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Exploring Learning Analytics for the Course Design Improvement: The Results of a Pilot Experiment

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Abstract. One of the most crucial challenges in e-learning is the course's quality and learning analytics to ensure it is one of the prominent avenues to be taken in the field. The paper initially aims to present the literature review findings on the benefits and challenges of learning analytics for higher education. Secondly, it shows the results of the pilot experiment. The experiment methodology comprises two cases. The first case presents course design quality solely based on learning analytics data. The second case describes the course design's quality using the proposed framework based on both data from learning analytics and a survey including specified criteria. Although the pilot experiment is limited to the number of courses included and a small sample, it provided significant insights into the benefits and challenges of learning analytics as a tool for course design improvement and course design quality interpretation.

Keywords: learning analytics, course design, quality, evaluation, higher education.

1. Introduction

Researchers from different perspectives discussed the quality of the course design by focusing on managerial and process aspects (Baldwin and Ching, 2019), engineering requirements, and component-based view (Almaiah and Alyoussef, 2019) tried to incorporate quality standards. (Baldwin and Ching, 2019) states that "there are many online course design evaluation instruments created by individual schools, learning companies, consortiums and publishers. While these evaluation instruments serve a valuable function, there is an opportunity to simplify the process and offer instructors creating online courses an easy-to-use course design checklist to help improve the quality of their online courses."

To design a high-quality online course, one must maximise user satisfaction and encourage learning outcomes differently from traditional education. The term "quality" varies among researchers. The higher education (HE) institutions are "under increasing scrutiny by both governments and consumer-learners regarding the quality of their educational offerings." (Lenert, 2017). As the Covid-19 pandemic moved all learning processes to online mode with spectacular opportunities to gather every student "click" in the virtual learning environment (VLE), learning analytics (LA) came into play to a great extent. The field of LA has experienced significant advances in the past years, led by the promise of improving teaching and learning processes (Leitner et al., 2017), but still meet various challenges to be easily implemented (Tsai et al., 2020; Zawacki-Richter et al., 2019). (Tsai et al., 2020) summarises the motivation to apply LA to learning performance, student satisfaction and other learning course improvements.

The main challenge facing LA designers and researchers is invalid inferences or misinterpreting results from studies or cases. LA in an area of research frequently relies on user-behavioural data (e.g., how many times the video was watched, number of those who attended class, numbers of posts on a discussion forum) without enriching these data with user-perspective or contextual data (Lodge et al., 2017). However, these data types are rarely enough to acquire a deep understanding of the intervention or impact (Dollinger and Lodge, 2019). Therefore, it is critical to involve educators in LA and learning design research and practice. The LA provided are often misaligned with real educator concerns; simultaneously, educators need guidance in making the best use of LA for learning design (Macfadyen et al., 2020a). In their 2019 systematic review, Mangaroska and Giannakos identify a range of persistent gaps in learning design and LA (Mangaroska and Giannakos, 2019). By taking this into account, this research focuses on educators' position, students' perception and course component-based approach to analyse LA benefits and challenges from the empirical point of view.

This paper contributes to the field of LA as follows: 1) it provides a framework for incorporating contextual data into pure user-behavioural data; 2) it provides empirical results drowned by qualitative and quantitative research perspectives and compares the obtained results. The triangulation of the research provides evidence-based data on the benefits and challenges of LA for the course design improvement.

The paper is organised as follows: the first section describes the phenomena of LA under discussion, analysis of course design evaluation strategies. The second section presents the research methodology, and the results of the empirical study are shown in the fourth section. The paper ends with the discussion and conclusions, including limitations of the research and avenues for future research.

2. Literature Review

There is a wealth of research and knowledge about effective online learning practices (O'Keefe et al., 2020). A growing body of research focuses on effective pedagogies for fully online courses (Sellnow-Richmond et al., 2020). Research on learning design (LD) frameworks also presents many different approaches (Muñoz-Cristóbal et al., 2018). Although the dynamics between LA and LD have garnered interest among educational technology researchers and practitioners (Kaliisa et al., 2020), no unique solution, neither pedagogical nor technological, has been found.

Before designing any online course, the critical course design principles are the main pillars for any entity. According to (Lenert, 2017), before "determining what features constitute quality in online learning, it is important to keep in mind principles of quality teaching in general". Based on (O'Keefe et al., 2020) research, the essential course design principles are:

1. Familiarity with basic quality standards for online courses[1].
2. Use of measurable learning objectives/outcomes.
3. Alignment of content, activities, and assessments to learning objectives/outcomes.
4. Translate face-to-face strategies to the online environment and media-rich and/or courseware options to enhance the learning experience.
5. Use of Universal Design for Learning[2].
6. Design with equity in mind.

2.1. LA for Course Design Improvement

Olney et al. (2019) confirm conclusion of (Baldwin and Ching, 2019) that "most sources seemed to agree on four general areas of course quality: (1) the extent to which the course interface is well organised and easy to navigate; (2) the clarity of learning objectives and performance standards; (3) the strength and diversity of interpersonal interaction; and (4) the extent to which technology is effectively used." As LD significantly influences learner engagement and academic outcomes (Macfadyen et al., 2020), evaluating the quality of online learning is an essential part of continuous improvement. Although sources differed widely in their conceptions of the critical elements of course quality (ranging from ISO standards to developed quality models), based on literature analysis by (Jaggars and Xu, 2016), there are four online course design and instructional features which influence students' course learning outcomes: (1) organisation and presentation – the extent to which the course interface is well organised and easy to navigate, (2) learning objectives and assessments – the clarity of learning objectives and performance standards, (3) interpersonal interaction – the strength and diversity of interpersonal interaction, and (4) use of technology – the extent to which technology is effectively used. Moreover, the authors systemised all the evaluation approaches and provided four categories of evaluation methods: (1) practitioner-oriented literature, (2) surveys, (3) controlled studies, and (4) course quality rubrics, which pull together work from the first three strands – besides these methods, LA find their place in course design improvement as well (Di Mitri et al., 2018; Mangaroska and Giannakos, 2019; Tsai et al., 2020). For example, the study by (Martin et al., 2016) states that "improving the effectiveness of online courses is an endeavour that requires quality standards to guide design, development, and delivery of online courses". The authors explored how LA was used to monitor student learning and engagement in an online course and provided types of data collected and analyses conducted for the various pedagogical Quality Matters characteristics in online courses to monitor student learning and engagement.

LA allows using "the data associated with a learner's interactions to make pedagogically informed decisions and evaluations" and "takes up where LD finishes in

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[1] The Importance of Course Quality Standards in Online Education - Center for Teaching and Learning | Wiley Education Services

[2] UDL: The UDL Guidelines (cast.org)

the educational experience continuum – implementation and outcomes" (Lockyer and Dawson, 2011). Tracking student activity in the VLE has been proven to provide evidence of the success of an intervention (Adlington and Wright, 2012), but explaining performance or course design by utilising only VLE data remains challenging.

(Vieira et al., 2018) explored the topicalities of applying visual LA, together with an area where they could be effectively used. Visualisation-based LA technologies are the dominant element in analysing the learning process (Larrabee Sønderlund et al., 2019). However, many challenges are associated with applying visual LA tools in the learning environment. According to (Vieira et al., 2018), because the social sciences tend to adopt technology slowly compared to technological innovation, it can be challenging to transfer emerging technologies to the study environment. However, the pandemic of the Covid-19 virus has shown that educational institutions have reorganised quite rapidly, and technological measures have become part of daily operations. Second, although visualisation tools help students and teachers enrich the learning process, visualisations are often challenging to interpret. Third, often the visualisations are straightforward, giving limited user interactivity. Therefore, it can be assumed that if teachers had access to effective data visualisations, they could use them to provide informative feedback and improve teaching materials.

Similarly, giving students access to these tools would also encourage their reflection, develop meta-cognitive skills, and allow them to choose their learning path (Vieira, Parsons and Byrd, 2018). (Baldwin and Ching, 2019) points out that "great insight into the student experience can be gained by visualising the data to inform design. Interpreting these visualisations and comparing the outputs with other data sources can be used as a powerful research and scholarship tool that can inform both curriculum design and learning and teaching practice."

LA has also been studied in various other topics (Clow, 2013; Knight et al., 2013; Nouira et al., 2019; Sergis and Sampson, 2016) regarding study success with the help of LA more than a decade (Ifenthaler and Yau, 2020). Several recent systematic reviews of LA intervention in higher education can be found (Avella et al., 2016; El Alfy et al., 2019; Leitner et al., 2017; Mangaroska and Giannakos, 2019; Vieira et al., 2018; Wong and Li, 2020) highlighting mainly these challenges:

a. human tendencies to resist change, concerns related to privacy and ethical use of data, unstructured data analysis and the need for context-specific LA, lack of adequate skills;
b. limited insights from aggregate data/selection of acceptable variables;
c. the availability of multiple and diverse data analysis methods poses the challenge of selecting the most appropriate methods for the research in hand, intervention not sustainable at scale;
d. reliance on students' contribution of data, limited usefulness for students at a low knowledge level, reliance on teachers' experience;
e. too many variables and their combinations, lack of best practices;
f. difficulty in reaching at-risk students, in coordinating different groups of professionals working together, in evaluating the effectiveness of the intervention, in generalising the results of intervention; distraction for students;

g. lack of benchmarking information;
h. the unknown long-term effectiveness and others.

According to (Wong and Li, 2020) LA "intervention has the potential to extend its scope of practices further to serve a wider range of purposes, but more studies on the empirical evidence, even with null or negative results, are needed to support its long-term effectiveness and sustainability." (Tsai et al., 2019) state challenges in resources, stakeholder buy-in, ethics, and privacy.

In summary, the challenges in the scope of this research are considered as follows:

1. The main challenge facing LA designers and researchers is invalid inferences or misinterpreting results from studies or cases. Therefore, there is a need to enrich raw data with user-perspective or contextual data.
2. The second challenge is a range of persistent gaps in the research on LD and LA, which raises the critical need to involve educators in LA and LD research and practice.
3. The LA field has seen a gradual shift from purely data-driven approaches to more holistic views of improving student learning outcomes through data-informed LD (Blumenstein, 2020). Recently LA only began to connect with learning theories. It led to LD frameworks embedding into LA analysis.

2.2. Existing Approaches and Frameworks in the LA Field

Different conceptual models and frameworks of LA were proposed in the literature. Recently, a critical analysis of 18 LA frameworks by (Kaliisa et al., 2021) shows that existing LA adoption frameworks have established valuable theoretical and pedagogical guidelines. To conclude, the frameworks are designed to be general and high-level, avoiding addressing the implementation details. According to Kaliisa et al. (2021), "the large number of frameworks not concretised into technological artefacts and concrete data streams could make it hard <…> making pedagogically informed learning and teaching decisions based on the analytics". Moreover, there is "a need for empirical validation of the existing frameworks to provide a deeper understanding of how LA frameworks can contribute to the quality and efficiency of LA initiatives". The evolution of LA frameworks shows its complexity and trend to big data analytics in e-learning. There are several high-level frameworks, e.g., (Chatti et al., 2012) mapped LA and its related fields to the four dimensions of the reference model (namely data and environments (what?), stakeholders (who?), objectives (why?), and methods (how?)). (Greller and Drachsler, 2012) explored the LA framework model with six different dimensions: stakeholders, data, objective, instruments, external limitations, internal limitations to "guide for setting up LA services in support of educational practice and learner guidance, in quality assurance, curriculum development, and in improving teacher effectiveness and efficiency". (Di Mitri et al., 2018) provided a conceptual model for multimodal LA. The authors emphasise the necessity to use multimodal data for supporting learning activities through intelligent tutoring and LA. The research highlighted three main challenges: 1) a lack of understanding of how multimodal data relate to learning and how these data can support learners achieving the learning goals; 2) how to combine human and machine interpretations of multimodal data. Furthermore,

3) how to unify different terminologies from the fields of machine learning and learning science.

Another, a new three-level framework, the LA Learning Gain Design (LALGD) model, suggested by (Blumenstein, 2020), aligns meaningful data capture with pedagogical intentions and learning outcomes. The research contributes to the ongoing development of LA-LD frameworks (Macfadyen et al., 2020). The authors state that the model is suitable for various settings – face to face, blended, or entirely online – contributes to data-informed learning and teaching pedagogies in HE. However, the model is at its conceptual level. (Law and Liang, 2020) provided a multilevel framework and method for LA integrated LD. The LA-integrated LD framework is still at a preliminary stage of development, particularly the LA components in the LD. Therefore more informed and evidence-based justifications are needed.

Besides the general frameworks of LA, there are more specific initiatives to develop data models in LA (Lukarov et al., 2014), to analyse models of LA (Ifenthaler and Widanapathirana, 2014; Sciarrone and Temperini, 2019), another trend is to integrate the use of Big Data and LA in higher education (Otoo-Arthur and Van Zyl, 2019).

LA enables the optimisation of learning through the analysis techniques of data produced by learning processes. The literature review shows that "for LA to be successful, technical, managerial and human aspects need to work together to provide momentum to LA initiatives" (El Alfy et al., 2019). With all this support LA field will gradually shift "from purely data-driven approaches to more holistic views of improving student learning outcomes through data-informed LD" (Blumenstein, 2020).

3. Research Methodology

The framework for the analysis of course design is based on (Jaggars and Xu, 2016) research. This framework is component-based and allows for the course analysis in a structured manner (Fig. 1).

The framework addresses four areas of course design features:

1. Organisation and presentation – a focus on the organisation of materials.
2. Learning objectives and assessments – a focus on clearly outlined course levels and unit-level goals, along with clear expectations for assignments.
3. Interpersonal interaction – a focus on the effectiveness of interpersonal interaction in reinforcing course content and objectives and
4. Use of technology – a focus on the effectiveness of the chosen technology to support learning objectives.

Based on these four categories, the benefits and challenges of LA for the course design improvement will be explored by applying two cases: 1) The course design improvement solely based on data from LA + the framework; 2) The course design's improvements based on both data from LA and a survey including specified criteria + the framework.

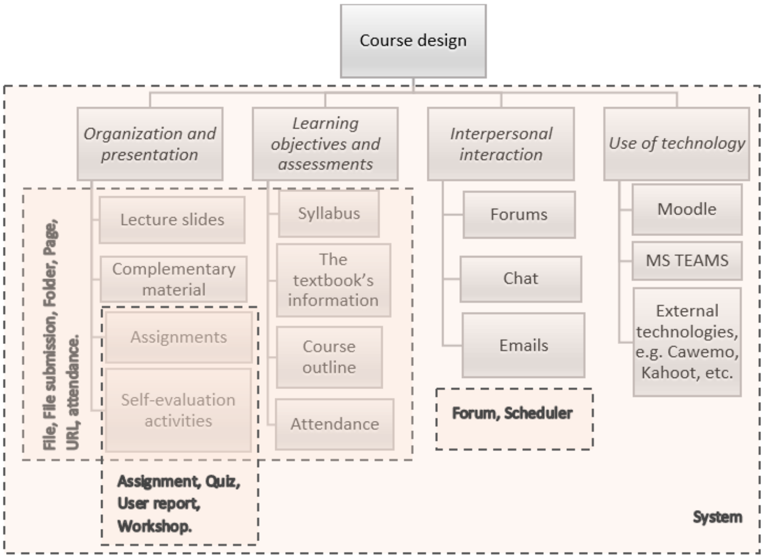

Fig. 1. A framework for component-based course analysis

The research questions about the course design are as follows:

RQ1. What can LA tell about course components' organisation and presentation/ learning objectives and assessments/ interpersonal interaction/use of technology?

RQ2. What could course design quality aspects be revealed by LA and suggested to improve?

3.1. Description of the Framework

The online course was structured into ten hubs:

A first general hub provides comprehensive course information – i.e., the syllabus, the textbook's data and assessment. From the second to the seventh, each thematic unit has a hub composed of:

1. Lecture slides: Learning materials in PowerPoint slides or Acrobat PDF documents to allow for any time, anywhere access for students.
2. Complementary material: Solved problems, videos or internet links to access extra reading material.
3. Assignments: Tasks to accomplish.
4. Self-evaluation activities: Short quizzes in the form of true/false or multiple-choice questions where students can self-test their knowledge or learning. Students know their scores in real-time, receiving immediate feedback on the correct response for each question.

The eighth hub was devoted to written work to upload both the document and the presentation – practical activity planning: Students can consult deadlines, access work specifications and submit their practical work. Specifically, groups had three practical sessions with follow-up tasks. The teacher returned feedback on the practical work through the platform. The ninth hub consisted of the final exam quiz. The last hub is about wrapping up the course and course evaluation quiz.

Accordingly, in VLE "Moodle", all the beforementioned components can be provided using different functionalities, e.g., file, file submission, folder, page, URL, attendance, etc. Specifically for assessment, other tools, such as assignments, quizzes, user reports, and workshops, are applied.

Two documents were uploaded to clarify and state the learning objectives of the course and evaluation strategy: the official syllabus for the university site formed the extra outline of the course to fix the timetable, topics, and assessment strategy. Attendance as a requirement of the university's legacy is incorporated here as well. There was no VLE "Moodle" functionality taken to assign specific learning objectives and assessments within the discussion course. Therefore, VLE "Moodle" traditional functionalities were used, e.g., file, file submission, folder, page, URL, attendance, etc.

The VLE influences the design and pedagogy of online courses (Baldwin and Ching, 2019). Different technologies were incorporated within VLE "Moodle" to support learning objectives: padlet.com, Google, Jamboard, cawemo.com, Tableau.com, Kahoot, etc. The following interaction activities were incorporated:

Within VLE "Moodle":

1. Chat: or chat room (possibility of opening a particular day, at a specified time, weekly, etc.);
2. Forum: different types of forums;
3. Assignment: homework with teacher evaluation (different types: text online, file repository, advanced file repository, off-line activity);
4. Quiz: following multiple-choice, true/false, numeric questions;
5. Workshop: refurbishment work with student evaluation.

Outside VLE "Moodle": MS Teams, Kahoot, Padlet, Jamboard.

1. Chat room (possibility of opening a specific day, at a specified time, weekly, etc.);
2. Forum: different types of forums (topics imposed by the teacher, topics proposed by students, evaluation or possible comments, etc.);
3. Groups: members of a course can be separated into groups (e.g., have access to restricted parts of the forum).
4. Quiz: following multiple-choice, true/false, numeric questions.

The Interpersonal interaction factor assesses the effectiveness of interpersonal interaction in reinforcing course content and objectives. As (Jebari et al., 2017) point out, VLE "Moodle" provides educational or communicative functions to create an online learning environment: an application or interactive course, the network of interactions between educators, learners and learning resources.

The framework (Fig. 1) for component-based course analysis allowed systematically transforming and adding contextual information to the data points in log files. It led to the structural analysis of each category (Organization and presentation, Learning objectives and assessments, Interpersonal interaction, Use of technology) at different granularity levels. Knowing the learning value of each component opens the prospects for possible improvement of the course design.

3.2. Data Analysis

A log file in computing is a file that records all the activity that has occurred on a system[3]. The data source for the analysis of LA was taken from log files recorded by VLE "Moodle" in the period 01/02/2021–01/04/2021. As in the paper, two cases are represented, therefore for the first case, VLE "Moodle" log files in MS Excel spreadsheet were downloaded after the course and analysed without additional data preparation and transformation except for coding any sensitive information. For the second case, the file for analysis was prepared based on the proposed framework. As downloaded log file records collected more information than needed (e.g., related user status) or in an inappropriate format for analysis (e.g., date and time data are presented in the same column), the data has been transformed to meet the following criteria:

1. The data shall correspond to the period under consideration –> filtering and removal of data.
2. Remove log file records that are not related to the study process.
3. Exclude date and time into separate dimensions –> data transformation.
4. Identification of essential data to enable questions raised in the first step –> qualitative analysis of the data.
5. Confidentiality of log file records –> the coding of data, e.g., student name.

The original data included 3765 log file records, with 3691 log file records remaining after the primary filtering of log file records (steps 1 and 2). There were 3286 log file records left after unrelated student log file records were removed. The following attributes have been left based on the log files data: Date, time, Full username, Event context, Component, Event name, Description, Origin, IP address and additional metadata fulfilled: with course design categories and subcategories.

The online survey was created to compare the results received from two different sources: log files from "Moodle" (students' behaviour) and the online survey (students' opinions). The online survey consisted of 65 questions within a set of criteria evaluated on a 5-point Likert scale that helped determine participants' perceptions of the course quality and students' level of satisfaction with the course at the end of the course. The distribution of components per lecture is provided in Table 1 - 65 components in total. The students evaluated each component per lecture using the five criteria: Usefulness, Informative, Understandable, Interesting, and Difficulty.

Table 1. Number of components per lecture in the course

# Lecture	1	2	3	4	5	6	7	8
# Components per Lecture	5	8	8	14	12	11	6	1

Also, students were asked to provide recommendations for course improvements in the future. The MS Excel spreadsheet with data was imported into Tableau[4] to create an

[3] Log file definition and meaning | Collins English Dictionary (collinsdictionary.com)
[4] Business Intelligence and Analytics Software (tableau.com)

interactive visualisation to process data, and JASP[5] was used to perform statistical analysis of data.

Descriptive, non-parametric inferential statistics and visual LA are used to analyse the quantitative data because, due to the small sample size (n = 7) more sophisticated analysis methods would be inappropriate (Konietschke et al., 2021). The participants' responses were reviewed and looked for patterns and insights to help us find synergies with data provided by LA. The results are discussed in the next section.

4. Results

As mentioned previously, the benefits and challenges of LA for the course design improvement can be explored systematically incorporating component-oriented framework: organisation and presentation; learning objectives and assessments; interpersonal interaction and use of technology. To see how course design can be improved with the help of LA, the results of two cases are presented: 1) The course design improvement solely based on data from LA; 2) The course design's improvements are based on both data from LA and a survey including specified criteria.

4.1. The 1st Case: The Course Design Improvement solely based on Data from LA

For the first case, simply VLE "Moodle" log files were downloaded after the course and analysed without additional data preparation and transformation except for coding any sensitive information, e.g., students' names. Based on the material provided in the downloaded document (Date, time, Full username, Event context, Component, Event name, Description, Origin, IP address). This type of data can be downloaded by any university teaching staff and analysed. The data were imported in Tableau, and graphical representations were provided (Fig. 2).

Applying the visual approach, it is evident that the number of log file records shows how many times the student referred to the VLE in specific/general activities. As the number of log file records has increased over time, it can be concluded that students visited the course more actively. Several assumptions based on these outputs can be made: the course material engaged students progressively, the number of assessments increased over time. Such conclusions are not vigorous and come from a simple interpretation based on "single click" data. Moreover, looking at the data from this perspective, it does not reveal anything about the features of the LD of the course: organisation and presentation; learning objectives and assessments; interpersonal interaction and use of technology. Only one thing is observable – the interaction level during the course was deficient. So, one factor that must be considered while improving the course design – is to increase interpersonal interaction level. Still, the question is if

[5] JASP - A Fresh Way to Do Statistics (jasp-stats.org)

such a conclusion is not misleading? Relying on (Pérez-Pérez et al., 2020) findings that "perceiving the Moodle course as a formal and instructor-monitored platform that requires students to compose messages in an academic style, which takes additional time and effort, may create a barrier to students' full participation in discussions." Therefore, other tools should be considered.

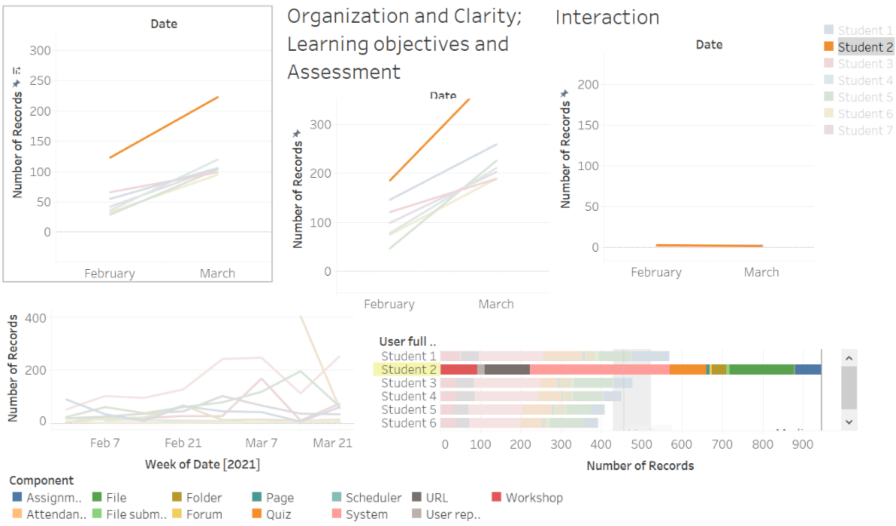

Fig. 2. A dashboard for course design analysis

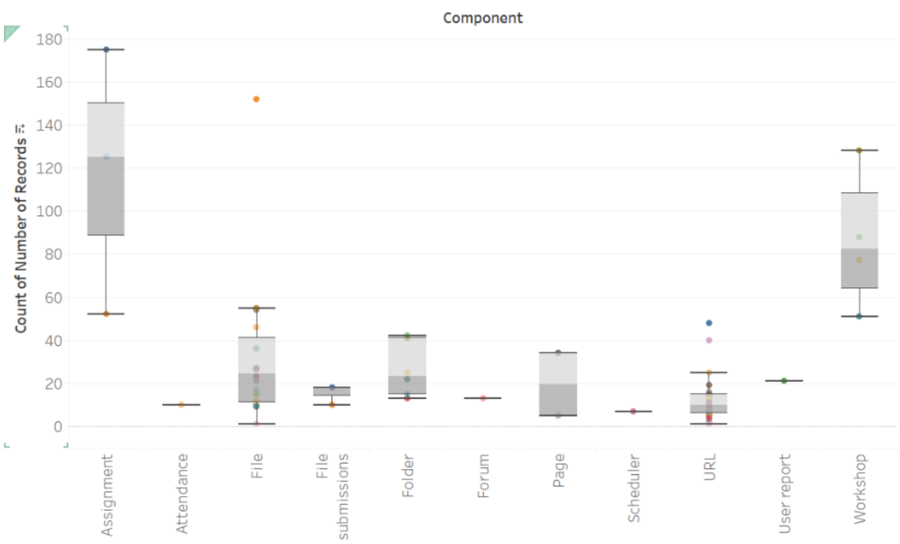

Fig. 3. VLE "Moodle" components and most frequently visited elements of the course

Analysing VLE "Moodle" components (Fig. 3), it can be observed that most visited components are "Assignment" and "Workshop", less "File", "Folder", "Page" and "URL". However, identifying the challenging task is complicated because of not proper coding of the component. Without additional information, it is difficult to analyse which elements were beneficial to the students. The boxplot charts represent the components used at least and at most in the course. E.g., the minimal count of 55 in "Assignments" shows that assignment in lecture 4 was less visited than the Individual assignment in lecture 3 (the maximum count of 175).

Another case was analysed and presented below to have more profound insights about the course. The main challenge is how to distinguish shortcomings of the course design? The provided example shows that other information should be considered in addition to existing information in log files, i.e., additional metadata to describe all the components within the course and surveys to evaluate them from a student perspective.

4.2. The 2nd Case: The Course Design's Improvements Prospects based on both Data from LA and a Criteria based Survey

LA must be expanded with extra metadata to get practical insights about the quality of the course. One approach is applicable by many researchers to apply qualitative research and develop data-driven decisions with users' perceptions. The online questionnaire was constructed to get users (students) perceptions of the course and answers collected. The structure of the survey is based on the framework presented beforementioned. The criteria included: Usefulness, Informative, Understandable, Interesting, and Difficulty of the components within the course. The distribution of averages is represented in Fig. 4.

	# Lecture							
Criteria	1	2	3	4	5	6	7	8
Difficulty	3.071	2.589	2.875	2.990	2.831	2.883	2.619	3.214
Informative	4.036	4.714	4.804	4.755	4.792	4.779	5.000	4.929
Interesting	4.714	4.393	4.571	4.429	4.610	4.688	4.929	4.429
Understandable	4.762	4.714	4.696	4.439	4.649	4.740	4.952	4.857
Usefulness	4.086	4.661	4.768	4.633	4.740	4.727	4.929	5.000

Fig. 4. The distribution of averages by students' perception

It can be observed that the students perceived the course as not difficult. The first lecture was less informative and valuable than others, the second, fourth and eighth lectures were less attractive, and only the fourth was less understandable.

Table 2. Dunn's Post Hoc Comparisons – Lecture #

Comparison	z	W i	W j	p	
1 - 7	-2.869	1065.324	1244.829	0.002	**
1 - 8	-1.915	1065.324	1222.643	0.028	*
2 - 6	-2.460	1045.095	1150.444	0.007	**
2 - 7	-4.012	1045.095	1244.829	< 0.001	***
2 - 8	-2.437	1045.095	1222.643	0.007	**
3 - 7	-2.686	1111.098	1244.829	0.004	**
4 - 5	-1.678	1049.902	1112.235	0.047	*
4 - 6	-2.707	1049.902	1150.444	0.003	**
4 - 7	-4.334	1049.902	1244.829	< 0.001	***
4 - 8	-2.479	1049.902	1222.643	0.007	**
5 - 7	-2.834	1112.235	1244.829	0.002	**
6 - 7	-2.018	1150.444	1244.829	0.022	*

* p < 0.05, ** p < 0.01, *** p < 0.001

The Post hoc Dunn test (Table 2) revealed statistically significant differences between the lectures (the significant values only left) that the last lectures of the course were better evaluated than the first one.

The analysis shows a statistically significant difference in students' perception about lectures, $\chi^2(7) = 28.668$, $p < 0.001$, with a very small effect size $\eta^2 = 0.01$.

Looking at the course design from the proposed framework view (Fig. 5), it can be stated that, in general, all the features have high evaluations, except interpersonal communication. As each feature is comprised of sub-features, more sophisticated insights can be drawn by expanding it to the corresponding granularity

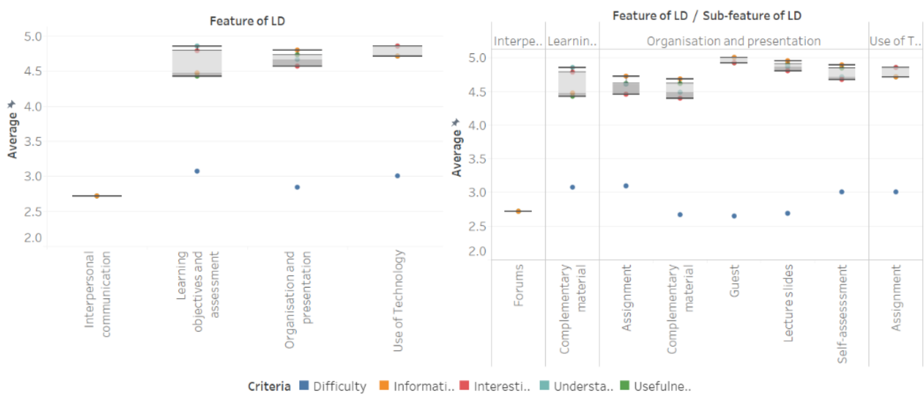

Fig. 5. The distributions of averages by students' perception

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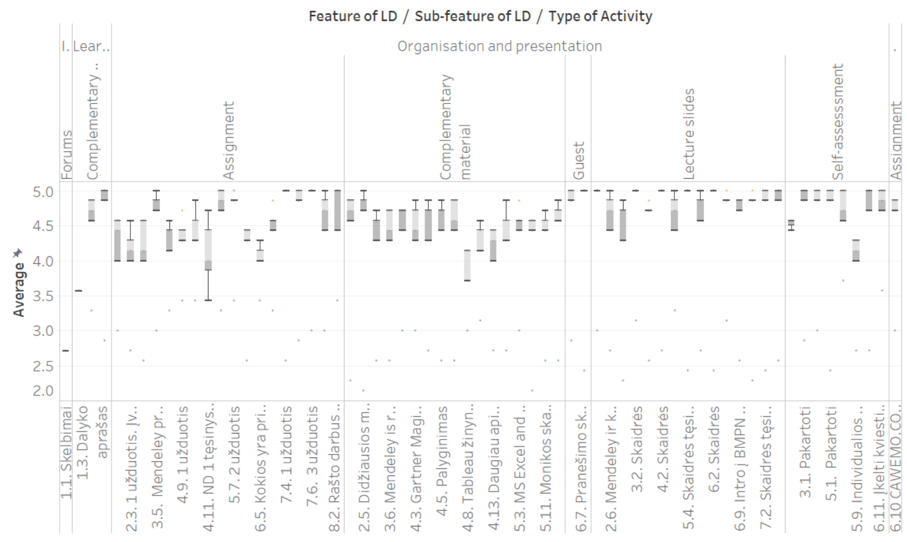

Fig. 6. The distributions of averages by students' perception in detailed granularity

Moreover, changing the granularity to specific tasks within the course (Fig. 6), it can be observed, e.g., how the difficulty of assignments was changing through the course: Exercises 4.11 is recommended to reconsider as the variability of evaluation is high (from 3.4 to 4.7), and understandability is relatively low (3.8 in average). Also, although two invited guests were evaluated well, the presentation of the second guest has by agreement of all students the highest rate of 5.

The analysis of learning course design from a LA perspective, including the features of LD, shows similar results (Fig. 7). The boxplot charts represent the components which were used at least and at most in the course overtime regarding the categories of the framework presented in the Fig. 1. It can be observed that interpersonal interaction using VLE "Moodle" Forums was not actual, no high value from students' qualitative study, neither log counts show an increased number of visits, even the number of visits slightly dropped over time. Learning objectives and assessment evaluated highly in both research: log file shows that the most crucial document through all the studying time was not the "Syllabus" but the "Outline of work" provided as supplementary material. The popularity was almost the same over time. Mostly visited components belongs to "Assignment", "Lecture slides" and "Self-assessment" categories within the "Organisation and presentation" category. The information obtained in qualitative research confirms the benefits of the course guests in favour of the second guest. His presentation was used by students mostly. Visiting assignment documents decreased over time, but in comparison with self-assessment documents and activities, the latter mentioned categories' visits increased.

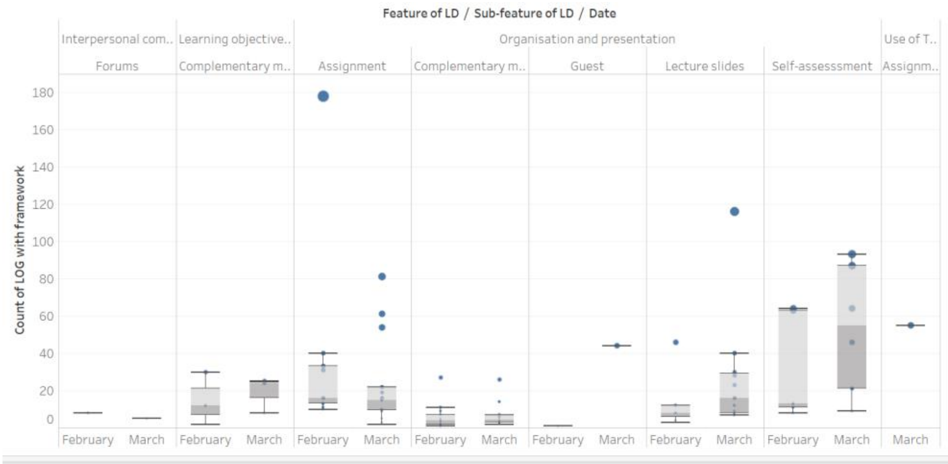

Fig. 7. The distributions of visit numbers per category

To answer the research questions, main aspects must be considered: 1) granularity level of the analysis, which allows getting valuable insights about the elements of the course – which of them are the most valuable for students (including the qualitative and quantitative criteria); 2) the data and metadata available about each element to create as much as possible contextual information. From the experiment done, it can be concluded that the second experimental phase added beneficial value to the LA by providing qualitative evidence-based interpretations on all categories within the framework. Overall, the course was evaluated (survey data) positively. The LA shows the consistent use of the components within the whole course to interpret that the course design is of high quality. Still, some components are shown by both cases not in use: tools of VLE "Moodle" for interpersonal communication, some of the complementary material. Also, the first lecture must be reconsidered to be more valuable for the students. Based on the pilot experiment, the benefits of LA for course design improvement are pinpointing the most effective techniques and spotting areas of concern. The challenges, such as lack of complete data, metadata forces different interpretations of results obtained, make it very inefficient to perform analysis (e.g., the component "Slides" can be used both for organisation and assessment) and without contextual view can lead to misleading interpretations. Another challenge relates to the LD framework chosen to analyse LA. Although usually, those frameworks are context-independent, they highly influence the structure, conceptual approach, and granularity level.

5. Discussion

The paper aimed to explore the benefits and challenges of LA for the course design improvement from a theoretical perspective and contribute to the research area by providing some evidence-based results. From the literature review on the benefits and challenges of LA for the HE, the main findings are: 1) the necessity of the framework needed for the interpretation of the outputs of LA; 2) the necessity of the more detailed description of metadata of components within the course; 3) the necessity of the more sophisticated evaluation tools incorporated within the course to receive students' perception about the course. The research design revealed some prominent prospects researchers and practitioners could consider benefitting most from LA: 1) granularity level of the analysis, which allows getting valuable insights about the elements of the course – which of them are the most valuable (including the qualitative and quantitative criteria) for students; 2) the data and metadata available about each element to create as much as possible contextual information.

The results of the first pilot experiment show that the students' visits to VLE "Moodle" increased over time; the most important (mostly visited) components of the course were: "Assignment" and "Workshop", less "File", "Folder", "Page" and "URL". To conclude, the existing approach to log files within VLE "Moodle" cannot provide enough information about the quality of course design. The second pilot experiment analysed the course design's quality based on both data from LA and a survey including specified criteria: it helped to confirm the most valuable resources and techniques for students and recognise the elements to reconsider: e.g., the first lecture of the course, the difficulty of the course, etc. An analysis from different perspectives helped explore the relationship of gathered information and minimised interpretations if done solely based on data from LA.

6. Conclusions

Although the research provided significant insights into the benefits and challenges of LA as a tool for course design improvement and course design quality interpretation, the obtained results cannot be generalised. The study has obvious limitations that need to be addressed. At first, the pilot experiment is limited to the number of courses (only one intensive master's degree course) at only one HE institution included. Another limitation is the nature of self-report survey data and the small sample size. Because of the latter, more sophisticated statistical analysis methods have not been applied.

The practical work has been done to implement a proof of concept of the proposed approach based on VLE "Moodle" course log files/descriptors. Therefore, for the courses within VLE "Moodle", it is possible to apply the same analysis using the framework described. However, there is a need for adaptation and further investigation to develop comprehensive LA frameworks that incorporate course design improvement strategies and build effective learning systems in any VLE.

Accordingly, future research will provide further empirical evidence regarding the benefits and challenges and the validity of different LA frameworks to implement. More importantly, the effectiveness of LA frameworks for improving course design is to be addressed in rigorous empirical research.

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