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Towards Personalized Learning Objectives in MOOCs

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Abstract. Instead of measuring success in Massive Open Online Courses (MOOCs) based on certification and completion-rates, researchers started to define success with alternative metrics recently, for example by evaluating the intention-behavior gap and goal achievement. Especially self-regulated and goal-oriented learning have been identified as critical skills to be successful in online learning environments with low guidance like MOOCs, but technical support is rare. Therefore, this paper examines the current technical capabilities and limitations of goal-oriented learning in MOOCs. An observational study to explore how well learners in five MOOCs achieved their initial learning objectives was conducted, and the results are compared with similar studies. Afterwards, a concept with a focus on technical feasibility and automation outlines how personalized learning objectives can be supported and implemented on a MOOC platform.

Keywords: Learning objectives · MOOCs
Goal-oriented learning · Self-regulated learning
Learning analytics · E-learning

1 Introduction

Massive Open Online Courses (MOOCs) offer the opportunity of free education for everyone who has access to the Internet. Since the first evaluations of such online courses, a main criticism is the low completion rate ranging from 5 to 10%, which has been discussed frequently [3,11]. This certification-centered focus is reasonable from the perspective of a MOOC platform provider or teaching team since these stakeholders are interested in the success of their courses. Nevertheless, it turned out that a lot of learners dropped out of courses for different reasons, mostly due to poor time management or course difficulty [13]. The initial assumption that MOOCs will largely attract less-educated people and students had to be adjusted. Lifelong learners, especially well-educated professionals, form a large part of the learning community and not necessarily all of them are interested in gaining a certificate [4]. Therefore, the meaning of success in MOOCs was discussed again since a dropout can also mean that a learner got all the knowledge it needed at this time [17]. Thus, alternative measurements

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were proposed. For example, Renz, Schwerer, and Meinel [20] introduced the concept of a learning material consumption rate, next to the completion rate, to determine success. From the learner's perspective, the meaning of success is connected to their motivation and goals, and lifelong learners have varying learning objectives. Therefore, researchers started to define success based on the intention-behavior gap [7] to measure achievement based on students' individual reported goals. Unfortunately, courses with self-reported learning goals based on learners' intention are rarely implemented and conducted. In terms of personalization the preparation of alternative learning paths, either by varying topics or proficiency levels, requires additional resources. This results mostly in increased production time and cost. Modularization can confuse students more than it supports them [12]. Instead, goal-oriented learning – as part of a broader self-regulated learning strategy – has been identified as a valuable skillset in online learning environments [13,28]. Nevertheless, technical support for personalized learning objectives in MOOCs is limited.

Thus, this paper provides two contributions to the field of technology enhanced learning. To examine the current technical capabilities and limitations of goal-oriented learning, an observational study is presented to explore how well learners in MOOCs achieved their initially specified learning objectives, based on five courses ($N = 25,801$). The results are compared with similar studies, to examine their general validity and emphasize the importance of such work. Secondly, a concept is outlined how personalized learning objectives can be supported and implemented on a MOOC platform. Thereby, the focus is set on technical feasibility and a high level of automation, which is a critical issue for the success of goal setting and self-evaluation in such a high-scalable online learning environment.

2 Pedagogical Rationale

Mayes and De Freitas [18] described learning outcomes of e-learning environments in higher and further education. They extended Goodyear's [6] three kinds of learning in higher education – which are *academic*, *generic competence* and *individual reflexivity* – by *skill*-based outcomes to fully encompass further education. They presented design principles of learning environments, whereas many researchers recommend to apply constructivism in distance education [9]. They summarized the following principles:

- The learner actively constructs knowledge, through achieving understanding
- Learning depends on what we already know, or what we can already do
- Learning is self-regulated
- Learning is goal-oriented
- Learning is cumulative

The authors outlined two main aspects for activities to construct understanding: interactions with material systems and concepts in the domain, and interactions where learners discuss their developing understanding and competence. In the research literature they recognized an increasing focus on the design of learner-centered methods and environments, whereby the ultimate goal of educational technology is the achievement of individualized instruction. Nevertheless, personalization at scale comes with many instructional and technical hurdles. Thereby, goal setting is a first step to understand learners' intention and motivation.

Also, self-regulated and goal-oriented learning have been identified as important topics in educational psychology due to their influence on learners' achievement [5,15]. Especially in large-scale online learning environments with little support and guidance like MOOCs, self-direction is a critical skill for learners' goal achievement [13,28], but many learners have difficulties in applying self-regulation [16]. A lot of models and frameworks for self-regulated learning have been proposed. This work focuses on the following metacognitive strategies, which were especially developed to support goal-oriented learning [5,15,29]:

Goal setting to agree on the effort required to achieve objectives on different learning content granularity.
Strategic planning to determine the sequence, schedule and completion of activities to accomplish learning goals.
Self-evaluation to monitor the learning progress and outcome in relation to the defined learning goals.

3 The Status Quo of Learning Objectives in MOOCs

For the support of self-regulated learning in MOOCs certain approaches have been researched, for example a time planner to schedule the next learning session [22], recommendations of learning strategies [14] or personalized feedback with dashboards [2]. Yet, no approach is applied largely. Additionally, few related work is available which examines goal-oriented learning in MOOCs. This work aims to fill this gap by better supporting the strategies of goal-oriented and self-regulated learning in MOOCs. Therefore, this section investigates the current capabilities and limitations of goal setting and self-evaluation on a state-of-the-art MOOC platform before comparing the results with similar studies.

3.1 Evaluated Courses

To investigate the targeted and accomplished learning objectives of MOOC participants, five courses have been examined in this study (Table 1). These courses were conducted on openHPI[1], the MOOC platform of Hasso Plattner Institute. The taught topics are all based on the field of information technology and computer science and the required proficiency levels range from beginner to academic and professionals. In total, 25,801 learners had been enrolled at *course middle*. The *middle* is a course-specific date, which marks the last reasonable point to enroll for a course with the possibility to still gain a *Record of Achievement*. A *Record of Achievement* is issued to those who have earned more than 50% of the

[1] https://open.hpi.de/.

maximum number of points for the sum of all graded assignments. A *Confirmation of Participation* is issued to those who have completed at least 50% of the course material.

The first course, *Object-Oriented Programming in Java* (javaeinstieg2017), was a four weeks course for beginners running from March 27, 2017 through May 14, 2017. Every week introduced different Java language features and object-oriented programming concepts with video lectures, followed by self tests and online programming exercises. Most of the programming exercises were graded for the final certificate. Additionally, an optional team peer assessment was conducted, where learners had the chance to gain bonus points. A total number of 9,242 enrollments were taken at course middle. The next course was a two weeks workshop with the topic *Introduction into a Java IDE* (javawork2017). This course was held from May 01, 2017 through May 15, 2017 and built upon the taught concepts of the javaeinstieg2017 course. Thus, a basic knowledge about the Java programming language was recommended. The first two weeks showed practical knowledge with lecture videos, followed by ungraded self tests. At the end a graded peer assessment was conducted, which was the requirement to gain a certificate. 4,112 learners enrolled at course middle. The third course was a two week course as well, and addressed the question *How does a search engine work?* (searchengine2017) from May 29, 2017 through June 20, 2017. The course was designed to be an introduction of the topic for persons outside the discipline, but also as a starting point for professionals and academic people who want to get a first overview. The course structure followed the typical MOOC approach with consecutive videos and self tests. At the end a graded exam was performed and 4,145 participants had been enrolled at course middle. The fourth course about *Mainframes* (mainframes2017) was held from June 05, 2017 through July 27, 2017. This six weeks course provided an in-depth perspective on mainframe architectures, application development, databases, security and storage management. Thus, this courses mainly targeted academic and professional people. Next to the video lectures and self tests, a weekly graded assignment was conducted, as well as a graded exam at the end of the course. At course middle 3,026 learners had been enrolled. The *In-Memory Data Management* (imdb2017) course

Table 1. Evaluated courses

Course	Enrollments		No-Shows		Weeks	Language
	Middle	End	Middle	End		
javaeinstieg2017	9242	10402	2632	2387	4	German
javawork2017	4112	4336	2631	2241	2	German
searchengine2017	4145	4484	2443	1824	2	German
mainframes2017	3026	3396	1356	1281	6	German
imdb2017	5276	5825	2874	2697	6	English
Total	25801	28443	11936	10430	-	-

dealt with the management of enterprise data in column-oriented in-memory databases and their inner mechanics. The course was running for six weeks from September 18, 2017 through November 18, 2017 and 5,276 learners enrolled in it. Due to the specific technical focus, the target groups were academics and professionals. This course was graded by a weekly assignment and a final exam.

In summary, the evaluated courses provide a well-balanced data basis with different course lengths, target groups and proficiency levels, as well as different theoretical and practical examination modalities. All of them offered the two introduced certificate types: a *Record of Achievement* and a *Confirmation of Participation*. Table 1 also displays the number of enrollments and *no-shows*. Based on Hill's [8] definition of *no-shows* (learners who enrolled for a course but never viewed any content), an overall *show rate* of 53.78% at course middle was reached. Additionally, following the definitions of Renz, Schwerer, and Meinel [20] a total *completion rate* of 29.02% and *consumption rate* of 52.30% were measured. When comparing the *show rate* and *consumption rate*, it can be seen that almost all active learners that enrolled before course middle visited more than 50% of all learning content and therefore gained a *Confirmation of Participation*.

3.2 Methodology

When accessing one of the courses for the first time, a welcome text is presented to the learner with general information about the course. The following item is an optional pre-course survey, which asks the learner about its primary goal for the enrollment into this course amongst other general questions. Based on the platform's feature set and available certificates, four mutually exclusive objectives are provided:

Objective 1 – I would like to receive a record of achievement in the end and learn the course content.
Objective 2 – I am mainly interested in learning the course content. The record of achievement is not important to me.
Objective 3 – I am only interested in selected learning units.
Objective 4 – I just want to look around.

An overview of all criteria to achieve and to exceed the learning objectives is shown in Table 2. The achievement of objective 1 and 2 can be traced by course completion if a certain certificate was gained. To accomplish objective 1, a *Record of Achievement* needs to be reached. For objective 2 the assumption was made, that if a learner consumed the majority of learning content (50%), a *Confirmation of Participation* was achieved.

For the accomplishment of objective 3 and 4 a behavioral analysis based on user interaction events was conducted. To achieve objective 3, the user needs to watch at least 1 video lecture. This is the base unit to measure if the user consumed and interacted with any learning content since there is no platform feature available that enables the user to select the specific learning content she

Table 2. Criteria for learning objective achievement

Objective	Criteria to achieve objective	Criteria to exceed objective
Objective 1	Accomplish record of achievement	n/a
Objective 2	Accomplish confirmation of part	Accomplish objective 1
Objective 3	Watch at least 1 video	Accomplish objective 1 or 2
Objective 4	Visit at least 3 items	Accomplish objective 1 or 2 or 3

is interested in. For objective 4, the visit of at least 3 items is defined as the criteria to achieve the learning goal. This specific number was chosen because the first visited item is the welcome text when entering the course, the second is the survey itself, and the third item visit is the proof that at least one learning item was visited. These assumptions already show limitations of the platform regarding goal setting and evaluation.

By following this approach, no post-course survey was necessary to determine goal achievement of all students that responded to the pre-course survey. All measurements are based on platform data, which should reduce the influence of the survivorship bias. Therefore, it was not required that learners finished the course or sending a post-course survey via email to all participants.

3.3 Pre-course Survey

The results of the pre-course survey for every course can be seen in Table 3. A total amount of 9,698 users provided their learning objective. In relation to the total number of *shows at course middle*[2] (13,865) a response rate of 69.95% was reached. Between 22.52% and 36.03% stated, that they want to receive a *Record of Achievement* (objective 1), with a total result of 26.63%. The majority of users (61.54%) are mainly interested in learning the course content, without the need to gain a *Record of Achievement*, and therefore chose objective 2, ranging from 54.41% to 65.80%. Between 3.62% and 5.41% selected objective 3, since they are only interested in selected learning units, with a total result of 4.45%. At last, 7.37% stated that they only want to look around (objective 4), with a range from 5.94% to 10.74%.

3.4 Goal Achievement Analysis

When assessing the results of the pre-course survey, it is notable that only about one quarter of the users are interesting in a graded performance appraisal and considerably more than half of the users are mainly interested in the content itself without the need of a *Record of Achievement*. This reflects the varying learning objectives of lifelong learners since especially well-educated professionals

[2] Based on the *total enrollments at course middle* minus the *total number of no-shows at course middle* from Table 1.

form a large part of the learning community and not all of them are necessarily interested in gaining a certificate [4].

Table 3. Pre-course survey: what is your primary goal for the enrollment into this course?

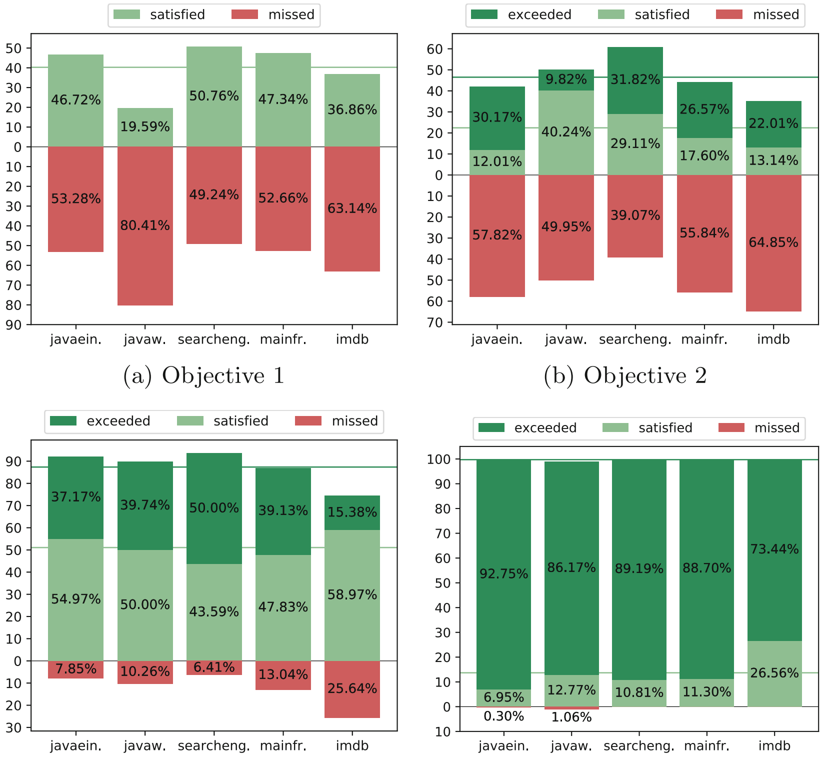
Course	Objective 1	Objective 2	Objective 3	Objective 4
javaeinstieg2017	1006 (22.52%)	2940 (65.80%)	191 (04.27%)	331 (07.41%)
javawork2017	342 (23.73%)	927 (64.33%)	78 (05.41%)	94 (06.52%)
searchengine2017	528 (32.18%)	924 (56.31%)	78 (04.75%)	111 (06.76%)
mainframes2017	319 (29.79%)	591 (55.18%)	46 (04.30%)	115 (10.74%)
imdb2017	388 (36.03%)	586 (54.41%)	39 (03.62%)	64 (05.94%)
Total	2583 (26.63%)	5968 (61.54%)	432 (04.45%)	715 (07.37%)

Table 4. Achieved learning objectives of all courses

Objective	Satisfied	Exceeded	Satisfied or exce.	Missed
Objective 1	1099 (42.55%)	n/a	1099 (42.55%)	1484 (57.45%)
Objective 2	1176 (19.71%)	1558 (26.11%)	2734 (45.81%)	3234 (54.19%)
Objective 3	223 (51.62%)	165 (38.19%)	388 (89.81%)	44 (10.19%)
Objective 4	77 (10.77%)	636 (88.95%)	713 (99.72%)	2 (00.28%)
Total	2386 (25.09%)	2359 (24.81%)	4745 (49.90%)	4764 (50.10%)

Few users stated that they are only interested in selected learning units or only want to look around. This may be related to the fact that at course start only the first week was available, and the remaining content followed week by week. This is a typical approach in MOOCs to foster discussions in the forum and support the mastery learning approach. Nevertheless, this reveals the shortcoming that at course beginn it is hard to get an overview of all content and topics that will be taught in the following weeks.

In Table 4 the overall goal achievement is displayed. At first, it can be seen that nearly half of the users achieved or exceeded their goals and the other half missed their objective. Also the total satisfied and exceeded achievements are almost equally distributed. From this insight it can be derived that there is a large user group that either changes their goal during course runtime or drop out due to course difficulty, poor time management, illness or other issues. In both cases it shows the limitation that learning objectives cannot be set in a proper way which allows the user to also adjust them at a later point of time. Nevertheless, the results show a big range when comparing the different learning objectives with each other since the objectives with the highest achievement rate required much less course activity and vice versa.



(a) Objective 1

(b) Objective 2

(c) Objective 3

(d) Objective 4

Fig. 1. Achieved learning objectives per course

Figure 1 displays the individual achievement rates for all courses, grouped by the defined objectives. These results are centered around a zero line in order to allow an easy comparison of the achieved learning objectives. Satisfying and exceeding a goal are stacked upwards, whereas missing a learning goal is stacked downwards. Additionally, the first horizontal line in the upper space marks the average mean of satisfying a goal, and the second line the average mean of satisfying and exceeding a goal combined. The specific mean values can be seen in Table 4. Compared with a standard deviation of 0.1155 for satisfying objective 1, it is notable that only the *javawork2017* course showed a greater deviation. This can be attributed to the fact that this course was only graded by a peer assessment, which required much more effort than a typical multiple choice examination. The highest achievement rate was reached by the *searchengine2017* course. This course was only graded by a single final exam without any weekly assignments, which reduced the required effort. The other three courses were graded by weekly assignments and a final exam. The achievement rates of objective 2 show a much higher variation, and objective 3 and 4 show overall high achievement rates, since these goals require less engagement. All in all, the individual achievement rates across the different courses point to the fact that goal achievement strongly depends on the course design, examination and difficulty of different goals.

3.5 Related Research

Obviously, a sample size of five courses does not allow to draw general statements about goal achievement rates in MOOCs. Therefore, related and similar studies are presented in this section. A case study by Wilkowski, Deutsch, and Russell [25] about one course showed that 52.5% of their participants ($N = 20,977$) intended to complete their evaluated course with a (free of charge) certificate, from which 27% met or exceeded this goal at the end. The other learners preferred to learn new skills or explore the course content. Combined with these students who targeted smaller learning goals, a total number of 42.4% met or exceeded their goals at the end. The authors recommended to offer more personalized course designs based on students' goals, to move beyond the one-size-fits-all approach in MOOCs.

Another study with 37,880 enrollments across six courses by Staubitz and Meinel [24] showed that only a few learners (0.64–1.24%) are interested in gaining a (charged) verified certificate to earn credits for their degree, on-the-job training or job applications. From the participants who booked this certificate option, between 63.3% and 92.0% gained a certificate at the end, whereby the paid fee increased the motivation. Henderikx, Kreijns, and Kalz [7] examined the success of two MOOCs based on the intention-behavior gap. In the first course 59% of their participants achieved or achieved more than initially intended ($N_1 = 65$). An even higher success rate of 70% was found in the second course ($N_2 = 101$). These results are based on a subset of learners who responded to the post-survey which leads to survival bias. Nevertheless, they "underline the importance of individual perspectives" and recommend to consider that "individual goal achievement does not necessarily matches goal achievement from the institutional perspective." Other studies, which measured certificate achievement based on students' self-reported intention to complete a course, found completion rates between 22 and 29% [19,26] or around 9% [15].

3.6 Discussion

To summarize regardless of the variation in the reported goal achievement rates, a substantial percentage of students both meet or exceed, or miss their goals in MOOCs. The specific ratio is course-specific and probably depends on the course design and difficulty. Nevertheless, this and related studies show the importance to better support the presented strategies for self-regulated and goal-oriented learning in MOOC environments. Thereby, different shortcomings have been identified.

Currently, goal setting is mostly done with a pre-course survey. This maybe helps the teaching team to get a broad insight into the overall motivation of their learning community. However, the learners have mostly neither a possibility to self-evaluate their learning process and outcome regarding their stated learning objective, nor be able to adjust their objective during the course runtime. Learner dashboards mostly focus on overall course completion [10], which does not reflect the objective of a large amount of learners, as the analysis has shown.

Also, the measurement of goal achievement is mostly done manually since the survey responses cannot be processed automatically. Sub-goals like the completion of a certain topic section or week are only provided if the teaching team prepares such survey answers. Generic answers like "I am only interested in selected learning units" as in this study include a certain bias since the learner is not aware of which selected learning units are available at all. Furthermore, some studies about strategic planning were briefly presented [14,22], but these were not a focus topic of this paper's analysis. However, strategic planning must be considered in a concept to better support personalized learning objectives, next to goal setting and self-evaluation.

4 A Concept to Support Personalized Learning Objectives in MOOC Environments

This section outlines a concept to support goal setting, strategic planning and self-evaluation, to implement goal-oriented learning as personalized learning objectives in MOOCs. It builds on top of the previously identified capabilities and shortcomings of MOOC platforms in general but with a technical focus on feasibility and automation in the context of the openHPI platform. Nevertheless, the introduced features should be realizable on any other MOOC platform as well.

4.1 Goal Setting

Currently, goal setting is mostly done with pre-course surveys in many MOOC platforms. This should be implemented as a course-independent platform feature, which offers the available learning objectives in a clear way. It needs to be studied if this should be a mandatory step, e.g. as part of the course enrollment process, or as an optional advice, which can be shown to the user while browsing through the course. Therefore, a multivariate experiment can be used to examine if this is accepted and used by all learners or only by a sub-group. Also, it should be possible to change the targeted objective at any given time. By implementing such a feature, goal setting does not need to be maintained by the teaching team as a survey anymore. Also, it is finally possible to evaluate the learning objectives inside the platform itself to further monitor the learning progress based on them.

In order to offer course-specific learning objectives, the learning content needs to be categorized and labeled first. Typically, knowledge transfer in MOOCs is based on video lectures and assessed with quizzes. Video segmentation is a well researched field, e.g. by visual transition detection [27], and can be further improved with outline extraction through analyzing the presentation slides [1]. Related quiz questions could be identified with natural language processing techniques. Also the course structure itself supports the categorization, since it already offers an order and titles for each learning item and section.

The biggest challenge could be a practical one: the availability of content. Quite often course content is provided and uploaded during the course runtime when users already started to learn. This is problematic with regard to the selection of learning objectives. It could be solved by either offering new goals as soon as they are available or by supporting the teaching team to implement a structured course outline before course start without the content. A course builder tool could enable to plan the weeks of a course ahead and help to enrich them with goal metadata. The requirements for such a tool should be developed in cooperation of real world teaching teams. Interviews are necessary to understand their production processes, dependencies and deadlines. However, these processes vary strongly between organizations and machine-based automations always come with a certain error-rate. Therefore it must be ensured that labeled content can be corrected and improved by human, either teaching teams or learners.

4.2 Strategic Planning

Strategic planning methods were identified as positive predictors of goal achievement [15]. Especially regarding learning objectives technical support to plan time management and effort regulation come in handy. Features like custom reminders, priorities and due dates for certain learning items or goals are straightforward to implement and well testable with control groups. Some first work was already done in this field [22] but needs to be carried out in-depth. To further increase learning efficiency, mobile learning can be used to integrate learning activities into daily routines, sending push notification as reminders or to parallelize learning tasks with second screen companion applications [21].

4.3 Self-evaluation

Learner dashboards are a common practice to monitor learning progress and goal achievement. The design and evaluation of such visualization tools can be done on different levels like metacognitive, cognitive, behavioral, emotional, self-regulative or tool usability. However, a strong mismatch between a dashboard's goal and its evaluation was identified in a literature review of 26 papers, for which reason Jivet et al. [10] proposed certain design recommendations. They emphasize dashboards as pedagogical tools designed on educational concepts, whereas the comparison with peers should be used with caution. Also, only a subgroup of learners will benefit at large from such tools and it should be integrated into the regular learning activities. To examine the overall tool, also Scheffel et al. [23] proposed an evaluation framework for learners and teachers. Nevertheless, goal monitoring and achievement was not considered in these studies.

A central course dashboard also provides the opportunity to become a personal assistant which helps to navigate through the course content. Next to such a central element, smaller widgets attached to the learning content could provide instant feedback about it and the individual performance. Additionally, when achieving a smaller learning objective a greater one could be promoted to further increase motivation and engagement. The technical foundation for such tools are advanced learning analytics capabilities, as presented in [20].

5 Conclusion

This paper introduced the potential of personalized learning objectives in Massive Open Online Course to shift the focus from completion-centered success rates based on gained certificates to individual course goals which better accomplish the needs of lifelong learners. Therefore, the current status quo of learning objectives in MOOCs was examined with an observational study of five courses how well learners in MOOCs achieved their initially intended learning objectives. The results and the comparison with similar studies show that goal achievement rates are course-specific and likely depend on course design, examination modalities and difficulty. In total, almost 70% of all active learners at course middle provided a course objective ($N = 13,865$). 49,90% of learners achieved or exceeded their goals, but also the effort required for a specific goal heavily affected the achievement rates. Nevertheless, technical support for personalized learning objectives is rare. Most studies rely on self-reported data from user surveys, which does not allow to provide feedback based on the selected goals and also the teaching team cannot draw any further conclusions about progress and success afterwards.

From a pedagogical perspective, self-regulated and goal-oriented learning were identified as critical skills for learner achievement, especially in online learning environments with low guidance and support like MOOCs. Therefore, the strategies goal setting, strategic planning and self-evaluation were outlined with possible implementations in a concept to support personalized learning objectives in MOOCs. Thereby, the focus was set on technical feasibility and automation to provide such functionality on a platform level instead of individual course designs by different teaching teams. This should pave the way for further research in this field and support the transition from a one-size-fits-all approach in online learning at scale to a more individual learning experience tailored for the needs of lifelong learners.

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