Using Log Data to Evaluate MOOC Engagement and Inform Instructional Design

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ABSTRACT: Traditional educational studies verify the performance of courses through questionnaires, interviews and observations, which can be an arduous task for researchers. It is easier to verify the effectiveness of online courses as all the interactions between students and the courseware are recorded. However, the utilization of these activity data is lack of theoretical framework. In this paper, we propose to utilize learning interaction theory and web analytics knowledge to evaluate MOOC engagement and inform instructional design. This framework is composed of learner-interface, learner-content and learner-community interaction. 15 indicators derived from web analytics are proposed to help teachers better understand the engagement level of their courses in three interaction dimensions.

To illustrate how the above analysis can facilitate teaching in practice, we used log data of 10 MOOCs owned by The University of Hong Kong on edX. Results and corresponding insights are offered. 10 experts are invited to evaluate the proposed framework. Most of them have showed positive attitudes. In the future, we will cooperate with MOOC designers and verify whether this framework can help them teaching and improve MOOC engagement.

Keywords: MOOCs, Log Data, Learning Analytics, Learning Design

1 INTRODUCTION

The flexibility of the learning conditions and the ability to record and process a large amount of data are two major advantages of online learning over traditional learning. Traditional educational studies analyze the learner behavior through expert observations, questionnaires, interviews and other methods (Lodico & Voegtle, 2010). These methods require substantial efforts and generate overestimated results since less motivated students are less likely to participate in the surveys or interviews. Compared with these methods, it is easier for online behavior analysis to generate unbiased results as all students' online behaviors will be analyzed. Since all the data is automatically stored in LMS, data collection is relatively effortless.

Online behavior analysis can facilitate MOOC development in two ways: (1) building a real-time learning dashboard to help teachers monitor the learning status of the whole class (Schwendimann et al., 2017); (2) generating the course's report every year or semester which can help teachers review the performance of their courses. Molenaar et al., (2018) proved that dashboards can influence teaching progressively. Ogata et al., (2018) have proposed the Learning Evidence Analytics Framework (LEAF) for evidence-based education. However, there were little details on how to extract evidences from log data. In addition, the indicators adopted by existing dashboards remained also lack of theoretical framework. Therefore, it is necessary to adopt a theoretical framework with higher level indicators to verify the engagement of online courses.

There are many engagement studies examining the interaction in distance education. Interaction has been considered as one of the most important components for effective traditional learning and online learning. Moore (1989) proposed that learning process should be classified into three types of interactions (learner-content, learner-learner and learner-instructor interaction). A new type of interaction, learner-interface interaction, has been identified in distant education (Hillman et al., 1994). This theoretical framework can be utilized to evaluate the engagement performance of online courses and offer actionable insights to teachers.

We utilize the knowledge of web analytics and learning interaction theory and to propose a MOOC engagement evaluation framework. In detail, the major contributions of this paper can be summarized as follows:

- We re-define four web analytics terminologies in the learning context which help develop indicators for online courses evaluation framework and teacher-facing dashboards;
- We utilize the learner interaction theory to propose a MOOC engagement evaluation framework to verify the engagement of MOOCs in learner-interface interaction, learner-content interaction and learner-community interaction;
- We use 10 MOOCs' log data to demonstrate how to conduct the behavior analysis with the MOOC engagement evaluation framework and identify the strengths and problems in these courses and their course components.

The rest of the paper is organized as follows. In Section 2, we give a short introduction of the dataset involved in this study. In Section 3, we re-define the web analytics terminologies in the online learning context to facilitate evaluating online courses' performance. We utilize the learning interaction theory to propose the course evaluation framework in Section 4. The implementation of the above framework is described in Section 5 and conclusions are given in Section 6.

2 DATASET DESCRIPTION

Ten MOOCs owned by The University of Hong Kong on edX are analyzed in this study. Overall, our dataset contains around 20 million logs generated by 30450 students. The rich diversity of these ten MOOCs can be reflected in academic category, instructional design, duration, availability of historical data, etc. Details of the ten MOOC information can be checked in Table 1.

Table 1: Details of the 10 MOOCs.

cid	course id	#students	Days
0	HKU01x/14	5521	73
1	HKU01x/15	2936	80
2	HKU02.1x	2564	37
3	HKU02.2x	1260	41
4	HKU03x/15	3803	70
5	HKU03x/16	2213	63
6	HKU04x/15	3571	49
7	HKU04x/16	2000	38
8	HKU05.1x	4927	42
9	HKU06.1x	1497	42

3 WEB ANALYTICS IN ONLINE LEARNING

Traditionally, researchers verified the effectiveness of courses via students' academic performance, questionnaires and interviews. However, it is not applicable for MOOCs as not many MOOCs contain compulsory and rigid assessments. Therefore, we need to verify the engagement of MOOCs without assessment data. To solve this problem, web analytics knowledge is involved as online courses share the same major data source (log data) with web analytics.

Web analytics is defined as the assessment of a variety of data to help create generalized understanding of the visitor experiences (Peterson, 2004). With web analytics, people can verify the engagement of their online marketing campaigns for continual improvement. If we consider each course as a website and each learner as the website visitor, we can easily measure the engagement with web analytics indicators. In the following part, we will first give the online learning context definitions of four important web analytics concepts:

- **Session/Visit**: When a learner triggers the next event within 30 minutes, these events will be considered as within one session/visit. The intention is to avoid the cases where students may have left the system but have not logged out. This can be shown as long staying time without triggering any events. Average number of sessions can reflect the course's ability in keeping learnings frequently checking the courseware. In addition, average duration of sessions can be considered as the rough learning time of students. Courses with longer average session can be considered as more attractive in gaining learners' attention.

- **Page View**: In web analytics, a page view is considered as one load of a web page. The interpretations of a page are different in different platforms because of the different course structures. Since we extracted the data from edX, one page is identified as one subsection in this study and correspondingly, one page view is one view of the loaded subsection.

- **Interested/Time-engaging Learner**: A learner who spends more than *n* minutes will be considered as an interested/time-engaging learner. The Interested learner proportion can be an important indicator to measure the possibility of the courses in attracting learners' attention to stay longer. Unlike web analytics, we will use the median time student spent across courses instead of the average time student spent as the value of *n*.

- **Heavy/Action-engaging Learner**: The learner with more than *n* events will be regarded as heavy or action-engaging. The heavy/action-engaging learner proportion is the percentage of learners who trigger more than n events. It can be used to measure the ability of courses in driving learners to actions. The median number of events students triggered will be the threshold to distinguish whether learners are action-engaging.

4 MOOC EVALUATION FRAMEWORK

Interaction plays a very important role in traditional classrooms and distant education. Many researchers have dedicated on interaction studies in learning context. One of the most classical studies is proposed by Moore (1989). He classified learning interactions into three types: learner-content, learner-instructor and learner-learner interaction. Furthermore, learner-interface interaction has been identified as the fourth type of interaction in distant education (Hillman et al., 1994). These categorizations can help us verify the engagement of online courses.

First, we need to map the learners' online activities with these four types of interactions. Students' interactions with the courseware belong to the learner-interface interaction while students' activities with htmls, videos and problems belong to the learner-content interaction. As all the learner-instructor and learner-learner interactions happen in the forum, we merge them into learner-community interaction. Therefore, our evaluation framework measures the learning engagement of MOOC in learner-interface, learner-content and learner-community interaction. Each type of interaction will be measured based on several indicators. The indicator summary of each interaction type is given in Table 2.

Table 2: Indicators of learner-interface, learner-content and learner-community interaction.

Learner-Interface Interaction	Learner-Content Interaction		Learner-Community Interaction
• weekly time spent • triggered events • active learner proportion • time-engaging learner proportion • action-engaging learner proportion	html	• active reader proportion • average page views	• forum active learner proportion • number of learner posts • number of instructor posts • average replies of threads
	video	• active watcher proportion • average page views	
	problem	• active problem-solver proportion • average triggered events	

4.1 LEARNER-INTERFACE INTERACTION

In learner-interface interaction, general learning activities between students and the courseware are considered. This type of interaction was recognized by Hillman (1994). Students' learning experience with interface can be identified via the following five aspects:

- **weekly time spent**: It refers to the total staying time of all sessions over the past complete week. It is assumed that students will spend more time in the course if they find the course attractive. Therefore, this indicator can reflect whether a course is time level engaging;

- **total triggered events**: This indicator is the number of events learners have triggered across weeks. We will compare the average total triggered events among courses. Courses with higher total triggered events can be considered more action level engaging;

- **active learner proportion**: Active learners are the learners who access the courseware at least once. This concept has been widely used in the domain of learning analytics, such as edX Insights[1]. The active learner proportion is the ratio of active learners to all registered learners. We adopted the active learner proportion to better compare among courses;

- **time-engaging learner proportion**: This is the percentage of learners who spend more than *n* minutes in the course. A course with higher time-engaging learner proportion can be more attractive. We use the median duration of all sessions (25 minutes) in the dataset as *n*.

- **action-engaging learner proportion**: A learner who triggers more than *n* events is an action-engaging learner. Higher action-engaging learner proportion indicates the course is well designed in driving students into actions. Here, *n* is median triggered events (20) in dataset.

4.2 LEARNER-CONTENT INTERACTION

[1] https://insights.edx.org/courses/

Activities where learners encounter with learning materials are considered in the learner-content interaction, such as watching the video, answering the MCQs, etc. This interaction is considered as one of the most key factors in learning process (Moore, 1989).

Basically, there are three common types of course materials in online learning environments which are html (static course content), video and problem. Different courses have different proportions of these materials. We will assign indicators based on the type of course materials. Details of these three types and corresponding indicators are given below.

4.2.1 Interaction with htmls

For online courses, pages with static course content (slides, reading materials, etc.) will be considered here. Interactions with such materials include viewing and closing the pages. Therefore, how many learners access the html and how many times they viewed are considered to measure the engagement level between learners and static course content.

- **active reader proportion**: Learners who have accessed the page will be considered as active of the corresponding html. The active reader proportion can give teachers an overview on their static course content' s ability in attracting learners' attention. If reading and guiding materials are attractive to learners and have high referring ability, learners will be willing to access more htmls which. This can be reflected as high average active reader proportion;

- **average page views**: Different from active reader proportion, this indicator measures the htmls' ability in keeping learners coming back. Reading materials with high average page views can be informative or interesting and motivate learners to repetitively read it.

4.2.2 Interaction with videos

Video lectures have been considered as one of the most important online learning materials (Wang & Kelly, 2017). Unlike htmls, students have more interactions with video (play, pause and jump). Due to the limitation of edX, the exact watching duration cannot be derived from log data. Thus, we measure learner-video interactions via active watcher proportion and average page views.

- **active watcher proportion**: It refers to the students who have played the video. This indicator can help us measure the referring ability of videos. If the videos have high referring ability to other videos, learners tend to access other videos after watching one and this will be reflected as high overall active watcher proportion;

- **average page views**: This indicator refers to the number of times active learners have watched the video. Reloading and refreshing video behaviors are filtered out. Videos which has high average page views can be considered as well delivered.

4.2.3 Interaction with problems

Problem is a more active learning material format compared with html and video. The participation rate is used to evaluate the interaction between students and problems. As some of the problems are in the participation level without grading, the rate of correctness is not considered here. The problem interaction is measured via the following metrics.

- **active problem-solver proportion**: Learners who manipulate with the problem will be considered as active problem-solver. Active problem-solver proportion is the participation rate of problems. If the course has high participation rate, it may indicate that this course can motivate learners to actions;

- **average triggered events**: Well-designed problems can increase students' motivation to interact with problems and reflect as high average triggered events. However, if the number of triggered events is too high, it may indicate that learners are gaming the system and such behaviors should be filtered out.

4.3 LEARNER-COMMUNITY INTERACTION

The learner-community interaction is the combination of the learner-learner interaction and learner-instructor interaction. Feeling of isolation is one of the biggest concerns with online education (Hodges & Kim, 2010). Therefore, it is very important for us to measure the engagement of learner-community interaction. In forums, learners discuss course content and build connection with fellow participates while instructors monitor the dynamics of the course and offer some help to students who encountered problem in real time (Almatrafi & Johri, 2018). We measure the learner-community interaction based on the following metrics:

- **active learner proportion**: It refers to the number of learners who are active in the forum to all learners. Students who create the thread, reply others, vote, etc. are considered as active in the forum;

- **number of learner posts**: Posts refer to thread, reply and comment. Total number of posts can reflect the active level of the forum;

- **number of instructor posts**: Staff's posts can boost learners' participation to a certain degree (Almatrafi & Johri, 2018). We use the number of instructor posts across courses as one of the indicators to measure the interactions between learners and instructors;

- **average replies of threads**: Number of replies from classmates or teachers and the average reply time of each thread can measure the level of interaction between students and the community (Idowu & McCalla, 2018). For the sake of convenience, we used the number of replies of threads to measure the engagement level of forum.

5 PRACTICE OF MOOC EVALUATION FRAMEWRK

The engagement of 10 MOOCs are evaluated with the framework in Section 4. Insights are offered to demonstrate how this framework can facilitate teaching and instructional design. As the original course id is long and difficult to be shown in the figure, we use a number (cid) to represent a course.

5.1 LEARNER-INTERFACE INTERACTION COMPARISON

We utilized five indicators introduced in Section 4.1 to measure the engagement of ten MOOCs in learner-interface interaction. The results are displayed in Figure 1 and insights are as follows:

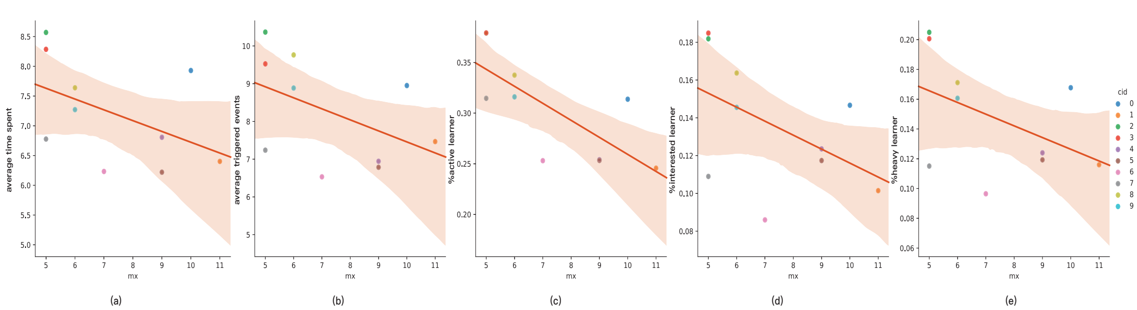

Figure 1: Comparison of the learner-Interface interaction

- Online engagement has roughly negative relationship with course duration as shown in Figure 1. It may be better to split the long duration MOOC (e.g., 10-12 weeks) into several short MOOCs (e.g., 4-5 weeks). HKU2.1x (cid: 2) and HKU2.2X (cid: 3) are two parts of the one MOOC. After splitting into two MOOCs, students' engagement with interface has been continually high during the whole process. Thus, teachers may avoid making their MOOCs too long in duration (e.g., 10-12 weeks) and try to split into several short duration MOOCs;

- It is necessary to make certain changes or improvements based on students' performance in the previous cohorts. HKU01x/14 (cid: 0) and HKU01x/15 (cid: 1) belong to the same MOOC. With no changes in the second run (HKU01x/15), all parameters except active learner proportion have decreased indicated by the independent t test results (weekly time spent: $t=8.124$, $p<0.001$; average triggered events: $t=7.861$, $p<0.001$; time-engaging learner proportion: $t=2.12$, $p<0.05$; action-engaging learner proportion: $t=2.197$, $p<0.05$);

5.2 LEARNER-CONTENT INTERACTION COMPARISON

Learners' interactions with learning content are evaluated based on the material type. As html, video and problem are three types of learning materials, we will discuss them separately. With the indicators mentioned in Section 4.2, we can evaluate the engagement of learner materials on single file level, section level and course level. For convenience's sake, learning materials are evaluated on the course level in this paper.

5.2.1 Learner-Html Interaction Comparison

We use active reader proportion and average page views to measure learner-html interaction. Results are displayed in Figure 2 and insights are as follows:

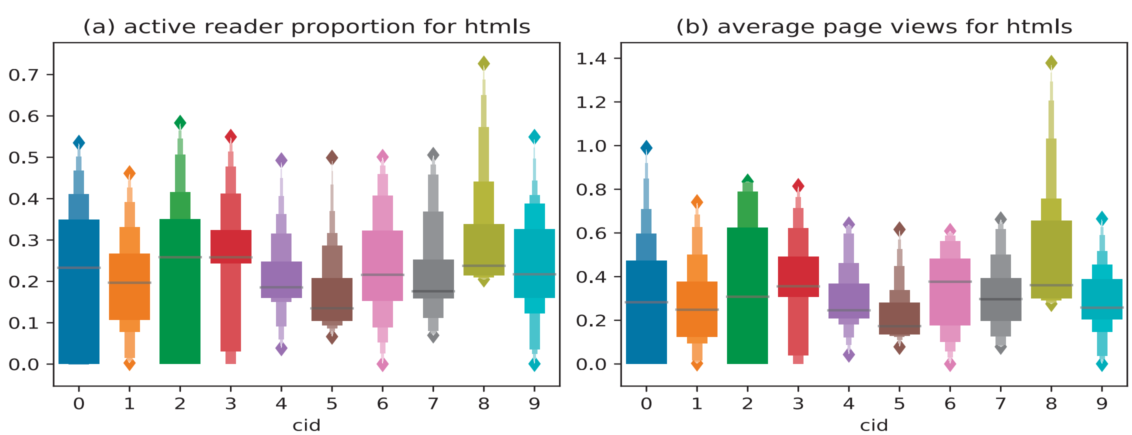

Figure 2: Comparison of the learner-html interaction

- Static course content of HKU06.1x (cid: 9) should be re-designed. From Figure 2(b), it has the lowest average page views among 10 MOOCs and most of its page views are less than 1.3. After checking this course, we found that the potential problem may be (1) the guiding materials are a short description of corresponding section content without any encouraging words and figures and (2) the recommendation list is too long (over 20 materials) while without pointing out the relationship between course content and recommendation materials. Instructors can make corresponding changes to static course content.

5.2.2 Learner-Video Interaction Comparison

Learner-video interactions are evaluated based on two indicators: active watcher proportion and average page views. Figure 3 displays the comparison results and insights are as follows:

- Different sessions of the same course tend to have the similar active watcher proportion and average page views (cid: 0-1, 2-3, 4-5, 6-7). The possible reason would be that video lectures will not be changed in the re-runs;

- HKU03x/15 (cid: 4) and HKU03x/16 (cid: 5) should improve the referring ability among video lectures. Though the active watcher proportion of these two courses are low (around 0.1), the average page views are high in Figure 3. It indicates that learners who have watched their videos like their videos and repeatedly watch them. However, most of learners did not access their videos. Instructors may improve the referring ability among video lectures so that learners can access more videos after watching one.

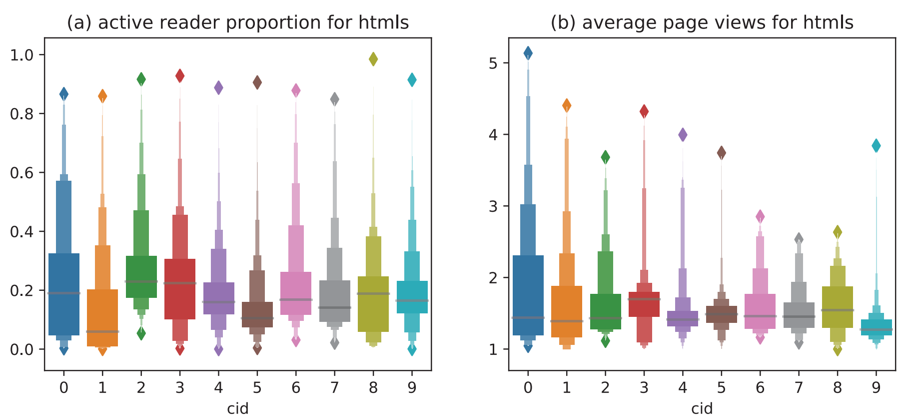

Figure 3: Comparison of the learner-video interaction

5.2.3 Learner-Problem Interaction Comparison

Indicators introduced in Section 4.2.2 are involved to evaluate the engagement level of learner-problem interaction. Results are depicted in Figure 4 and insights are as follows:

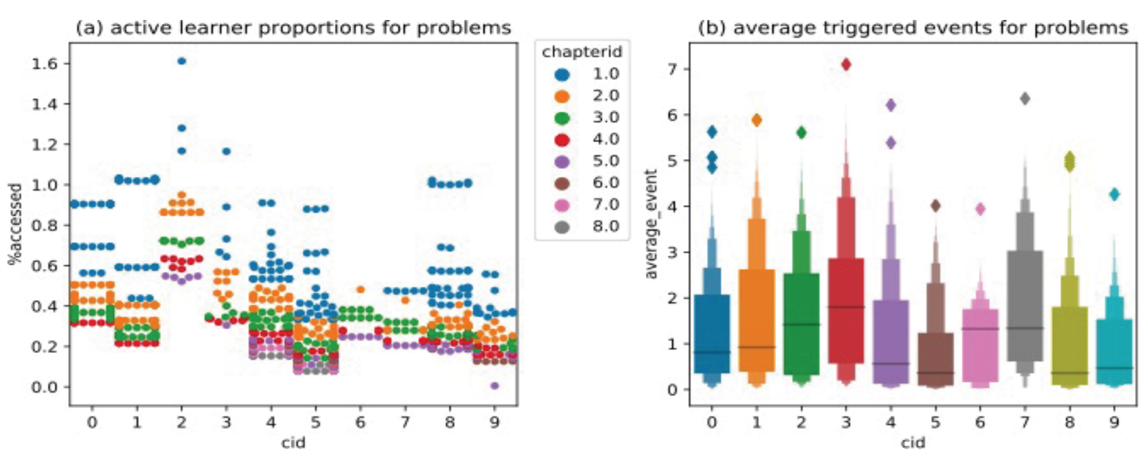

Figure 4: Comparison of the learner-problem interaction

- The active problem-solver proportion is highly correlated with the delivering time. The active problem-solver proportion gradually decreases when the chapter id [2] becomes larger. Teachers can utilize this to better design their problems;

- Teachers need to focus on the quality of problems. In Figure 4, one dot represents a problem. We can see that there is no direct relationship between the number of problems and active problem-solver proportion or average triggered events from Figure 4;

- Instructors of HKU04x/15 (cid: 6) and HKU04x/16 (cid: 7) can consider revising problem formats and content. In Figure 4, their active problem-solver proportion remains low. After checking the course contents, the possible reason is that all problems of this course are text input which need many steps to finish. Therefore, learners are less willing to attend even in the first week. It will be better if teachers can reduce the steps of text input questions.

5.3 LEARNER-COMMUNITY INTERACTION COMPARISON

Lastly, we compared 10 MOOCs' learner-community engagement level using the five indicators introduced in Section 4.3. Results are displayed in Figure 5 and insights are as follows:

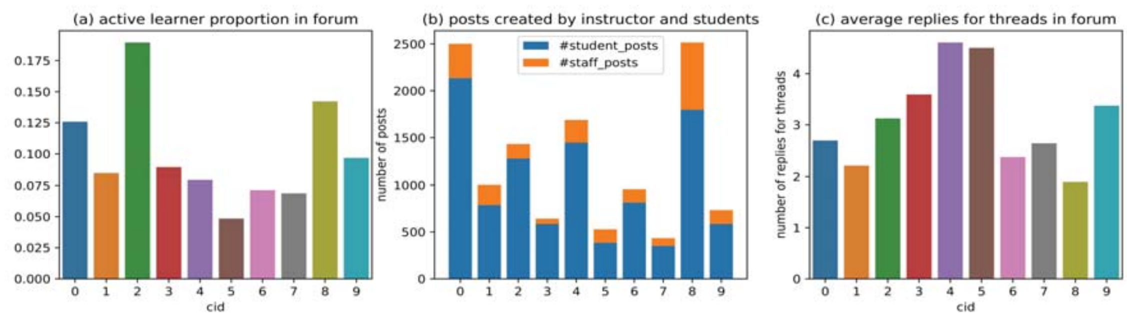

Figure 5: Comparison of the learner-community interaction

- From Figure 5, the active learner proportion and total number of posts in forum are relatively higher when there are more staff's posts;

- Teachers of HKU03/16 (cid: 5) should offer one forum entry below the course materials. In Figure 5, active learner proportion in forum and total number of posts are low compared with other MOOCs which have the similar number of staffs' posts. After observing its course forum, we found that instructors generated many posts in the forum. However, few learners have noticed those posts because it is not part of the course activities. From Figure 5(c), average replies of threads in this course are high. This indicates that learners who noticed the discussion in the forum are willing to share their thoughts in the forum.

5.4 MECHANISM EVALUATION OF THIRD-PARTY EXPERTS

To verify the effectiveness of our framework, ten third-party instructional designers are invited to comment on the framework and insights we displayed before. Nine of them showed positive attitudes on the framework and were willing to use the framework for their next MOOC while the remaining expert preferred utilizing log data by herself to observe students' behaviour. 4 experts held high expectations for clickstream data. They believed it would reduce teachers' burdens and generate more objective results. Some of them also mentioned that clickstream data can tell the teachers what

[2] The order of delivering time. Welcome and Farewell sections are not considered here

happens in the course but cannot identify the specific reasons behind. To find the reason, they would like to discuss with data scientists and verify the potential reasons by traditional approach (interviews, questionnaires, etc.). Therefore, we plan to cooperate with more MOOC instructors and check whether this framework will help them teaching.

6 CONCLUSION

In this study, we utilize the learning interaction theory first proposed by Moore to evaluate the engagement level of MOOCs in three dimensions (learner-interface, learner-content and learner-community interaction). 15 indicators are proposed based on web analytics and assigned to each dimension of the framework.

We demonstrate how to utilize the engagement evaluation framework with 10 MOOCs' log data offered by HKU. Some insights are derived, such as courses with short duration (4-5 weeks) tend to have higher engagement in terms of learner-interface interaction. It may be better to split the long duration MOOC (10-12 weeks) into several short MOOCs. 10 experts are invited to give comments on the proposed framework and 9 of them showed positive attitudes. Some experts have concerns about finding the specific reasons behind the bad performance. Therefore, we are considering cooperating with MOOC instructors to use our framework and further check whether there will be improvement in engagement after instructors adopting the framework.

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