six features. Before participants have been presented with the new features they are asked to grade the usability of their current LMS. After having rated all features and having picked their favourites, they are asked what they expect the usability of the LMS to be when their favourite features have been added. This allows to quantify the improvement these features are expected to have. It is important to quantify this in addition to grading all features, as features having high grades does not directly imply that these features have any meaningful effect on the overall usability.

Additionally, participants are asked to provide basic demographic information about themselves, such as age, gender, country of origin and university. Additionally they are asked to provide their role, and field of study at the university.

Furthermore, participants are encouraged to provide comments on how they view the current state of their LMS, comment on the suggested features, as well as suggest features of their own as part of several optional open questions.

3.2 Participants

Students in higher education have been selected as the target audience. However, to make it more broadly applicable, the questionnaire has been developed to support participants who are otherwise engaged in the use of Canvas, such as by lecturers, as well as recent students. While the additional group of university staff has been included, they are not the focus of the study, and no actions will be taken to encourage more participation by this group. Students that have graduated in the past 5 years have been included as they would have similar experiences with LMSs as the group of current students. People who have not been active in institutions of higher education in the past 5 years are excluded from this study.

For this research, it was the goal that at least two reasonably large groups from different universities are included in the study.

3.3 Data Collection

The data is collected by means of an online questionnaire. The primary means of distributing the questionnaire was through use of WhatsApp groups. The link to participate in the study was shared in at least two student WhatsApp groups, each linked to a different bachelor's programme and university. The students were asked to fill in the questionnaire without any direct incentive provided.

3.4 Data Analysis

The 42 results were screened for unreliable input, after which a single entry was rejected as it contained provably intentionally incorrectly provided input.

The results were then imported in statistical software, IBM SPSS to be precise, to perform quantitative analysis on the various types of results. This was mainly used to discover correlations between various demographic variables and the ratings of the six features. To determine whether variables are correlated and how strongly,

Table 1. Features as proposed in the questionnaire

Feature	Title	Description
1	Material Difficulty & Usefulness Ratings	You can easily see how different learning materials have been rated by you or fellow students based on difficulty and usefulness of the content. **Advantages** • Allows you to prioritise certain materials based on how useful they are • Allows you to plan more time for materials that are rated as higher difficulty *Manual student input required to function*
2	Expected Time Required	Display the expected time required to complete course material. Based on time spent by other students, or as expected by teachers. Can also take into account if you are often faster or slower than the class average. **Advantages** • Allows to you plan more accurately, as you will have a better idea of required time No *manual input required*
3	Popular Content	Highlight content that many other students are interacting with right now. This content is likely to also be most relevant to you. **Advantages** • Quickly find the most relevant content, without having to search through the list *No manual input required*
4	Relevant Content by Date	Content can be sorted by date, and content relevant today is highlighted at the top. To facilitate this, teachers have to specify during which periods/days specific content is most relevant. **Advantages** • Quickly find today's most relevant content, without having to search through the entire list *Manual teacher input required*
5	Peer Comparisons	View study metrics as compared to other students. Can be used to see how you are performing as compared to others, as well as remind you of exercises that others have already handed in. **Advantages** • See how you are doing compared to others • Could help you catch that you are forgetting something *No manual input required*
6	Related Previous Content	When your current course builds on skills from previous courses, show links to learning material from previous courses to easily revise if needed. **Advantages** • Allows you to quickly revise old materials in case you have forgotten certain details *Manual teacher input required*

mainly the Spearman's rank correlation coefficient was used. Various plots were developed in R using the ggplot2 library, to visualise various results and relations.

The open questions were qualitatively analysed, categorised and then used to further develop and support the conclusion to this study.

3.5 Limitations

As this is an online questionnaire and is asked to be filled in without any form of compensation, it would not be realistically possible to create a questionnaire that requires a large amount of time to fill it in. As such, it was determined that it would only be reasonable to include a maximum number of six features. For better results, it would be interesting to include a larger number of features. Additionally, it would greatly benefit a future study if more participants could be reached. Additionally, of students not studying a computer science related degree, it is likely that participants are friends of the author of this paper, and may therefore not fully reflect the actual population of these degrees. Finally, the six features as presented in the questionnaire were selected from the larger determined list of LA features through no scientific method. Instead they were simply selected based on how promising they sounded, and whether they were different enough from features already present in LMSs and features already proposed in the questionnaire.

4 RESULTS

The primary objective of the questionnaire was to discover how useful the six proposed features are perceived to be by students. As such each participant was asked to grade every feature on a scale of one through ten. A visualisation of the distribution of these ratings are displayed in figure 2.

From these results, we can conclude various points:

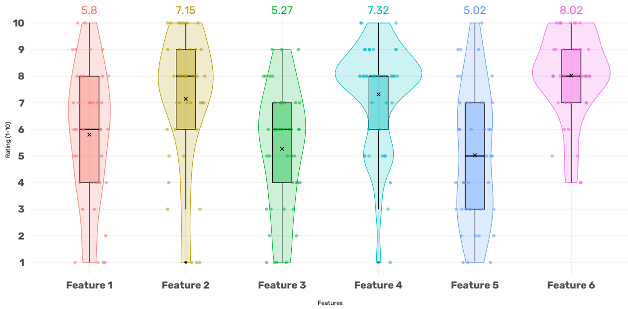

Fig. 2. The ratings given to each feature by participants of the questionnaire

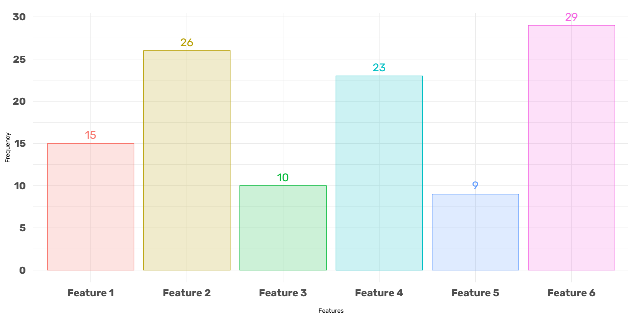

Fig. 3. The frequency in which the different features were selected by the participants of the questionnaire

- Feature 6 - Related Previous Content is rated highest by all metrics with an average grade of 8.0, and not a single participant rated it below a grade of 4.
- Feature 4 - Relevant Content by Date ranked second highest on average. There is more disagreement here than on feature 6, but the general sentiment is still highly positive.
- Feature 2 - Expected Time Required is the third highest rated feature in this lineup, and is overall received more positively than feature 4.
- Feature 1 - Material Difficulty & Usefulness Ratings has mixed results, but more than half of the participants still deemed it to be at least somewhat useful to them.
- Feature 3 - Popular Content also received mixed results, but even fewer people saw it as very useful.
- Feature 5 - Peer Comparisons appears to be a very controversial feature, with many participants having a strong dislike towards it, but with others still being very positive towards it.

In figure 3, it is shown what number of times participants have selected each feature based on whether they want to see it be implemented in their LMS. Conclusions that can be made from this statistic are as follows:

- Feature 6 - Related Previous Content is picked most often among all features, with 71% of participants selecting it, just as it ranked highest in ratings.

Table 2. Percentages of the questionnaire population that stated they want to see each feature added to their LMS. The top 3 features have been highlighted.

Feature	% of participants that selected the feature
Feature 1 - Material Difficulty & Usefulness Ratings	37%
Feature 2 - Expected Time Required	**63%**
Feature 3 - Popular Content	24%
Feature 4 - Relevant Content by Date	**56%**
Feature 5 - Peer Comparisons	22%
Feature 6 - Related Previous Content	**71%**

Table 3. The different fields of study as selected by participants.

Field of Study	Number of Participants
Industrial Design	13
Computer Science & Information Technology	11
Social Sciences	6
Other	11

- Feature 2 - Expected Time Required was selected by 63% of participants. It appears to interest more people than Feature 4, while Feature 4 did receive a higher average grade.
- Feature 4 - Relevant Content by Date ranks in third place by total number of people that picked it, with 56% of participants choosing to see it in their LMS.

The average grade given to the usability of a LMS increased by 1.15 points from a 6.68 to 7.83 after the student's desired features would have been added. This quantifiably indicates that these features are expected to actually improve the user experience of students.

4.1 Demographics

Part of the insight that this paper aims to provide is to determine whether certain preferences differ based on certain audiences. Certain correlations that have been examined as part of this study will be presented.

4.1.1 Study population. The population as reached by the questionnaire is made up of students of the degrees as seen in table 3. The fields of study that had fewer than 5 participants were aggregated into the Other category, as there are not enough students to provide any meaningful insights. Of all participating Brightspace users, 52% of them are students of Industrial Design degrees, 82% of Canvas users are in the field of Computer Science & Information Technology, and 67% of Blackboard students are in Social Sciences. With 56% of the participants in this study being users of Brightspace, and users of this LMS being of varying fields of study, this LMS is represented best within this dataset. In total students of 10 different universities participated. However with 39% of all participants being students of Windesheim University of Applied Sciences, and 22%

Table 4. The different LMS used as selected by participants.

LMS	Number of Participants
Brightspace	23
Canvas	11
Blackboard	6
Moodle	1

Table 5. The different types of enrolment as selected by participants.

Type of enrolment	Number of Participants
Bachelor	29
Master	10
Not currently enrolled	2

of all participants being enrolled at the University of Twente, these institutions are over-represented here.

As seen in table 5, most participants are students of a bachelor's degree, but also a sizeable portion of Master's students were reached.

4.1.2 Notable correlations. The dataset as collected as part of this study showed the following correlations. Note that due to the small size of this dataset, no strong claim can be made on the significance of these correlations.

- Students in the field of computer science and information technology naturally rate themselves as more proficient in technology.
- People rating the usability of their LMS higher tend to also rate Feature 2 higher.
- People who rated Feature 1 higher also tend to rate Feature 2 higher, and vice versa.
- People who rated Feature 2 higher also tend to rate Feature 5 higher, and vice versa.
- The ratings of Feature 2 and Feature 6 appear to be negatively correlated.
- Feature 2 tended to be more positively received by people already more satisfied with their LMS.
- People who gave higher grades for Feature 6 showed a more consistent improvement in the reported usability of the LMS when their desired features were implemented.

4.1.3 Inconclusive correlations. Due to the specific nature of the collected dataset and how it was collected, some metrics appear to show some kind of correlation, but they are linked to multiple variables. Some identified linked variables are listed below to provide context for results of this and future studies.

- In the data collected as part of this research, nearly all users of canvas are from the University of Twente, are students in computer science, identify as male, tend to be older, and are more likely to currently be doing a Master's degree.
- Over half of the users of Brightspace are students of Industrial Design in this dataset.

Table 6. Certain interesting issues that were mentioned most frequently

Issue	LMS	Number of mentions
Inconsistency in organisation of data	Brightspace, Canvas, Blackboard	6
Bad experience on mobile	Brightspace, Canvas, Blackboard	4
Finding back assignments to view feedback is difficult	Brightspace	3
Certain pages are very slow (People)	Canvas	3
Assignments are hard to find	Brightspace	2

- The age of students of Industrial Design related degrees is lower than that of students of other degrees. No student of Industrial Design in this dataset was 22 years of age or older.
- Feature 1 is rated higher by men, users of Canvas, and older users.
- Feature 3 was disliked more often by Master students, who are usually also male and computer science students.

4.1.4 Notable lack of correlation.

- No significant correlation was found between self-proclaimed technological proficiency and feature preferences.
- No significant correlation was found between the LMS used and any feature preferences.
- Gender shows no significant correlation with any feature preferences when looking at the entire study population.

4.2 Other observations

As part of this questionnaire, students were able to provide comments on what issues they identified in their current LMS. 46% of students provided their problems as part of this open question. A list of some problems they identified can be found in table 6.

5 DISCUSSION

5.1 Identified Features

From the results, we find that three features stand out as favourites. Feature 6 is quite universally liked and selected most often, with Feature 2 being a close second and followed by Feature 4. The other three features are graded around a six on average and picked by no more than 37% of the participants, so while these features could still improve the usability of a sizeable portion of students, these should not be the focus.

However, aside from rating three proposed features highly, students have also identified some other key areas for improvement, as also listed in table 6. The problem most students listed was that the organisation of data in the LMS is very inconsistent. While it is possible to attribute this issue to the teachers who place the data in the LMS, they are not the only ones as fault, as it is possible for an LMS to enforce or encourage well-designed material organisation

[Cobb et al. 2018]. The current data seems to suggest that neither Brightspace, Canvas, nor Blackboard adequately stimulate this.

Another issue that seems to be observed universally is the absence of a robust mobile application. Users of the three biggest LMSs have all described the experience on mobile to be inadequate, and having to manually fall back to the web application at times.

For Brightspace specifically, users have found the assignments to be hard to find, especially when they have already submitted it, and are looking to view the feedback on said assignment.

Finally, Canvas users mention that the people and group pages are slow, and in general not pleasant to use when dealing with larger amounts of groups and people.

It is important to realise that these basic issues might be just as important as the six proposed features, or even more so, to fix if improving usability of the LMS is the goal.

5.2 Other observations

Features 3 and 4 are very similar in their nature, as their primary goal is to identify the most relevant content at a given moment in time, and highlight these items at the top. It is therefore interesting to see that feature 3, in which relevant content is selected based on peer interactions, is rated much lower than feature 4.

5.3 Risks and concerns

Participants were provided the option to share comments on the proposed features. One student used this to share that they only wished to see feature 6 added, as all other features would make them feel pressured and give them anxiety. Multiple other students shared the concern that feature 5 with peer comparisons would result in students feeling too pressured to perform well, to the point of inducing anxiety.

This is in line with what was previously determined, in that Peer Comparisons are at risk of making students more performance oriented, instead of mastery oriented.

In the case of features 1 and 2 it is possible that students having this information beforehand working on the material themselves can have detrimental effects on their planning. This concern was shared by one questionnaire participant.

5.4 Visualisations

Simple LMS-agnostic visualisations are provided for reference. These visualisations were developed mainly to help convey what the different features do. They are by no means strong suggestions for how these features should look in production.

In figure 4, it is shown what Feature 6 could look like. With the materials related to the current course on the left, certain materials are linked to related older content on which the newer content builds.

Figure 5 shows how Feature 2 could be visualised. This visualisation simply shows the addition of a time icon and the total time this student is expected to need to complete the task. Additionally, the stopwatch is coloured based on the total duration.

Finally, figure 6 displays a possible representation of Feature 4, in which the list of materials is simply subdivided based on their period of relevance. The content relevant today is grouped at the top by default.

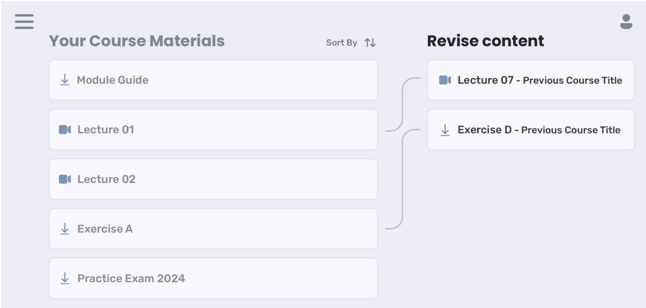

Fig. 4. Simplified visualisation of Feature 6 - Relevant Previous Content. The current course material on the left is linked to old course material to be revised on the right

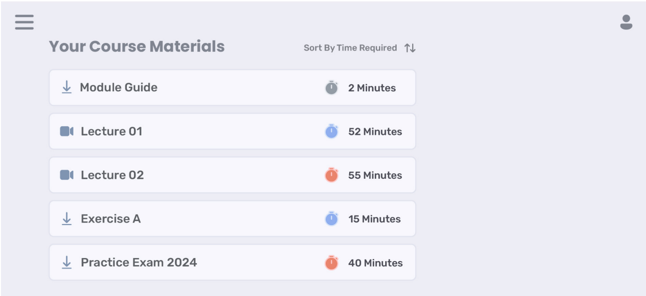

Fig. 5. Simplified visualisation of Feature 2 - Expected Time Required.

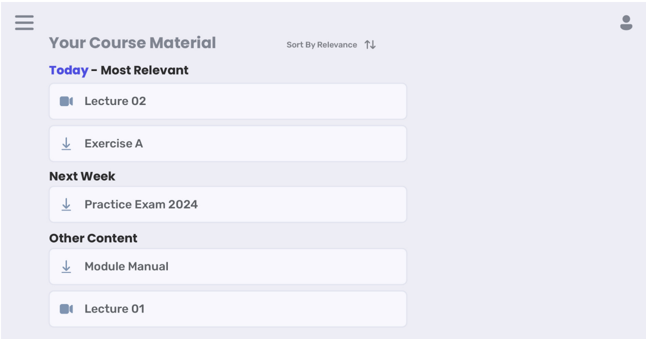

Fig. 6. Simplified visualisation of Feature 4 - Relevant Content by Date

5.5 Implementation Requirements

Features 6 and 4 are most realistic and straightforward based on implementation difficulty. Feature 2 requires some data that might be hard to obtain. All features could make potential use of AI to reduce required manual interactions.

5.5.1 Feature 6 - Related Previous Content. This feature requires materials to hold references to other materials. The specific references could historically only be linked by teachers. However, AI could potentially automate much of this progress based simply on the module manual or a similar document and contents of all other materials.

5.5.2 Feature 2 - Expected Time Required. For video content file metadata could simply be used to determine playtime. For reading content, anything from word count to AI could be used to determine required time. For assignments, one would probably require either manual input, or some way of tracking how long a student spends on it, potentially outside the browser. This method would also be required to get the student's speed as compared to their peer average.

5.5.3 Feature 4 - Relevant Content by Date. This feature requires the system to record for each learning material when it becomes relevant and when it ends being relevant. It could additionally link to deadlines or exams, and their dates, to get more details about when it is truly most relevant. This dates and links should most likely be manually selected by the teachers.

5.6 Lessons learned

As part of this research many learning analytics features were identified, of which a subset was actually provided for review by questionnaire participants. This setup worked to get a general overview of how useful these features are expected to be by students, and how much they expect their usability to improve by it. However, it did not measure if these are the features they want to see most. The questionnaire allowed students to provide insights in what other things they would like to see in their LMS, but it did not quantify how important they found those suggestions in comparison to the six proposed features. So while the overall questionnaire setup was satisfactory, this addition would have been done differently with the current insights.

5.7 Future Research

While this study compares ratings between different LMSs, it did not allow for entirely fair comparison between the two, as multiple variables were inherently linked due to the nature of the study population. The majority of Brightspace users were students of Industrial Design degrees, while the majority of canvas users were Computer Science and Information Technology students. Therefore it cannot be confidently argued whether changes in reviews are related to the specific LMS used, or the type of people and their qualities as found in the specific degrees. Additionally, while this study focused primarily on student-facing features and the usability as perceived by students, future research could be performed to see whether teachers see value in these features as well. Their view on the matter is quite essential as well, as they too are primary stakeholders in the LMS, and they are required to interact more with the LMS to facilitate certain proposed features. More research could be done to identify how best to visually represent certain features to best encourage proper use, and aid understanding of the data. Finally, it would be important to research what effects these features would have on the educational skills and performance of students.

6 CONCLUSION

While students are not decidedly unhappy with the current state of their LMS, they do still decisively identify the benefits of certain additions and fixes. With the state of the art in Learning Analytics spanning a wide variety of different features, theories and applications, one thing is certain; The rise of Artificial Intelligence (AI) allows for an increasing number of features to be applied in a convincing manner, as this technology has the potential to solve numerous challenges previously preventing adoption of these features.

While it is possible to suggest a diverse array of features to add to LMSs, it should be explored in which features students are actually interested. As such, of the features proposed to them as part of this study, students identified certain features as the most beneficial to them. The most notable feature which students selected was one in which current learning materials shows references to materials from previous courses on which the current course builds. This would allow the students to easily revise old content in case they have forgotten certain details. Another feature generally identified as useful is displaying the expected time required to complete various learning materials, such as lectures, assignments or recommended reading materials. The third novel feature identified is one in which every learning material is assigned a period in which it is most relevant, so that students can easily sort materials based on what is most relevant on a given day.

Aside from these novel features, students have also identified other issues which if fixed stand to drastically improve their perceived usability of the system.

While it has become clear that many students would like to see these features added, developers of LMSs also need to know whether it is possible and worth the cost to implement such features. As such, it has been explored what data would be necessary to implement these features, and how realistic it might be. While a sizeable amount of manual teacher input and interaction with the LMS would historically have been required to facilitate these features, the recent advancements of AI have provided new opportunities. It stands to reason that some of the data required can now be generated by AI based on the course material content, and knowledge of student courses and website interactions.

Historically, many novel Learning Analytics features have never been implemented in mainstream Learning Management Systems. However, with the current developments in technology and the state of the art in Learning Analytics, it is more likely than ever that big changes to our Learning Management Systems are on the horizon.

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