



Using learning analytics to improve the educational design of MOOCs

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ARTICLE INFO

Received 2022-03-11

Revised 2022-05-21

Accepted 2022-05-25

Published 2022-08-01

Keywords

MOOC

Educational Design

ADDIE

Learning Analytics

ABSTRACT

In recent years, the interest in Massive Open Online Courses (MOOCs) and Learning Analytics research have highly increased in the areas of educational technologies. The emergence of new learning technologies requires new perspectives on Educational Design. When the areas of MOOCs, Learning Analytics and Instructional Design developed, the interest and connection between these three concepts became important for research. Learning Analytics provides progress information and other individualized support in MOOC settings where teachers are not able to provide learners with individual attention, which would be possible in a traditional face-to-face setting. Through collective views over the learning process, the overall progress and performance are indicated. Moreover, results can lead to Educational Design improvements. Every time a learner interacts with the system, data is created and collected. Many Educational Designers do not take advantage of this data and thereby, losing the possibility to impact the course design in a powerful way. This research work strongly focuses on the implication of Learning Analytics for Educational Design in MOOCs. Many methods and algorithms are used in the analytical learning process in MOOCs. Currently, a great variety of learning data exists. First, well-known Instructional Design patterns from different models were collected and listed. In a second step, through the collected data is used to point out which of these patterns can be answered by using Learning Analytics methods. The findings of the study show that it is possible to better understand which environments and experiences are best suited for learning by analyzing students' behaviors online. These results have great potential for a rapidly and easier understanding and optimization of the learning process for educators.



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1. Introduction

Consideration of the future status of education leads in turn to an increased focus on available and relevant technologies. It is fair to say that two of the most important factors likely to contribute to and shape the future of education are Big Data and analytics. There is a view that data-based results lead to increased organizational output and productivity [1]. The latest advances in technology; the increase in the use of technological devices; and the Internet have had a global influence on the emergence of new educational models such as Massive Open Online Courses (MOOCs). MOOCs tend to be available as free and open licensed courses in online environments – they provide significant opportunities for distance learners with easy access to information. Therefore, the development of innovative perspectives to further increase engagement and effectiveness seems appropriate, coupled with a careful eye on the data used and information held in these environments [2]. MOOCs offer scope for innovation in the field of open and distance learning from elementary education to higher education [3] and ongoing adult education. They were first conceived by Stephen Downes and George

Siemens as an approach to address information exchange [4]; react to students' inquiries for knowledge; integrate IT-tools; and decrease the cost of access to education [5]. MOOCs have since led to ready access to education worldwide, allowing anyone with an Internet connection to take courses from providers such as Coursera, Udacity, and Udemy [6]. It is fair to say, though, that the completion rates of many MOOCs can be poor. Given the large number of participants (up to several thousand for a single MOOC), a great deal of course related data is stored in the databases of MOOCs' servers [7]. The accumulation of such data leads to so-called Big Data. This term refers to "datasets whose size is beyond the ability of typical database software tools to capture, store, manage, and analyze" [8]. The analysis of this data in the educational context falls within the scope of Learning Analytics. One of the aims of Learning Analytics is to provide information about the learning process to the various stakeholders involved in teaching and learning [9]. With the diffusion and maturation of Learning Analytics, it is important that there is close cooperation with the related field of educational design in ongoing research [10]. Educational design serves to create learning experiences and learning environments that support educational activities [11]. It is a field of study concerned with improving teaching and learning [12]. In 2007, Reiser and Dempsey suggested that educational design could be used as a systematic process employed to develop education and training programs in a consistent and reliable fashion [13]. It is a complex process that is creative, active, and iterative in nature. Bandhana concurs, stating that educational design is a tested and proven methodology for developing education [14].

Apart from analyzing the impact of the educational design, Learning Analytics can also support the regulation and redesign processes by facilitating the identification of design elements that should be revised before reuse [15]. Educational design and Learning Analytics are both domains of research and action that seek to improve learning effectiveness. This common aim raises the potential of synergies between the two fields [16]. Educational design has a significant effect on deep and meaningful learning [17]. Parry states that providers of MOOCs, even with evidence on the impact of various factors on success, do not yet fully understand how best to implement successful MOOCs [18]. McAuley et. al also suggest that new forms of education, training and technical characteristics associated with online learning are different to traditional settings, and that these differences need to be extended to new learning methodologies and frameworks [4]. Given the uniqueness of the MOOC environment, the creation of educational design principles is vital to improve learner outcomes [19]. Additionally, these principles can enhance educational design for MOOCs and ultimately improve student learning, retention, and completion rates. The relationship between Learning Analytics and educational design provides a link to comprehensive data collection and analysis to examine learning experiences, establish the design process, and inform educators who create these designs. The integration and synergy of Learning Analytics into educational design have been described as crucial [20]. The importance of Learning Analytics in educational design goes far beyond tactical module improvements. Learning Analytics has the potential to provide significant benefits to learners, course designers, and to the educational institution itself. Every time students interact with MOOCs, another piece of data is created and collected. Every login, button click, chat entry, assessment, and time stamp is tracked and recorded. Many educational designers don't take full advantage of data, but with Learning Analytics, data can be used in powerful ways to impact not only course design, but much more besides. In this chapter, we focus on the implications of Learning Analytics for educational design in MOOCs using the well-established ADDIE Model (see later). The volume of data obtained within the scope of MOOC studies can lead to challenges in the implementation of educational design. Accordingly, we describe how we might improve established Instructional Design patterns for MOOCs by using information gathered automatically through Learning Analytics techniques.

2. Research Questions

Learning Analytics is one approach that might help to reduce complexity in educational design and develop models. It can be used within educational design to design and deliver an improved learning experience, using available data. With Learning Analytics and the available data, instructors possibly observe the benefits of using and implementing learning experiences as designers. Given this, educational design offers Learning Analytics a domain vocabulary, representing the elements of a learning system to which analytics can be applied. In turn, Learning Analytics offers educational design a higher degree of rigor by validating or refuting assumptions about the effects of various designs in diverse contexts. However, making these links operational and coherent is still an open task. Thus, this study investigates how Learning Analytics can improve the educational design of

MOOCs. The study was carried out using the first Austrian MOOC platform, known as iMooX, and asks the following research questions:

RQ1: Which educational design indicators, taken from an existing framework, are also relevant for application to MOOCs?

RQ2: Which education design indicators can be full or partly answered by using Learning Analytic methods?

3. From ADDIE to Educational Design & MOOCs

3.1. ADDIE educational design model

The ADDIE Model is an iterative educational design process, whereby the results of the formative evaluation of a phase may lead the educational designer back to any previous phase. The end product of one phase is the starting point of the next. As seen in [Figure 1](#), ADDIE is a common mnemonic for the five major steps in the educational design process, namely: A = Analysis, D = Design, D = Development, I = Implementation and E = Evaluation. These steps sometimes overlap and can be interrelated; however, they provide a dynamic, flexible guideline for developing effective and efficient instruction.

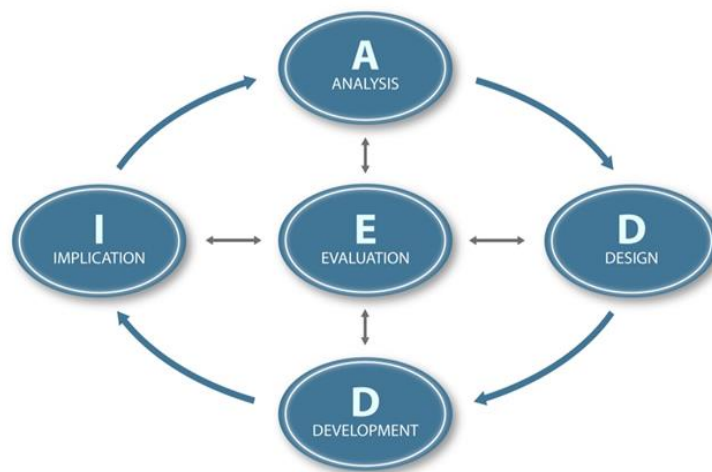


Fig. 1. ADDIE Model

3.2. Educational Design of MOOCs

Given the special nature of MOOCs, the creation of educational design principles is vital to improve learner outcomes [19]. These principles are applied: (1) to activate and engage learners through meaningful learning tasks and activities that are anchored in state-of-the-art online learning and might have professional relevance for participants too; (2) to guide decision-making and management of course content, technologies, processes, and management on a massive scale; (3) to improve Instructional Design for MOOCs, and potentially enhance student learning and retention and completion rates. Little effort to date has been made to extract Instructional Design principles for MOOCs. In fact, studies [21]–[23] show that such principles are rarely used in the design of MOOCs. Given this, the educational design of MOOCs is an important issue to study further, especially since certain shortcomings have been attributed to the poor educational design of MOOCs, for example, significantly high participant drop-out rates [24], limited learner motivation, and learner engagement [25], and the poor instructional quality [23]. There may be further issues, of course, but we might expect good educational design to play an important role. Duisterwinkel et al. developed a general step-by-step plan for creating an educational design. Four phases are distinguished [26]: (1) Orienting oneself with regard to the subject; formulating learning objectives and assessment; (2) Designing the educational functions, content and associated learning activities; (3) Making choices with regard to teaching materials (books, articles, syllabuses, assignments), teaching methods (e.g., collaboration) and practical factors (location, time, group size, etc.); (4) Understanding and/or establishing the characteristics of the course and the potential audience.

3.3. Learning Analytics and educational design of MOOCs – bringing them together

Learning Analytics approaches have made an effective contribution to the educational design field for many years, even before the terms Learning Analytics and educational design were coined [27].

Data collected through Learning Analytics in computer-based education systems such as learning management systems (LMS), can be interpreted by teachers, educational and Instructional Designers and other educational stakeholders to better understand learner engagement, progression, and achievement [28]. Furthermore, such learner-centric data may help formulate future pedagogical decisions on how to modify the learning environment to improve student learning processes. Learning Analytics can help to identify at-risk learners and provide appropriate interventions, transform pedagogical approaches, and help students gain insight into their own learning. Thus, taking into consideration the purpose, strengths and weaknesses of educational design and analytics, there is a natural and synergistic relationship that emerges between the two domains, which has led to growing interest and some initial effort in bringing them together [29], [30]. Reciprocally, well-formulated Learning Analytics can be helpful to inform instructors and designers regarding the outcomes of their MOOC designs [31]–[33]. Learning Analytics can provide evidence of the impact of a design in one or several learning situations, such as the engagement patterns in activities proposed by the learning design, the learning paths followed by students, and the time consumed to complete activities and assessment, etc. [34], [35]. To date, relatively little research has been conducted into how useful educational theories are when working with Learning Analytics. We have therefore chosen to focus on generic educational design questions relevant to several theoretical frameworks adopted by Van den Bogaard et al. [36] with a close look to Learning Analytics. The authors suggested that instructors and educational designers can address some issues relating to educational design that might be answered using Learning Analytics. According to Van den Boogard et al. [36], Learning Analytics could be used in the following phases strongly relating to Duisterwinkel et al.'s plan [26]: (1) Subject orientation and learning objectives; (2) Learning activities using Learning Analytics; (3) Group activities, online collaboration and the contributions of the students towards a joint assignment; (4) Assessment, as it is an essential part of learning because the student is given feedback on their progress and how well they have understood the course material; (5) Learning materials and resources in a digital learning environment; (6) Context, characteristics of the students and making links between the different components of a learning environment. We suggest that MOOCs are more effective in the sense of educational design if these design principles (patterns) are put into practice. In our case, we have used a xMOOC platform to investigate which of these principles can be automatically assisted by Learning Analytics, and how.

4. Research Process

Van den Bogaard et al [36] explored educational design questions based on several theoretical frameworks, seeking to point out indicators relevant to Learning Analytics in general [36]. In this study, a range of established Instructional Design patterns - derived from Van den Boogard - were collected and listed. Once educational design patterns had been identified, we took a closer look into existing Learning Analytics measurements on iMooX. The Austrian MOOC platform iMooX was founded by the University of Graz and Graz University of Technology at the end of 2013. The main purpose of iMooX was to make academic and general content accessible to a broad public, empowering them to extend their knowledge. In contrast to competitors in the US, all learning materials used in the courses of iMooX are exclusively provided as Open Educational Resource (OER) under the Creative Common license. Since 2013, more than 100 MOOCs with over 60,000 learners have been run on the iMooX platform. Our research sought to establish an improved understanding of which educational design patterns can be directly supported by Learning Analytics by conducting a number of oral interviews with Learning Analytics specialists and platform developers associated with the iMooX platform (n=11). All interviewees were asked if those patterns were currently supported or could be supported in future based on their knowledge in working with the MOOC platform. We asked each participant to review the same set of questions, summarized in Table 1 below, and discussed each point in detail to understand how data might help them in developing any future MOOCs. Each interview was analysed and afterwards we take a look if an indicator could be met whether partly or fully by an automated process.

5. Results and Discussion

In this section, we review and discuss the results of the study, summarised in Table 1. Based on our discussions with the interviewees, the table provides an overview of those activities which might be supported by the application of Learning Analytics techniques to MOOCs using the chosen indicators. Where data which can be automatically accessed on the system is available to address questions, we label this as “already done”; where there are data which might be accessible in the future, we designate this as “possible” (see Table 1).

Table 1. Assistance of educational design patterns according to Van den Boogard et al. [36] using Learning Analytics techniques of the iMooX-platform

	The Question	Not Possible	Possible	Already Done
<i>Subject Orientation</i>	Has the student read the learning objectives?		✓	
	Has the student read the information about the assessment?		✓	
	Does the student review the learning and assessment goals during the course?		✓	
<i>Learning Activities</i>	Has the student read the instructions for the learning activity?		✓	
	When students work together on a group assignment: Who did what part of the assignment?	✓		
	Did the student hand in the assignment(s), and when?			✓
	When and how often does the student contact the teacher/adviser with questions and what kind of questions do they ask?			✓
	When and how often do students ask fellow students for help and what kind of questions do they ask?		✓	
	Which learning pathways do students follow through the learning activities, and are certain pathways more effective than others?		✓	
	At what point does the student perform the learning activities?		✓	
	How much time do students spend on a learning activity? Is the time spent consistent with the planning of the teacher?			✓
	Do students follow their own progress?			✓
<i>Group Activities</i>	What has a student contributed in a group discussion?		✓	
	How many times has a student responded to discussions in a forum or social space?		✓	
	How extensive was the contribution of a student in a group discussion?	✓		
	What are the main topics that the students discuss?		✓	
<i>Assessment</i>	How close is the student to achieving the learning objectives?			✓
	How often does the student do a formative assessment?			✓
	Does the student review learning objectives and learning activities based on their scores for a formative test once they have received them?		✓	
	Do formative assessments support the student in passing the summative assessment?		✓	
	Are courses with many small summative assessments better for academic performance than one large summative assessment at the end?	✓		
<i>Learning Materials and Resources</i>	How many attempts does a student need to complete an assessment?			✓
	How long did the student view/read the material?			✓
	Did the student download the material?			✓
	What material is viewed the most frequently, or is most commonly used?			✓
	What material or additional resources does the student use on their own initiative?			✓
	Did the student watch the videos (how often, when did they fast-forward and rewind?)			✓
	What do the students highlight in the text, what kind of notes do they make?	✓		
<i>Context and Student Characteristics</i>	How successful was the student before they began the course ?		✓	
	What prior knowledge does the student have? Do they have the right prior knowledge?		✓	
	What is the student's background or motivation (previous education or other programs)?		✓	
	Has the student followed the set curriculum or did they create their own track?		✓	
	Is there a link between the student's score on the summative assessment and their study habits (does the student do all the activities, do they read all the materials, do they deliver their work on time, etc.)?		✓	
	Is there a link between how the student uses the learning materials and activities and their score on the formative tests?			✓
	Has the assessment method contributed to the learning objectives?	✓		
	When is a student likely to quit, or be forced to quit, their study program?		✓	

The following findings are noted:

- First, we reviewed whether it is possible to obtain data to allow us to assess the extent to which students have addressed subject orientation or familiarization with the topic. Data relating to whether students have read the learning objectives has been inferred by reviewing the duration that students have spent on this particular page. That is, an assessment can be made as to whether students have spent sufficient time on screen to read the texts on that page.
- Similarly, access to relevant data regarding the learning activities of any learner can be made from the reading data via the iMooX platform. Estimations can be made of whether students have read the instructions from an analysis of time spent on a page. Note that it was not possible to establish which sections have been completed by individual students for group assignments, because currently group assignments are not offered via the platform. Assignment delivery times and students' time and frequency of asking questions can be accessed automatically, although the nature of the questions requires a semantic analysis to be implemented.
- Information describing student engagement with learning activities can be gathered in a number of ways. For example, via data related to usage frequency and time spent by students in iMooX discussion forums. Although iMooX doesn't currently offer learning pathways, this transaction might be realized in the future by examining the attitudes of students. For example, it would be possible to get greater insight into learning pathways by analyzing sequences of watching videos and completing assessments. If a student uses the offered activity progress feature, student tracking information can be monitored on the system. Furthermore, measurement of the active time data between login and logout may add further potential to answer questions about the time spent on learning activities.
- Student contributions to group discussions can easily be measured with data from the discussion forum group activities questions. Data on forum participation and the number of students' responses in forums and social areas can be accessed automatically. Having said this, it is difficult to assess how significantly students are contributing with current Learning Analytics techniques. Frequently discussed topics are easily observed by reviewing the most frequently used words.
- Regarding assessment questions, student achievement of learning objectives can be measured using data reflecting achievement and failure per quiz and question. Assessment frequency can also be answered automatically by examination and quiz data. We are able to make inferences about students' goals and activities through their exam results data on the system. The repetition of exams after a failure, the playback of videos or access to content data can also be used to support this conclusion. If the weekly assessment is considered as formative assessment, the results of the summative assessment can be interpreted in the system. Finally, using the exam and quiz data, the number of attempts students needed to complete the assessment can be answered automatically.
- Learning materials and resources asks for access data to the students' reading time of materials, the frequency of downloading of materials as well as material or additional resources that students use on the system. Together, with the frequency of watching video data students' behaviours can be observed.
- Feedback forms might give further insight into students' achievements. Information captured at registration or available from previous study would also be useful in determining context and student characteristics.

6. Conclusion

In this research study, we have suggested that MOOCs need educational design. Following the idea that Learning Analytics techniques can support defined educational design patterns (RQ1), an existing framework was taken [36] and used to assess whether such patterns can be supported with currently existing Learning measurements using the MOOC-platform iMooX as an example (see Tab. 1). This brief analysis suggests that many educational design patterns can be addressed, and most others can be answered in future (RQ2). It is accepted that some of the data identified in the discussion above are proxy data, that is, we have assumed a link between certain measurable data and the behaviours that we are hoping to measure. Going forward, it would be helpful to analyse other MOOCs to see how and whether such an approach might work in practice, and whether the existing

educational design patterns and Learning Analytics techniques used here should be adapted or are sufficient. The following three key findings can be pointed out: (1) Learning Analytics can support the educational design of MOOCs; (2) Learning Analytics is unlikely to be able to replace the educational design process; (3) Learning Analytics applied to the context of MOOCs appears to offer useful insight and promises to be an interesting research field in the area of distance learning.

Acknowledgment

Contributions and development were partly delivered within the project “Learning Analytics: Effects of data analysis on learning success” (01/2020-12/2021) with Graz University of Technology and University of Graz as partners and the Province of Styria as funding body (12. Zukunftsfonds Steiermark).

Declarations

- Author contribution** : HK is working as an Instructional Designer and added the literature review, the state of the art and the basic concepts to the article. PL is the person who is implementing Learning Analytics measurements to the MOOC platform and therefore was able to provide all necessary steps for the results table and did a solid review of the final article. ME worked as a senior researcher and gave the ideas to the paper, did the final table, made the concluding notes. Furthermore, he takes care about the final proofread and the whole review process.
- Funding statement** : The research was done during a project called “Learning Analytics: Effects of data analysis on learning success” (01/2020-12/2021) with Graz University of Technology and University of Graz as partners and the Province of Styria as funding body (12. Zukunftsfonds Steiermark).
- Conflict of interest** : The authors declare no conflict of interest.
- Additional information** : No additional information is available for this paper.

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