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Integrating Survey and Learning Analytics Data for a Better Understanding of Engagement in MOOCs

Samoilova, E., Keusch, F., & Kreuter, F.

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University of Mannheim

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1. Introduction

While the popularity of MOOCs (Massive Online Open Courses) is increasing among both traditional and non-traditional university students, relatively low completion rates are often mentioned as a key point of criticism (Bates, 2012). Despite the prevalence of these unfavorable views, there is a growing body of research that explicitly focuses on the heterogeneity of learners that goes beyond an oversimplified categorization of participants into completers and non-completers (Koller, Ng, Do, & Chen, 2013; Kizilcec, Piech, & Schneider, 2013). Given different backgrounds, intentions, skill levels, and constraints of learners, one of the prerequisites for further improvement of MOOCs is a better understanding of how different subpopulations of learners interact with course components (Kizilcec et al., 2013) and what accounts for observed behavioral differences. To address this problem, researchers and practitioners use two main types of data: learning analytics (see Long & Siemens, 2011) and survey data. Although learning analytics provides new and innovative ways of measuring learning behavior, measurements of subjective states (e.g., believes about teaching and learning or course satisfaction) are still primarily based on survey data. For example, learner intention[1] (Koller et al., 2013; Reich, 2014; Kizilcec & Schneider, 2015) is considered to be one of the key pieces of information needed to understand retention and engagement in MOOCs. This construct is currently measured via web-based surveys of registered MOOC participants. The major challenge of using survey data to study MOOCs are very high unit non-response rates. Depending on whether the survey is conducted at the beginning or at the end of the course, papers report response rates in the range between 4 and 30 percent (Breslow et al., 2013; Reich, 2014; Kizilcec & Schneider, 2015). Such response rates are potentially problematic, as survey methodologists warn that low response rates might lead to non-response bias (see Groves & Peytcheva, 2008). While quality and interpretation of learning analytics data has been receiving some attention in the literature (DeBoer, Ho, Stump, & Breslow, 2014), survey data in MOOCs are often taken at their face value.

Drawing on data from the first session of the Coursera MOOC *Questionnaire Design for Social Surveys*, this chapter aims to demonstrate the importance as well as potential challenges of complementing learning analytics with survey data in studying engagement in MOOCs. Using activity logs and data from the pre- and post-course survey of 16,846 registered course participants, we examine the relationship between participation in course evaluation surveys and student behavioral engagement in the course. The findings suggest that for the given Coursera course the vast majority of our survey data stems from the most engaged students. The post-course survey data is almost entirely limited to most engaged students. In other words, our knowledge about the student subgroups who might need more support to successfully participate in the course is scarce. In the discussion section, we address possible approaches to collect relevant data on less engaged learners, in order to understand their challenges. In addition, we also discuss how in future engagement research, survey response rate can be used as a predictor to better understand engagement.

[1] While some authors use “intention,” “motivation,” and “goals” to refer to the same concept of participants’ intentions of participating in a course, we prefer to use “intention,” as the other two constructs are much broader than their use in the context of engagement.

2. Measuring success of MOOCs

In the first years of their existence MOOCs were praised for their potential to democratize education (Koller, 2013). Most MOOCs are undergraduate-level courses in various disciplines administered online and open to everybody without formal restrictions or required costs. Easy accessibility of such courses as well as high involvement from world leading universities in offering MOOCs raised hopes that this recent innovation can help reduce education gap. One of the most cogent criticism however that MOOCs faced in the first years of their advancement included very low completion rates (Koller et al., 2013). While thousands of students could join a single course at the same time, average completion rates are currently about 15 percent (Jordan, 2015).

These low completion rates are indeed alarming when viewed within the traditional education framework (Koller et al., 2013). Yet, MOOCs can hardly be measured against traditional standards, as they take place within much less formal settings (see Sefton-Green (2010) for more on informal education). Increasing spread of Internet access paired with increasing online learning offers made informal (out-of-school) learning more widespread (Means, Bakia, &, Murphy, 2014). As Collins and Halverson (2009) argued, this type of learning enabled by new technologies can be characterized (among other features) as interest-driven. Means et al. (2014) further described this type of learning as “self-directed” and “self-initiated” (p. 73). The authors have also identified at least five possible intentions associated with out-of-school learning: “episodic learning to satisfy curiosity; learning as entertainment; learning to enable better living; learning for professional advancement; and learning to reinforce or substitute for formal instruction” (p. 73). While all five categories can be thought of as intentions to prompt MOOCs learners to start and/or persists in a course, the main intention in traditional formal education is usually reduced to acquiring a degree. Consequently, using traditional metrics such as completion rates to evaluate success of MOOCs is clearly not tenable and should be replaced with better fitted measures (Breslow et al., 2013, Koller et al., 2013).

Acknowledgment of the vast learner diversity as well as the informal setting in MOOCs is mostly reflected in research on engagement. Engagement has been one of the central topics in studying learning in traditional as well as online classrooms. Although engagement is often defined in different ways (see Ainley, 2012; Skinner & Pitzer, 2012), this concept is primarily used to refer to one’s interactions with the learning environment (Järvelä & Renninger, 2014). In this chapter, we follow one of the most commonly used definitions of this construct in learning literature that acknowledges behavioral, cognitive, and affective aspects of engagement (Fredricks, Blumenfeld & Paris, 2004).

Most empirical studies on this subject focused on behavioral patterns of engagement aiming to problematize a dichotomous (completer versus non-completer) description of the MOOC learners. One of the most influential papers on behavioral engagement in MOOCs (Kizilcec et al., 2013) analyzed data from three of Stanford’s courses in computer science and identified four main groups of learners: completers, disengaging, auditors, and samplers. Completers were similar to common expectations with regards to traditional students. Although they had different levels of performance they all at least tried to engage with all of the course assignments. Disengaging students first showed the same patterns as completers, but then disengaged or completely disappeared from the course. While auditors engaged with lecture videos throughout the whole course period, samplers watched only few lectures. Anderson, Huttenlocher, Kleinberg, and Leskovec (2014) looked at three courses in a large scale quantitative analysis on one of the most popular MOOC platforms *Coursera*. They identified a slightly different pattern with five groups including viewers (same as auditors described above), solvers (students who engage in the assignments such as for example quizzes but do not engage in lecture videos), collectors (students who primarily download videos), all-rounders (those who equally engage in both lecture videos and assignments), and bystanders (participants who disappear after having registered for the course). Yet another approach to categorize behavioral engagement focused on the amount of time that learners use for various activities (Breslow et al., 2013).

While a taxonomy of behavioral engagement is clearly a better way to evaluate the quality of MOOCs when compared to course completion rates, we know very little about sub-groups of learners involved in the identified patterns of engagement. In other words, given a possibility of various intentions and backgrounds of the learners, especially in informal settings, interpreting a particular engagement or disengagement pattern as alarming is not a straightforward process. In other words, limited engagement in MOOCs for certain sub-groups does not necessarily mean lower satisfaction and a need for improvement. In order to fully understand engagement in MOOCs, research needs to consider non-behavioral aspects of engagement as well as learners' indentions that are closely intertwined with their behavior.

3. Measuring engagement and students' intention in MOOCs

Most data used to measure behavioral engagement in MOOCs come from activity logs collected during the course. Activity logs can include (yet are not limited to) clickstream data, text data from discussion forums, as well as log files with achievement results (e.g., grades). Such "pre-existing, machine-readable data" (Ferguson, 2012, p. 305) lead to the emergence of the entirely new field of learning analytics. The 1st International Conference on Learning Analytics and Knowledge defined learning analytics as "the measurement, collection, analysis and reporting" of learners' data (as cited in Long & Siemens, 2011, p. 34). Learning analytics data - considered a form of *found* (Japec et al., 2015) or *organic* data (Groves, 2011a; Groves, 2011b) in survey and data research communities – proves not only to help answering existing research questions, it also enables educational researchers to approach new ones. The research on typologies of behavioral engagement in MOOCs described above can hardly be imagined without available learning analytics data. Nevertheless, these sources of data are not well-suited (at least at the moment) to tackle measurement of subjective (non-behavioral) states. Therefore, survey data (when collected and analyzed properly) can provide higher quality measures for research questions concerned with learner intention or non-behavioral engagement. It is hence not surprising that the few existing attempts to collect data on intentions in MOOCs use survey instruments (Reich, 2014; Ho et al., 2015; Kizilcec & Schneider, 2015).

The major challenge of using survey data to study MOOCs are very high unit non-response rates, that is, students not participating in course evaluating surveys. For example, in the above mentioned studies of intention Reich (2014) reports a survey response rate of 27 percent, while Kizilcec & Schneider (2015) conducted surveys with less than seven percent. The survey response rate is an important indicator of survey data quality, as high non-response rates can indicate a potential non-response bias, defined as the difference between the estimate obtained from the data of respondents and the "true value" in the entire sample including non-respondents (Groves et al., 2009). In other words, non-response is a problem when non-respondents systematically differ from the respondents in the variables of interest. In the following two sections, we describe the use of the data from a social science Coursera MOOC to study the relationship between survey response rates and students' behavioral engagement.

4. Methodology

The data for this study come from the first session of the *Questionnaire Design for Social Surveys* MOOC taught by faculty of the University of Michigan in summer 2014. Overall, 16,846 international participants were enrolled in the course. The course is aimed at students and professionals from various disciplines involved in primary data collection. Topics covered in the course include the basic elements of designing and evaluating questionnaires. The course was composed of six unit weeks. Each unit contained a number of short pre-recorded video lectures, recommended readings, and quizzes addressing the unit content. The final exam was placed at the end of the sixth week and was aimed to cover content of the entire course. In addition to the quizzes, students had to engage in a peer-review project. 48.6 percent of the participants engaged in at least one of the course activities. 51.4 percent of the enrolled participants did not attempt to start any videos, did not submit any of the quizzes, and did not participate in the peer-review project. 0.3 percent (n=50) of people enrolled received a passing grade at the end of the course for finishing all required assignments (quizzes, final exam, and peer-review project).

Available learning analytics data included activity logs of the learners. Activity logs are comprised of submission data for the weekly quizzes and final exam, the peer review assignment, as well as data indicating whether the students attempted to view a video (i.e., downloaded or started streaming). It is important to note that in 2014, no detailed clickstream data for video watching were available, which would allow specific behavior such as for example pausing or percentage of the played material.

The survey data came from the pre- and post-course surveys. Both surveys were based on self-administered online questionnaires. The pre-course questionnaire included 15 questions mostly focused on the demographic questions of the user. The invitation for the survey was sent via email at the start of the course, which means that students could participate in the survey any time and not necessarily before they started working on the course material. The post-course questionnaire comprised 20 questions addressing various aspects of learners' course experiences. The invitation for the survey was sent after the course ended to all of the participants regardless of their engagement level. Both learning analytics and survey data included secondary data collected and anonymized by a Coursera team. Linking data was possible due to an existing ID assigned to each participants. The study was reviewed and considered as exempt by the Health Sciences and Behavioral Sciences Institutional Review Board (IRB-HSBS) of the University of Michigan. Although it is tenable to expect a higher response rate for the pre-course survey, the observed differences in the response rates for the two surveys are very large. While only 2.4 percent (n=406) of the enrolled students responded to the post-course survey, the response rate for the pre-course survey is 31.4 percent (n=5282). The post-course survey participants are not a complete subset of the pre-course survey participants, 75.3 percent (n=305) of those who responded to the post-course survey also responded to the survey at the start of the course. The distribution of the key demographic variables of the post-course respondents (based on their pre-course survey responses) is very similar to that of the pre-course survey respondents. As Table 1 demonstrates, the demographic characteristics of the learners suggests that the MOOC audience is highly educated, older than traditional university students, with a strong representation of students from the U.S., and has more women than men. Only 6.0 percent (n=317) of students reported to be unemployed, while not being involved in any educational program.

Table 1 Learner characteristics based on the pre-course survey. N=5,282

	Mean/%	**Median**	**SD**
Gender:			
- Female	52.5%		
- Male	46.6%		
- Other	0.3%		
Age	35.3	33.0	11.2
Highest level of schooling:			
- No high school degree	0.9%		
- High school degree	8.5%		
- Associate degree	2.2 %		
- Bachelor's degree	28.4%		
- Master’s or professional degree	47.0%		
- Doctorate degree	10.0%		
Involved in an educational program:			
- Full-time student	13.5%		
- Part-time students	22.1%		
Employment status:			
- Employed full-time (incl. self-employed)	59.9%		
- Employed part-time (incl. self-employed)	13.7%		
- Not employed	4.0%		
- Unemployed	6.0%		
US-based	24%		

The post-course survey (see Table 2) shows that most of the respondents reported to have a strong desire to take the course, rated the course highly, and had learned a lot.

Table 2 Selected items from the post-course survey. N=406
(1-strongly disagree, 2-disagree, 3-neither agree nor disagree, 4-agree, 5-strongly agree)

Items	Mean	Median	SD
I had a strong desire to take this course	4.1	4	0.8
Overall this was an excellent course	4.1	4	0.9
I learned a great deal in this course	3.6	3	1.0

In order to investigate existing learning patterns beyond a binary indictor of completion, we draw upon a parsimonious approach to categorize learning behavior across units applied by Kizilcec et al. (2013). In the first step, we differentiate between active and non-active students. 8,660 *non-active* students disappear from the course after registration, as opposed to 8,186 *active* students who engaged in one of the course activities at least once. Next, we differentiate the sample of active students further by describing each student's behavioral engagement across the six course unit-weeks. For each unit-week, the participants were assigned one of the following labels: at least 50 percent of the videos were started and the quiz was submitted (3); less than 50 percent of the videos were started and the quiz was submitted (2); only watching videos without submitting the quiz (1); no engagement (0). For example, if a learner started all of the videos in the first week and submitted the quiz but then only started videos during the other weeks without submitting the quizzes, she or he would be assigned the following six values: 3, 1, 1, 1, 1, 1. Clustering was performed on the sample of active students only, i.e., students who engaged with at least one of the videos or quizzes during the course. The peer-review activity logs were only used to describe the cluster solutions. To cluster the data we used a robust alternative to a k-means cluster analysis, Partitioning Around Medoids (PAM). Similar to Kizilcec et al. (2014) Manhattan distance was used. The identified clusters are compared based on the survey response rates. The comparison is based on descriptive statistics, the Chi Square and exact Fisher's tests, and odds ratios.

5. Results

The elbow method and the average silhouette approach suggest a three cluster solution for active students based on the PAM algorithm. The Silhouette test indicates a reasonable structure of the clusters (average silhouette score = 0.6). Table 3 summarizes behavioral patterns of the three cluster groups:

- *Diligent* students (n=1395) constitute 17.0 percent of the students who engaged with the course material at least once (active students) and 8.3 percent of all course participants. This group of students engaged with most of the course videos and submitted quizzes throughout all of the six weeks. 61.6 percent of the diligent students also submitted the peer-review project.

- *Auditors*' (n=1580) engagement with videos highly resemble the diligent students. While auditors start most of the videos during the whole durations of the course, only a small proportion of the students submit videos in the first three weeks. In the rest of the weeks, percentage of students who submit a weekly quiz approaches zero. 19.3 percent of the active participants and 9.4 percent of all participants are auditors. It is not surprising that only 1.7 percent of auditors submitted the peer-review project.

- *Browsers* (n=5211) are learners who browse through the course materials before completely disengaging from the course by the fourth week. Active students are mostly comprised of browsers (63.7%). Browsers also constitute 30.9 percent of all course participants. Only 2.2 percent of these learners took part in the peer-review project.

Table 3. Summary of learning behavior of active student clusters

	Diligent		Auditors		Browsers	
Average % of videos started by students	week 1	93.1	week 1	95.3	week 1	62.3
	week 2	91.5	week 2	93.2	week 2	18.2
	week 3	88.2	week 3	91.6	week 3	6.5
	week 4	84.1	week 4	89.4	week 4	0.6
	week 5	62.9	week 5	66.9	week 5	0.2
	week 6	65.2	week 6	70.9	week 6	0.2
% of students who submitted quizzes	week 1	99.2	week 1	18.3	week 1	33.6
	week 2	99.6	week 2	11.0	week 2	13.0
	week 3	98.8	week 3	4.6	week 3	3.8
	week 4	92.7	week 4	3.9	week 4	0.2
	week 5	85.2	week 5	2.4	week 5	0.1
	week 6	71.8	week 6	0.8	week 6	0.0
% of students who submitted a peer review project		61.6		1.7		2.2
Total		1395		1580		5211

Table 4 shows response rates for the course participants by their level of behavioral engagement. First we differentiate between active and non-active students. Given the response rate for all of the learners (31.4% for the pre-course survey and 2.4% for the post-course survey), it is clear that the response rate is notably higher among active learners compared to the non-active ones for both instruments. Among students who did not engage with the course after enrollment 20.4 percent responded to the pre-course survey, compared to 42.8 percent among the active students. Further delineation of active learners based on the three clusters provides more fine-grained information. Diligent students have the highest response (63.1%) rate followed by browsers (40.4%) and auditors

(32.8%). For the post-course survey, differentiating between various clusters is especially important, as responses are almost entirely limited to the diligent students. Response rates for the non-active students, browsers, and auditors are extremely low. In the diligent cluster, 21.1 percent of the learners participated in the post-course survey.

Table 4. Response rates for the pre- and post-course surveys by the level of students' behavioral engagement.

Response Rate	**Non-active**	**Active**		
Pre-course survey	20.4%	42.8%		
		Diligent	**Browsers**	**Auditors**
		63.1%	40.4%	32.8%
Post-course survey	**Non-active**	**Active**		
	0.3%	4.7%		
		Diligent	**Browsers**	**Auditors**
		21.1%	0.8%	2.9%
Total	8,660	1,395	5,211	1,580

Given that the number of responses for the post-course survey is very small, we will look at the odds ratio only for the pre-course survey. Figure 1. reports odds ratios for the association between responding to a pre-course survey and membership in one of the identified engagement groups (active, diligent, browsers, and auditors with non-active students serving as the reference group). As expected, for all of the engagement groups, odds ratios are higher than 1, indicating a positive association between the pre-course survey response and engagement. Moreover, Figure 1. demonstrates that lumping the three clusters (diligent, browsers, and auditors) together into one *active* student group obscures this relationship. Diligent students are 6.7 times more likely to have participated in the pre-course survey than non-active students. Estimated odds for browsers and auditors are 2.7 and 1.9, respectively. The difference in the likelihood to have participated in the pre-course survey is statistically significant (at the 5-percent level) between all engagement groups (each of these clusters was chosen as a reference category).

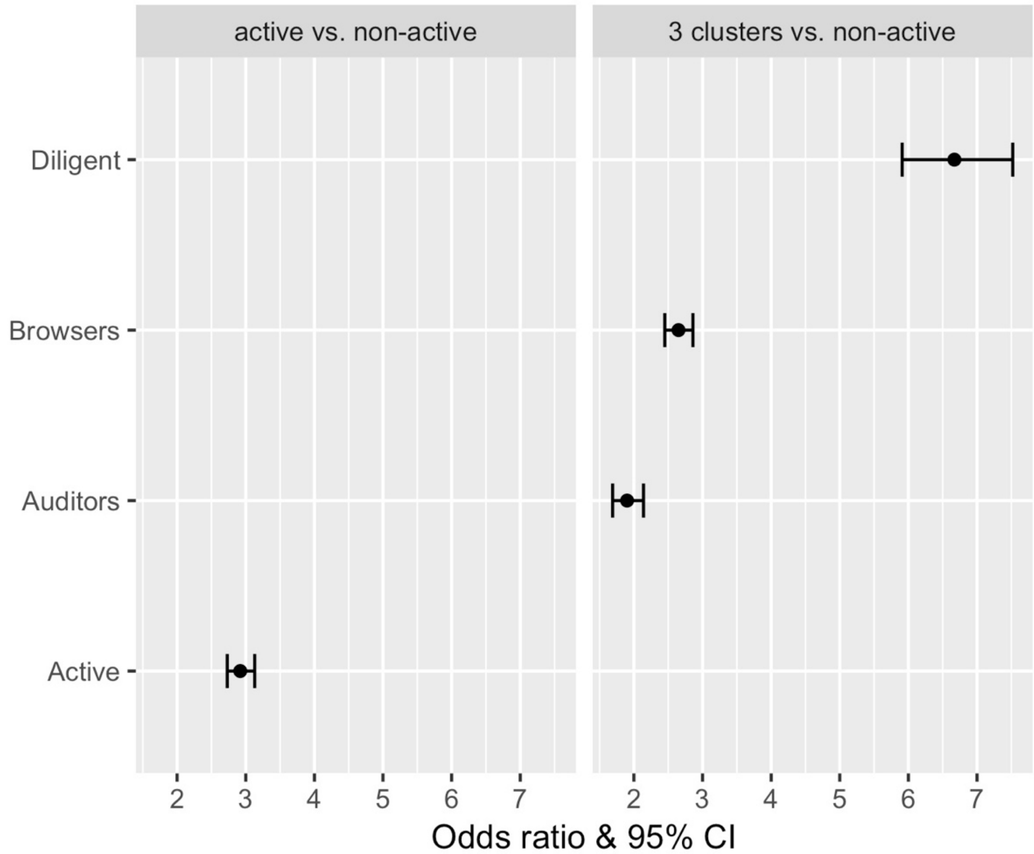

Figure 1. Estimated odds ratios and 95% confidence intervals of pre-course survey participation for engagement clusters

The above described differences in response rates across the identified clusters help interpret results of the pre- and post-course surveys. Table 4 illustrates some of the findings of the pre- and post-course survey by the level of students' behavioral engagement. One of the most interesting differences is a very high proportion of female students in the diligent cluster.

The above described differences in response rates across the identified clusters help interpret results of the pre- and post-course surveys. Table 4 illustrates some of the findings of the pre- and post-course survey by level of students' behavioral engagement. One of the most interesting differences is the over-representation of female respondents in the diligent cluster compared to the other clusters. From the available data, it is not clear whether the high proportion of female respondents is due to gender differences in the response rate to the pre-course survey (see Keusch (2015) for more information on higher response rates among women in web surveys), "true" gender differences across the engagement groups, or a combination of both.

Table 4 Selected items for the pre- and post-course surveys by the level of students' behavioral engagement. % of the respondents for the respective cluster/mean, median and SD.

	Non-active	Auditors	Browsers	Diligent
Pre-course survey:				
Female students	54.6%	36.6%	54.1%	84.3%
At least Master's or professional degree	51.6%	64.6%	57.3%	62.5%
Full-time students	25.4%	19.2%	21.8%	17.3%
Full-time (self-) employed	55.8%	61.5%	59.1%	63.6%
US-based	21.2%	14.6%	20.4%	22.5%
Total	**1767**	**522**	**2107**	**886**
Post-course survey:				
I had a strong desire to take this course	Mean=4.7 Median=5 SD=0.5	Mean=4.4 Median=4 SD=0.6	Mean=4.1 Median=4 SD=1.0	Mean=4.1 Median=4 SD=0.8
Overall this was an excellent course	Mean=4.4 Median=5 SD=0.7	Mean=4.2 Median=4 SD=0.9	Mean=4.2 Median=4 SD=0.7	Mean=4.1 Median=4 SD=0.8
I learned a great deal in this course	Mean=4 Median=4 SD=0.8	Mean=4 Median=4 SD=0.8	Mean=3.8 Median=4 SD=1.0	Mean=4.1 Median=4 SD=0.8
Total	**25**	**44**	**41**	**296**

Although the study is limited to data of a single MOOC within a specific context on the Coursera platform, the findings confirm reports in previous research. Although the relationship between survey response rates and the level of engagement was not the main investigation topic of these works, Kizilcec et al. (2013) and Rich (2014) reported very similar results.

6. Discussion and Conclusion

By using data from a social science course on the Coursera platform, we aimed to investigate the association between survey response and engagement, a relationship that was under-investigated in previous studies. In addition to comparing students who did not show any engagement with course materials against those who engaged in at least one activity, we categorized active students into three different clusters based on their engagement with the learning materials: diligent, browsers, and auditors. Although the study is limited to data from a single MOOC within a specific context on the Coursera platform, the findings confirm reports in previous research (Kizilcec et al., 2013; Rich, 2014). The results show that most of the survey data (especially with regards to the post-course evaluation) stems from the most engaged MOOC students. This is problematic, as we know very little about learners who were less engaged in the course and thus might need more support to successfully finish it. The possibility of non-response bias questions some of the established theses in the MOOC literature. For example, do students with non-traditional engagement patterns (i.e., auditors) really have high levels of satisfaction, as proposed by Kizilcec et al. (2013)? While this might just be the case, more data on non-respondents to the post-course satisfaction survey from these groups is needed to verify this claim.

The findings also demonstrate that activity logs can tell us a lot about learners' behavior but they are not enough to sufficiently understand students' engagement. To increase understanding, two possible approaches could be implemented in future projects. The first approach concerns improvement of the currently used data collection, including improvements to the instruments and the process with which the data are collected. Pre-course surveys could include questions about students' intention for the course, to allow subsetting analyses of activity logs and other learning metrics to those students that intended to engage in the course. Likewise one can filter out those that knew from the beginning that they won't have the time to finish the course or just wanted to take a peek. To gain more insight out of both pre- and post-course surveys steps could be taken to improve response rates (Keusch, 2015). One option could include explicitly targeting non-respondents classified as non-diligent students for the purpose of investigating reasons for their learning behavior. This approach could be combined with using incentives (Singer & Ye, 2012) to motivate response among the least engaged as well as qualitative approach, such as online focus groups, to study these sub-groups and their intentions in more depth.

Alternatively, one could empirically investigate a possibility of using behavioral measures (for example, participation in the pre-course survey) as a proxy for measuring subjective states, primarily learners' intention. Given that topic salience is one of the strongest predictors of survey participation (Adams & Umbach, 2012; Groves, Presser, & Dipko, 2004), we could hypothesize that respondents to the pre-course survey are more interested in the course topic than non-respondents. Since those who are more interested in the topic are more likely to be motivated and committed to finish the course at its start, the use of such a proxy is tenable. While some authors already suggested using behavioral measures obtained via learning analytics to study subjective aspects of learners' behavior (Koller et al., 2013), they did not go further than suggesting to use variables indicating students' engagement with the course material. Such an approach was rightfully criticized for "circular" reasoning (Ho et al., 2015). In contrast, survey response is different from engaging with the learning material. In addition, if participation in the pre-course survey (at best combined with other existing data, such as, for example, learner's location measured via IP address) could help predict learners' intentions for participation, one could implement interventions at an early stage of the course.

The accessibility of unobtrusive measures of actual behavior in online learning opens new opportunities for empirical research. Survey and learning analytics approaches could be used in a complementary manner, to increase our knowledge about the relationship between traditional self-reports and their possible proxies obtained via new sources of data. Integrating traditional data sources such as survey data with newly emerging organic types of data can result in a much more informative picture of learning experiences than if exclusively relying on one source of data (Samoilova, Keusch, Wolbring, 2016). Consequently, development of effective strategies of data integration are highly relevant for the advancement of MOOC research and practices.

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