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# Engagement Patterns of Participants in an Online Professional Development Programme: An Application of Mixture Modelling

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## Abstract

*Unhindered communication capabilities, in the form of internet, led us to believe that the difficult goal of "Education for All" is within our grasp. Recent studies have shown mixed results for learning over the internet, indicating that we are still far away from our desired goal. Online environments provide freedom to a large number of learners to learn at their own pace. Understanding the various ways in which participants engage with online content could help explain the mixed outcomes. This paper presents the results of an exploratory study on engagement patterns of 4567 elementary school teachers, in an online professional development programme. Using mixture modelling techniques, we identified five latent profiles of online engagement and seven latent classes based on off-platform activities. We present our findings followed by discussion and implications for online courses.*

## 1. Introduction

The past decade has witnessed a phenomenal rise in the use of Information and Communication Technologies (ICT) in education. It witnessed the introduction of Massively Open Online Courses (MOOC) which provided access to high quality content at little to no cost. The promises of low cost and flexible time make implementation of professional development programmes on the internet an attractive and viable option [1,2]. But studies have reported that learning over a distance, even before the advent of MOOCs, have always faced the challenge of ensuring learner persistence [3, 4]. Additionally, most MOOCs are not as "open" as the acronym would have one believe [5, 6]. In the era of digital technology and availability of large-scale data, empirical studies have suggested ways to determine participants who would dropout or suggest improvements to course designs based on recorded learner interactions [7, 8, 9]. Most of these studies have based their analysis on online data logs without accounting for learner's actions outside of the online course platform [10, 11]. We intend to address this gap by presenting the results of an exploratory study of learner engagement patterns using data from online logs and responses to a survey of off-platform activities within the context of an online professional development programme for teachers.

## 2. Background

### 2.1. Online professional development for teachers

In education, professional development (PD) courses for teachers help in efficient policy implementation and better student outcomes [12, 13]. Use of technology in delivering PD programmes to teachers enables administrators to provide "just-in-time" training required for maintaining a curriculum updated with recent developments [14]. Studies which evaluated impact of technology-based PD on teachers have reported either no-significant difference [15] or positive results [16, 17]. Similar to MOOCs, researchers have been investigating teacher's level of engagement in technology-based PDs and found influence of teacher's prior knowledge and experience [18, 19]. Our study intends to identify groups of teachers with similar learning practices and determine if any of participant's covariates (age, gender, work experience and educational background) are associated to their engagement with the online PD course.

### 2.2. Mixture modelling

Cluster analysis is used to determine similar groups within a given sample or population based on certain attributes. Cluster analysis has been demonstrated to be useful in identifying similar learning patterns in online

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learning environments [20]. Mixture Modeling also enables identification of homogenous groups within a given population, but unlike cluster analysis they involve formal statistical methods to confirm number of clusters instead of subjective choices and provide cluster membership probabilities which enable easy interpretation of groups [21, 22]. Mixture modelling allows for uncertainty and measurement errors by allowing individual respondents fractional memberships in all groups [23]. In mixture modelling, if the data analyzed is categorical then the process is referred to as latent class analysis and latent profile analysis if data is continuous [21, 23]. The statistical benefits of the method and availability of computing power and software [21, 22] enable implementation of mixture modelling for data mining purposes in large scale educational technology research.

Our study intends to explore the different engagement patterns of participants in an online professional development programme using both latent profile and latent class analysis.

## 3. Method

In this section we provide the context of the study, the data collected and the analytical procedures implemented in our study

### 3.1. Context

A statewide online professional development programme was offered to teachers teaching science and mathematics at grades 6, 7 and 8 in all state-administered elementary schools. Access to the online platform was provided to a total of 19,267 teachers in two batches. Randomly selected 10,535 teachers formed the first batch (May 2018 – August 2018), while the remaining 8,732 formed the second batch (September 2018 – December 2018). The course content was divided into five modules: Science, Mathematics, Classroom Management, School Comprehensive Evaluation (SCE) and Use of ICT in classrooms. Each topic within these five modules consisted of two forms of content, one created by the subject matter expert and other an authentic case study example (related to the topic) of a fellow teacher within the same educational system. The case-studies also provided contact details of the teacher if a participant wished to know further details. After completing the science and mathematics modules, teachers had to work on a classroom intervention project and submit a report which was peer evaluated by 5 other participants. Over all 7935 from the first batch and 8498 from the second batch completed the programme within the provided timelines. Additional time was provided to participants who did not complete on time from February 2019 to May 2019. For our study we analyzed data of 5,157 teachers who had registered and started the course before the end of May 2018 and completed the programme by end of August 2018.

### 3.2. Calculating time spent on online activities

During the course of the programme all pageview activities of the participants were logged using an external server which provides web analytics services. Pageview logs of participants were downloaded and analysed using R[24] with R-Studio[25] and “jsonlite” package [26] to extract time spent by each participant on each navigated page of the platform. Time spent on the content was calculated by taking the difference between consecutive timestamps of the pageview logs. We calculated total time spent by each participant on expert-made contents of Science, Math, Classroom Management, School Comprehensive Evaluation and ICT use and also the corresponding case studies. Each content had specific pages enabling easy calculation of time spent (in minutes) on specific contents by any participant.

### 3.3. Off-platform activities

A questionnaire was prepared based on Veletsianos, Collier, and Schneider’s study [27] of offline activities that participants of online courses undertake when learning. The list of items in the questionnaire were checked for face validity by experts and a few teachers in state-run schools who had undergone online training. This survey was translated to the regional language and then back-translated to confirm the accuracy of the translation. The questionnaire was filled online, by participants at the end of the programme. The final questionnaire had the following questions:

1. How many PDF files did you download? (None | About 25% | About 50% | About 75% | All)
2. How many Videos did you download? (None | About 25% | About 50% | About 75% | All)
3. How many hours did you spent offline on the course content? (None | Less than 5 hours | 5 to 10 hours | 10 to 50 hours | More than 50 hours)
4. Did you take/maintain notes related to the course offline (Yes | No)
5. Did you share your notes, PDfs or video with other participants? (Yes | No)
6. Did you discuss the content of the programme with other participant teachers? (No | Yes with < 5 | Yes with 5 - 10 | Yes with 11 - 20 | Yes with > 20)

7. Did you discuss the content of the programme with other teachers who were not participating? (Yes | No)
8. Did you join any Whatsapp or Facebook group for discussing the course content? (Yes | No)
9. Did you contact any of the teachers whose case-study was presented in the course? (Yes | No)

Responses to items 1, 2, 3 & 6 were recoded to binary (responses other than None/No were coded as Yes) during analysis to facilitate easy interpretation of the results.

### 3.1. Analysis

Mixture modelling using Mplus 8.2 [28] was implemented to determine the heterogeneity in online and offline activities among the participants of the programme. Categorical responses to the off-platform activities of participants were used to determine latent classes, while calculated time spent on specific course pages was used to determine latent profiles among the participants. Steps outlined by Wang & Wang [21] were followed to determine the final number of latent groups among the learners. Once the number of latent classes/profiles were determined we further investigated if these latent groups were associated with covariates like age, work-experience, gender and education using the 3-step method [29].

## 4. Findings

Of the 5157 participants, pageview data log of 590 learners was found to be incomplete and hence dropped from the analysis. The average age of the participants was 32.13 years with average work experience of 75.99 months. The dataset consists of 41.91% females. Additionally, 4.86% of teachers had professional teachers' certification (PTC), 51.76% had a graduation degree and 43.38% of the teachers had earned a post-graduate degree. Most participants (80.9%) of the programme had qualified the State level Teacher's Eligibility Test (TET).

### 4.1. Online

The summary of time spent by the participants on online content, presented in Table 1., indicates that most participants spent more time on viewing case-studies on classroom management. The precision of the pageview log was in minutes, thus interactions in seconds would not be captured, resulting in five of the ten content categories with participants spending 0 mins on the page.

**Table 1. Summary of time spent (mins.) in viewing online content**

| | Range | Mean | SD |
|---|---|---|---|
| Science Experts | 3 - 810 | 131.30 | 83.00 |
| Science Case-Studies | 3 - 456 | 78.52 | 51.39 |
| Math Experts | 2 - 546 | 84.69 | 66.27 |
| Math Case-Studies | 0 - 445 | 67.65 | 46.15 |
| Classroom Mgmt. Expert | 0 - 357 | 46.94 | 31.92 |
| Classroom Mgmt. Case-Studies | 9 - 1131 | 184.94 | 109.04 |
| SCE Experts | 0 - 141 | 13.81 | 14.04 |
| SCE Case-Studies | 0 - 179 | 26.67 | 20.07 |
| ICT Experts | 0 - 149 | 18.23 | 17.52 |
| ICT Case-Studies | 2 - 342 | 47.859 | 33.15 |

During latent profile analysis, the information criteria (AIC, BIC & ABIC), kept decreasing with additional number of profile class. Of the many statistically fit models, a 5-class solution (entropy = 0.882) was selected because the extracted latent profiles were simple to interpret. Although the Vuong-Lo-Mendell Rubin likelihood ratio test (LMR LRT) and the Adjusted LMR LRT results were not-significant, the Bootstrap likelihood ratio test (BLRT) was significant indicating that a 5-class solution was a better fit than the 4-class solution. Figure 1 presents the average minutes spent by participants on each content online within each profile class of the 5-class solution. The extracted profiles of the participants can be interpreted to be of Low (41.9%), Below Average (33.9%), Average (16.3%), Above Average (6.4%) and High (1.6%) levels of online engagement.

**Table 2. Associations of covariates with latent profiles**

| | Below Avg. | Avg. | Above Avg. | High |
|---|---|---|---|---|
| Age (Yrs.) | .036 (.01)* | .067 (.01)* | .125 (.02)* | .152 (.03)* |
| Work Exp. (Mths.) | -.002 (.00) | -.001 (.00) | -.004 (.00) | .000 (.00) |
| Female | .605 (.09)* | .854 (.10)* | .907 (.14)* | 1.026 (.26)* |
| TET Qual. | -.076 (.13) | .026 (.15) | -.165 (.20) | .270 (.41) |
| Graduate | .488 (.24)* | .742 (.31)* | .978 (.49)* | 1.462 (.60)* |
| Post-Graduate | .375 (.24) | .595 (.31) | .810 (.50) | .879 (.63) |

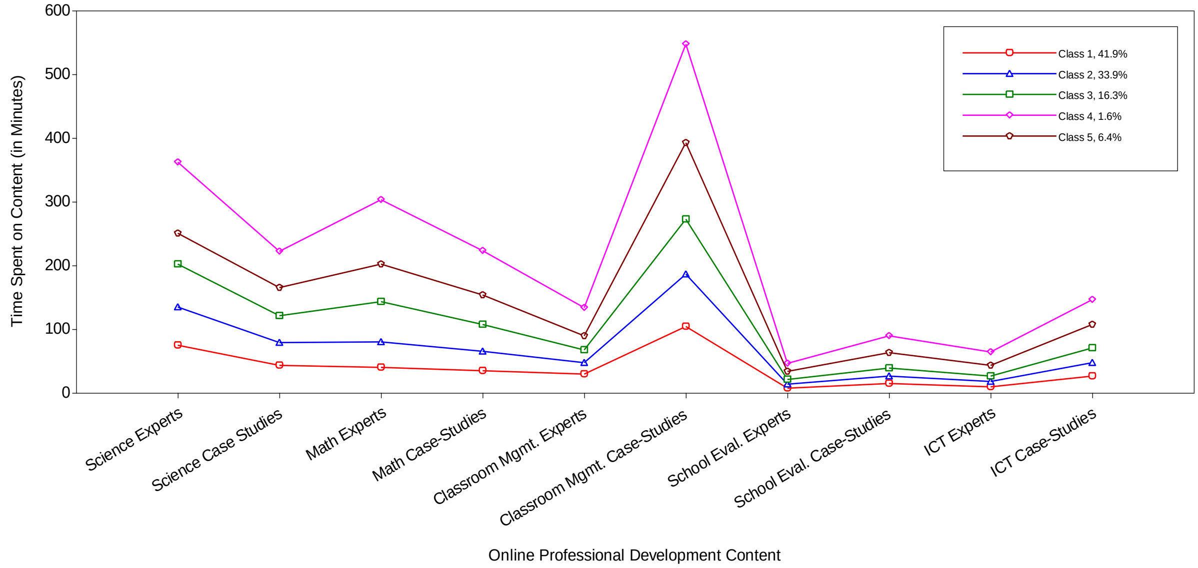


**Figure 1.Latent profiles extracted from online activities**

Table 2 presents the associations of covariates as they relate to membership of participants to different latent profiles (Note: * $p < 0.05$). The latent profiles are being compared with the profile having largest number of participants i.e. the low online engagement.

## 4.2. Off-platform tasks

The responses to the offline study practices survey indicated (Table 3) that a significant number of participants downloaded the PDF version of the training content (94.30%) and about 14.30% of the learners contacted the case-study teachers. The responses to questions related to number of hours spent studying offline were dropped from the model during analysis to improve classification. Latent class analysis of the responses to the offline activities questionnaire suggested 4-class solution based on lowest BIC and 7-class solution based on significant results of BLRT. Since high values of entropy are desired [21], the 7-class solution was selected (entropy = 0.796).

**Table 3. Summary of responses to off-platform activities**

| | No n (%) | Yes n (%) |
|---|---|---|
| Downloaded PDFs | 262 (5.70%) | 4305 (94.30%) |
| Downloaded Videos | 512 (11.20%) | 4055 (88.80%) |
| Took Notes | 1173 (25.70%) | 3394 (74.30%) |
| Shared Notes, PDFs & Videos | 3130 (68.50%) | 1437 (31.50%) |
| Discussed with Participants | 848 (18.60%) | 3719 (81.40%) |
| Discussed with Non-Participants | 2710 (59.40%) | 1856 (40.60%) |
| Joined WhatsApp or Facebook Group | 3123 (68.40%) | 1443 (31.60%) |
| Contacted Case-Study Teacher | 3912 (85.70%) | 655 (14.30%) |

The probability of off-platform activities which the participants engaged in during the online programme is presented in Figure 2 for each of the extracted classes. The associations of covariates with the latent classes is presented in Table 4 (Note: * $p < 0.05$).

**Table 4. Associations of covariates with latent classes**

| Latent Classes | 1 | 2 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|
| Age (Yrs.) | .112 (.03)* | -.026 (.02) | .009 (.02) | .054 (.04) | .058 (.04) | .008 (.02) |
| Wrk. Exp. (Mths.) | -.005 (.00) | .004 (.00) | .000 (.00) | .000 (.01) | -.001 (.01) | .004 (.00) |
| Female | -.716 (.24)* | -.899 (.14)* | -.177 (.11) | -.131 (.31) | -.180 (.26) | .017 (.17) |
| TET Qual. | -.144 (.32) | .150 (.22) | .019 (.18) | .051 (.44) | -.599 (.39) | .271 (.27) |
| Grad. | 1.200 (.71) | .080 (.34) | .161 (.30) | -.811 (.69) | 2.661 (2.63) | .270 (.50) |
| Post-Grad. | 1.020 (.73) | .290 (.35) | .294 (.31) | -.507 (.69) | 2.817 (2.68) | .426 (.51) |

## 4.3. Overall heterogeneity in engagement

We extracted the most likely classification of participants into five online latent profiles and seven

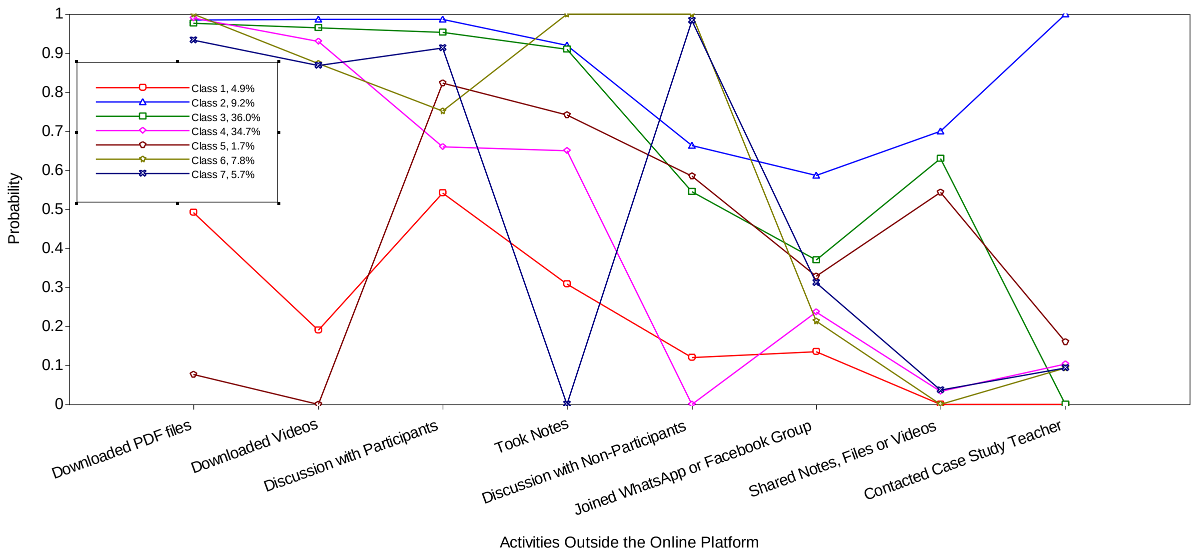


**Figure 2. Latent classes extracted from off-platform activities**

offline latent classes and present the distribution of participant engagement in a 7x5 matrix (Table 5.).

**Table 5. Distribution of participants into online latent profiles and offline latent classes**

| Offline Activity Latent Classes | Online level of Engagement | | | | |
|---|---|---|---|---|---|
| | Low | Below Avg. | Avg. | Above Avg. | High |
| 1 | 97 | 63 | 30 | 19 | 3 |
| 2 | 228 | 138 | 51 | 12 | 4 |
| 3 | 665 | 538 | 273 | 88 | 20 |
| 4 | 752 | 629 | 289 | 131 | 34 |
| 5 | 39 | 17 | 6 | 5 | 1 |
| 6 | 43 | 48 | 40 | 14 | 3 |
| 7 | 114 | 100 | 49 | 19 | 5 |

## 5. Discussion

### 6.1. Online activities

Most participant profiles have been classified as low engagement i.e. spending less time on viewing the online content. Results of the multinomial regression of latent classes on covariates indicated learners who spend more time on viewing online content were significantly older compared to the latent group with maximum learners. Additionally, latent groups with longer page viewing time consisted of more female and graduate degree holders.

We infer that age, gender and educational background seems to have some association with time spent on viewing content online. These findings are in accordance with previous studies which found that different participants interact differently in a professional development programme based on prior experience and educational background [18,19]. Although we do not see any significant change in work experience, age is correlated to work experience.

### 5.2. Off-platform activities

The range of seven latent classes extracted from the survey responses include classes with higher probability of offline activities (Class 2) to classes with low probability of engaging in off-platform activities (Class 1). Classes 3 to 7 can be differentiated on extreme probabilities on activities like downloading of files or videos (Class 5), contacting case study teacher (Class 3(No)), taking notes (Class 7(No),Class 6(Yes)), sharing notes/files (Class 6(No)), discussing with non-participants (Class 6 & 7 (Yes), Class 4 (No)). Our analysis of covariates indicated that all classes were similar with regards to work experience and educational background. Classes 3,4,5,6, and 7 were relatively similar on age and gender. Class 1 consisted of relatively elder participants. Also, females were significantly less in Class 1 & Class 2. Our findings augment the study by Veletsianos et al. [11, 27] by finding heterogenous groups of participants in an online programme based on their offline study practices.

### 5.3. Overall

Combining our findings of five online engagement profiles and seven off-platform study classes we potentially have thirty-five different forms of engagement by participants with the online professional development programme. Analyzing the distribution of participants in Table 5, we do note that for all offline classes except Class 6, online time spent viewing pages for maximum learners is low. Among them Class 2 and Class 5 have the most participants (52.66% & 57.35% respectively) classified as low online engagement. We do note that Class 2 consists of learners which high probability of engaging in off-platform activities, including contacting the case-study teachers, thus we could expect low engagement in the online environment. Interestingly, Class 5 participants indicated to have mostly engaged in discussion with other teachers or note taking and sharing, they were least probable to download course content files (PDFs or Videos) and less likely to contact a case-study teacher. Finally, two classes (Class 1 and Class 6) of the seven classes had more than 10% of its learners with above average or high online engagement. Since Class 1 has participants of low probability of engaging in offline activities it is reasonable to assume higher online activity among some of the participants. Participants of Class 6 however, did engage in downloading PDF files, taking notes and discussing course content with non-participating teachers. These findings show the stark variations in activities that learners engage in, which could be further explored to determine possible variation in outcomes.

### 5.4. Limitations

Our findings are based on 57.56% (4567 of 7935) of the total number of teachers who took training in the first batch. Analysis on the data of all teachers could be undertaken to validate our findings. Also, the calculations of time spent on viewing content did not include estimation of time spend on page at session end i.e. the time spent on a page at the end of a session was taken as 0 min (end of session was logged by server when time difference between two pageviews was more than 15 mins). Analysis could be rerun using different estimation methods [30] to determine its effect on our findings. Additionally, time spent viewing online content could also vary due to different speeds of reading or operation of personal device. Analyzing percentage of total time spent in viewing content could be considered as an alternative measure. The choice of using an external server for logging online activity was influenced by operational limitations of the study. These activity logs are susceptible for missing entries, but the design of the online course necessitated learners to visit specific pages to proceed towards other modules or sections of the course. This design enabled identification and removal of incomplete logs. Further, the minute level precision in recording pageview activity does prevent capture of actions which occur within few seconds. Effects of these missed time can be judged by using count of pageviews, instead of time on page, and verify if the results are replicated.

The off-platform activity questionnaire provides only limited view of the various other activities that participants might undertake. A random sample of the participants could be interviewed to investigate offline activities reported by them in the survey. Such an exercise could help in developing questionnaires which provide deeper insights into off-platform activities of the participants.

Finally, the classification of participants into thirty-five forms of engagement was according to the most-likely class/profile of the participants. Most likely classification may not reflect either true variations in engagement or interactions between online and off-platform activities. Other mixture modelling techniques, e.g. factor mixture modelling, could be explored to determine engagement patterns of the participants.

## 6. Conclusions and Implications

Our findings show that evaluations of learning over the internet need to consider offline activities of learners. This study presents the case for using latent class analysis and latent profile analysis to evaluate learner engagement on online learning platforms. This study can be extended by a qualitative study of the participants within each of the classified groups to gain deeper insights. Also, more complex latent class models, which combine online and off-platform activities along with participant covariates could be explored.

Future studies could use mixture modelling to determine which forms of learner engagement are effective based on certain outcome measures (e.g. standardized tests, self-efficacy beliefs etc.). Studies to verify the effects of design changes to learning platforms could be undertaken. These future investigations could assist in designing inclusive online learning environments. Finally, as predictive technologies are being applied in education, we need to be aware of the completeness of data and the limitations they impose on predictions made by the algorithms based only on online logs.

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