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Exploring associations between participant online content engagement and outcomes in an Online Professional Development Programme

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Abstract. Online Professional Development (PD) programmes for government school teachers provide benefits of low costs to the administration and flexible schedules for the participants. However, research on the use of technology in PD programmes has reported mixed results, thus warranting further investigation. Exploring the associations between the variation in engagement of and outcomes among the participants may provide insights for future research. The paper presents analysis of pageview logs and survey responses of 6933 participants of an online PD programme. First, four latent online engagement profiles were extracted using mixture modelling. Then, associations between participants' latent profiles and reported change in self-efficacy beliefs were analyzed. Finally, limitations and implications of the work are presented.

Keywords: Online Professional Development, Mixture Modelling, Latent Profile Analysis, Self-Efficacy Beliefs.

1 Introduction

The benefits of low cost and flexible schedules made it attractive and viable to adopt information technology to facilitate professional development (PD) programmes [1], [2]. The advances in data gathering and analysis, in recent times, provided precise tools to answer the “what works?” question for in-service teacher’s online PD. We present the results of an exploratory study of online learner’s engagement patterns and their association with outcomes within the context of an online professional development programme for teachers.

The next section (Section 2) provides the background of study viz. teacher professional development programme. Next, we present the method in section 3 and present the findings in section 3. Subsequently, we proceed to discuss these findings in section 5 and highlight the limitations of the work in section 6. Finally, we mention the implications of the study in section 7, followed by the acknowledgment section (Section 8).

2 Background

Teacher's PD programmes improve implementation of education policy and student outcomes [3], [4]. Many studies have indicated that improving teacher's self-efficacy beliefs is a desirable objective for PD programmes [5]–[8]. Teaching self-efficacy belief is defined as " the judgement of one's capabilities to influence student engagement and learning" [9]. Improving teacher's self-efficacy beliefs is associated with higher student achievement [9]–[11] and effective classroom practice [12]–[16].

Facilitating a PD programme for teachers involves huge costs, which can be reduced by adoption of technology. Evaluation studies of technology-based PD have reported mixed results [17]–[19], warranting additional research on outcomes of technology-based PD. Studies have not only found that participants in the same PD vary in their preference for and access to the different components of the programme [20], [21], but also found variation in outcomes for participants attending the same programme [22]. One of the affordances of technology-based PD is the ability to track and analyze participants engagement with the PD content. Tracking learners enables identification of specific content or activities which improve participant outcomes.

The prominent field that deals with studying a learner's engagement/participation in a programme is Educational Data Science (EDS). EDS grew due to Massive Open Online Courses (MOOCs) which generated huge amounts of data on participant's interaction with educational content [23], [24]. EDS is constituted of various sub-fields like Learning Analytics, Educational Data Mining, Institutional/ Academic Analytics, etc. [23]. Researchers who studied the patterns of participant engagement in MOOCs have classified them into either four [25] or seven [26] groups. Analyzing patterns of participant engagement one could identify areas of improvement in courses [27], design courses that accommodate different learning styles [28] and understand how to retain learners till the end of the course [29]. Kalakoski, Ratilainen, and Drupsteen [30] proposed the use of EDS methods to improve job training for professionals. Our study intends to identify groups of learners with similar engagement patterns and determine if the change in participant's self-efficacy is associated with their engagement pattern.

3 Method

3.1 Context

An online PD programme was offered to all teachers (19,267) in the state teaching science and mathematics at upper primary level in state-run primary schools. The training was offered in two batches and teachers were randomly assigned to one of the two batches. This article deals with the outcomes and engagement profiles of the participants in the first batch. In the first batch, a total of 10535 had registered and filled the pre-training survey of which 7935 participants completed the full programme and then completed the post-training survey. The course content consisted of Subject specific content (Science & Mathematics) and Managerial content (Classroom Management, School Comprehensive Evaluation (SCE) and Use of ICT). Content for the PD was

from two sources, subject matter expert and authentic case studies. The teachers were required to execute a real-world project in classroom, which was peer evaluated by other participants on the platform.

3.2 Self-Efficacy Belief

Participant's self-efficacy beliefs were measured via online surveys when they registered for the programme in May – June 2018 and later once they completed it. As self-efficacy beliefs are subject specific, teachers' self-efficacy beliefs about teaching Science and Mathematics were captured using instruments Science Teaching Efficacy Belief Instrument (STEBI) [31] and Mathematics Teaching Efficacy Belief Instrument (MTEBI) [32]. The subject specific self-efficacy scales each consist of two sub-constructs the personal subject teaching efficacy belief and the subject teaching outcome expectancy beliefs. In this article, we will be analyzing participant responses to only the personal science teaching efficacy belief. The personal science teaching efficacy belief subscales measure the teacher's own efficacy belief about teaching science using items like "I generally teach science effectively" and "I find it easy to explain to students why science experiments work". The scales were translated to local language by experts and validated by back translation. The responses to the survey were recorded on a 5-point Likert scale.

3.3 Online Content Engagement

Online activities of the participants on the platform were captured by logging pageviews on an external server. This provided pageview logs of the participants as they engaged with content on the PD website. Activity logs of participants were downloaded from the server in the form of json files. Data from the downloaded files was extracted using R [33] with R-Studio [34]. The difference between timestamps was used to calculate the time spent on the content. Additionally, time spent on pages at the end of the session was estimated using the user level average time spent on the page when the pageview was not at end of session.

3.4 Analysis

We analyzed the survey responses using Mplus 8.4 [35]. We conducted a confirmatory factor analysis. The responses to survey items were treated as categorical and the weighted least square (WLSMV) estimator [36] was used in the analysis. Measurement model consisting of both Pre-test and Post-Test responses was evaluated. Model Fit was evaluated based on criteria provided by Hu and Bentler [37] & Marsh, Hau and Wen [38] i.e. CFI \geq .95, TLI \geq .95, RMSEA \leq .06, & SRMR \leq .08. Items with standardized loadings less than 0.5 and with correlation with other items were dropped. The different patterns of engagement with online content were determined using mixture modelling [35], [39]. Percentage of total time calculated from pageview logs was used to determine latent profiles among the participants. Nylund, Asparouhov and Muthén [40] recommended the use of Bayesian Information Criteria (BIC) or Bootstrapped Likelihood Ratio tests (BLRT) to determine the appropriate number of

homogenous classes/profiles. They also note that at a higher number of observations ($n > 1000$) the performance of Likelihood Ratio tests (LRT), viz. VLMR LRT & ALMR LRT, is reliable. Also, they mention that the LRTs are robust and valid even if the distribution of data within classes/profile is non-normal. The steps outlined in the software user guide were followed to determine the final number of latent groups among the learners.

4 Findings

Complete pageview log and survey responses to both Pre and Post training were available for 6933 participants. Majority of the participants, 81%, had qualified the State's Teacher Eligibility Test (TET) and 44.9% of the total participants were females. Among the participants, 51.8% had a graduation degree and 44.5% of the teachers had earned a post-graduate degree while the rest had either a diploma or professional teachers' certification. The average work experience was 75.20 months and the average age was 32.14 years.

4.1 Self-Efficacy Beliefs

The analysis of survey responses resulted in a good model fit for measuring the latent constructs. The item-wise descriptive of survey responses is provided in the following table. The self-efficacy constructs at both time points demonstrated composite reliability of above 0.7 and had average variance explained more than 0.5.

Table 1. Responses to Personal Science Teaching Efficacy Scale

		Pre	Post	Pre	Post
	Range	M (SD)	M (SD)	Std. Loadings	Std. Loadings
				CR = .93 AVE= .57	CR = .94 AVE= .58
I am continually finding better ways to teach science.	1 - 5	4.469 (.58)	4.578 (.70)	0.657	0.588
I know how to teach science concepts effectively.	1 - 5	4.071 (.64)	4.478 (.60)	0.776	0.794
I am very effective in monitoring science experiments.	1 - 5	4.241 (.62)	4.492 (.61)	0.819	0.816
I generally teach science effectively.	1 - 5	4.332 (.58)	4.576 (.57)	0.823	0.822
I understand science concepts well enough to be effective in teaching elementary science.	1 - 5	4.318 (.59)	4.552 (.56)	0.839	0.846
I find it easy to explain to students why science experiments work.	1 - 5	4.284 (.61)	4.543 (.57)	0.841	0.850
I am always able to answer students' science questions.	1 - 5	4.086 (.73)	4.346 (.68)	0.754	0.753

		Pre	Post	Pre	Post
	Range	M (SD)	M (SD)	Std. Loadings	Std. Loadings
Given a choice, I would invite the principal to evaluate my science teaching.	1 - 5	4.128 (.73)	4.404 (.74)	0.577	0.611
When a student has difficulty understanding a science concept, I am usually not at a loss about how to help the student understand it better.	1 - 5	4.028 (.77)	4.347 (.79)	0.621	0.652
When teaching science, I usually welcome student questions.	1 - 5	4.555 (.53)	4.715 (.49)	0.712	0.741
I know how to motivate students to study science.	1 - 5	4.323 (.58)	4.603 (.54)	0.802	0.821
Correlation Pre vs Post				0.569	

4.2 Latent profiles of online engagement

Pageview logs of 8,131 participants were downloaded from the external server. The timestamped entry of page URL was used to determine the time spent on the page content. As the logging of pageviews was being maintained on an external server, entries for some participants were incomplete. We analyzed pageview logs of 7037 participants to identify the different online engagement profiles. The percentage of time spent on content was used for analyses. This enabled comparisons between time spent in one content with another while accounting for variations due to internet speeds, reading proficiency and module content. Also, the values were median centered to enable easy identification of the latent profiles in the output. The summary of the time spent on the content by the participants is tabulated as the percentage of total time logged online in Table 2. The range, mean and median values indicate that the time spent on each content is a long-tailed distribution.

Table 2. Percentage of time spent by participants in the online programme

Content	Time (as a percentage of total time)			
	Range	Mean	Std. Dev.	Median
Science Expert Content	0.77 - 38.95	11.795	4.44	11.526
Science Case Study	0.43 - 23.41	7.163	2.84	6.86
Math Expert Content	0.37 - 24.11	7.39	3.34	6.932
Math Case Study	0 - 21.71	6.115	2.31	5.888
Classroom Management Expert Content	0 - 18.49	4.459	2.19	4.073
Classroom Management Case Study	2.14 - 43.49	17.011	4.98	16.957
SCE Expert Content	0 - 10.08	1.239	1.07	0.914
SCE Case Study	0 - 15.39	2.418	1.22	2.18

Content	Time (as a percentage of total time)			
	Range	Mean	Std. Dev.	Median
ICT Use Expert Content	0 - 13.01	1.618	1.25	1.253
ICT Use Case Study	0.15 - 17.83	4.337	1.9	4.104
Grade Peer Projects	0 - 17.80	1.787	1.35	1.413
View Peer Feedback on Project	0 - 13.52	0.951	1.15	0.589

As the distribution of time spent is long-tailed, LRT tests are more valid than BLRT to determine the correct number of latent profiles. The latent profile analysis shows LRTs favor a four-profile solution. Thus, we accept the four-profile solution of the analysis. The extracted profiles of the participants can be interpreted based on the content they spent most of their time Project Feedback (5.0%), Subject Modules (57.9%), Case-Study Content (30.0%) and Expert Content (7.1%).

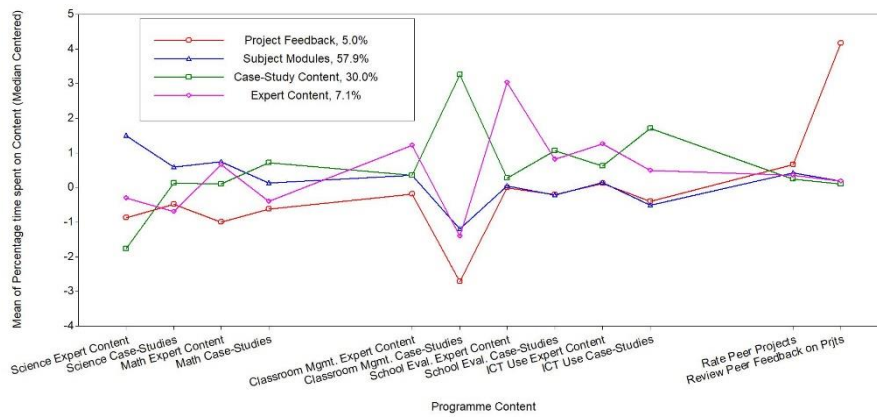


Fig. 1. Latent profiles of participants based on the percentage of time spent on content

4.3 Association of Online Content Engagement and Change in Self-Efficacy Belief

Alessandri, Zuffiano, and Perinelli's[41] method of setting up of the second-order latent variables which measure baseline and change in the latent constructs was implemented to analyze the association of the engagement patterns with the change in self-efficacy. The article's example was adapted for categorical responses using the Mplus user guide and reference materials available on their website. The model regressed the change in self-efficacy upon the profile membership indicators (here, the Most likely profile membership) and participant covariates. The relevant results of the analysis have been tabulated in the following table.

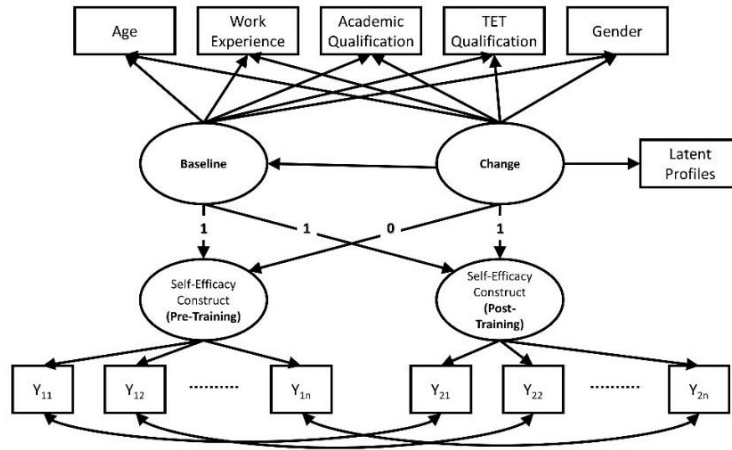


Fig. 2. Structural Model to evaluate association of latent online profiles to change in self-efficacy

Table 3. Association of most likely Online Latent profile with change in self-efficacy beliefs

Change in Self-Efficacy	Standardized Estimates [β (S.E.)]
Intercept	.668*** (.14)
Baseline	-.573*** (.02)
Project Feedback	.059 (.06)
Case Study Content	.028 (.03)
Expert Content	-.098 (.05)
Gender: Female	-.021 (.02)
Age	-.010 (.02)
Work Experience	-.022 (.02)
TET Qualified	-.043 (.04)
Education: (PTC/Diploma)	
Graduate	-.087 (.07)
Post Grad and above	-.135 (.07)
<u>Model Fit Indices</u>	
χ^2	1486.185
df	413
CFI	0.993
TLI	0.993
SRMR	0.031
RMSEA	0.019
RMSEA 90% CI	[.018 .020]
Note: "." p<0.1 "*" p<.05, "***" p<.01, "****" p<.001	

The findings show that the participants reported a large and significant positive change in their personal science teaching efficacy beliefs. Additionally, participants who reported low teaching efficacy beliefs benefitted significantly more from the programme. Participant's age, gender and work experience did not have a significant effect on the change in self-efficacy. We do notice a slight negative association with change in self-efficacy, at the 90% significance level, among participants who engaged more with expert content. Similarly, participants with post graduate degrees seemed to have an adverse association with change in self-efficacy (at 90% significance level).

5 Discussions

The different online engagement profile of the participants clearly shows 1. Variations in needs of teachers from a professional development course and 2. Need for an online PD programme which can offer the flexibility of indulging in desired content. The large, significant and positive change among the participants validate the design and content of the programme. Further, the effect size of the negative association of participants who indulged in expert content is very small and failed to be rejected at 95% significance. We could ignore the negative effects for practical reasons, but it satisfies the objective of the article by demonstrating the benefit of extracting latent engagement profiles of participants to evaluate the content of an online course.

6 Limitations

The external server used for tracking pageview activity provided log entries with time precision in minutes. Thus, page views which occurred within than a minute were not captured, thus time on content may have been underestimated. Further, for this article, we have used "most likely profile membership" to analyze the relationship between engagement profile and change in self-efficacy. Latent profile memberships in probabilities, with suitable transformations, could be used in the analysis to provide a more accurate estimate of the association.

7 Implications

The first implication of our findings is that the contents of this particular online PD programme for teachers were sufficiently varied to cater to all participants. Irrespective of whether the teachers engaged more with the subject specific content, case-studies, expert content or project feedback there was no variation (at 95% significance) in the reported positive change in science teaching self-efficacy. Thus, the online programme offered a sufficient balance of content from both experts and peers that the participants needed. Secondly, our study shows one way of evaluating the contents of online programmes. Extracting latent profiles based on navigation logs enables further investigation on the effects of the programme on subgroups of participants. This would facilitate

continuous improvement of content and design of the online course or programme. Future research could attempt at exploring these latent profiles with qualitative methods. Researchers could also investigate activities participants undertake outside the learning platform and the effect of these off-platform activities on outcomes.

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