Exploring factors that explain possible needs of mobile devices integrated in elearning through learning profiling

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Exploring factors that explain possible needs of mobile devices integrated in elearning through learning profiling

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Abstract

Profiling elearning students is a common practice in the field. It carries good intention. Which learner group requires more attention of the university administration in optimizing resources and creating incentives resulting into a social outcome that is efficient and makes all concerned parties better off? Results suggested that the learners who perceive higher in university’s CMS support, instructor instructional and communicational use of CMS, and affinity for technology may deserve better attention of the management.

Background and Introduction

Profiling elearning students is becoming a common practice in the field (e.g., Yu, DiGangi, Jannasch-Pennell, & Kaprolet, 2008; Yukselturk & Top, 2013). Using a Web survey or questionnaire, an increasing number of learner characteristics and demographics can be studied in a form of data. Given this easy access to the collected data, researchers have attempted to take into account multiple (i.e., two- or more-way) profiling variables (e.g., student affinity for technology) at once, in lieu of dealing with one variable at a time. This attempt makes the design of their research more sophisticated and more versatile. It also assists the researchers in finding hidden patterns of the learners and their behaviors (Shih, Jheng, & Lai, 2010). Most importantly, their study results enable the top management team to make informed decisions. One major advantage of two-step cluster analysis is it allows researchers to consider both continuous/numerical and categorical/nominal variables at a time as other clustering techniques, such as K-Means Cluster and Hierarchical Cluster in SPSS, are limited, as Schiopu (2010) claimed. The claim is also endorsed by Filho, Rocha, Siliva Júnior, Paranhos, Silva, and Duarte (2014).

The two purposes of this phase of the investigation are to (a) follow up on some of the results we stated in an earlier multiple regression study (Pan, Sivo, & Goldsmith, in press) on learner perceived success in elearning explained by four factors: perceived course management support by the university (coded, USC), perceived course management system use by instructor (coded, IUC), perceived instructor use of course management system for communications (coded, ICC), and perceived affinity for technology (coded, AFF) and (b) explore plausible patterns of the four stated learner success factors in relation to student expected instructor overall integration of mobile technology for the past year (coded, IIT) in support of elearning student success.

To race into the future, universities and colleges that offer elearning courses shall move from production orientation to marketing orientation. With the naïve thinking of selling as many seats as you can, the schools will not survive the intense competition against other elearning service providers, both non-for-profit and for-profit, on the market. The management shall attend to the customers’ or users’ needs and expectations. Given an assumption that student university experience is highly affected by their instructors’ integration of technology in the curriculum, as noted in the adopted survey, we intended to answer this question, “Which learner group(s) will require more attention of the university administration in optimizing limited resources and creating efficient incentives resulting into a social outcome that is efficient and makes all concerned parties better off? That is the goal of this study. This
stage of the investigation is supposed to benefit university distance education management team members and other related policy makers.

Three research questions were framed and studied.

1. To what degree do elearning students’ USC, IUC, ICC, and AFF contribute to the most plausible learner profile?
2. What does the sought learner profile mean in the context of IIT?
3. Is there any significant relationship between learner profile and their ownership of mobile technologies (i.e., laptop, tablet/iPad, and smartphone)?

Method

The secondary or archival data with a sample size of approximately 1,900 (undergraduate students of a U.S. southern state university) were analyzed for the present quantitative study. The said data were initially collected in a joint effort of the participating university and EDUCAUSE Center for Applied Research (ECAR) in 2013. Located in South Texas, the state university was classified as a Hispanic-serving institution, suggesting at least 25% of the Hispanic undergraduate students were enrolled full-time. A 2014 report stored by the National Center for Education Statistics showed that approximately 90% of the undergraduate students the Title V school served were Hispanic.

The joint survey research data indicated that 88% respondents were Hispanic; 63% were female; 65% were at age of 18 to 24; 32% were freshmen; 94% lived off campus; 70% were full-time undergraduate students; 62% perceived “some online” as the learning environment that they learned most; 85% perceived that the course management system (CMS) is a very or extremely important tool to achieve their academic success.

Pan and Garcia (2015) on the predictability of student technology affinity, student perceived distance between social life and school life, and student perceived best learning environment in their selection of elearning courses (vs. non-elearning courses), the two-step cluster analysis was chosen to identify reasonable student groups that are clustered on the bases of student-rated university support for CMS use from a mobile device (USC), expected instructor use of CMS (IUC), expected instructor use of CMS for communications (ICC), and perceived affinity for technology (AFF).

The USC factor was measured on a five-point semantic bipolar scale, with Excellent and Poor on both ends included, in addition to two additional options: Service Not Offered for Mobile Device and Haven’t Used Service in The Past Year. IUC and ICC were measured on a six-point semantic bipolar scale with More (or “5”) and Less (or “1”) noted at the ends, plus a “Don’t Know or N/A” option (or “0”) next to Less. The three factors each used one single variable or survey item. AFF, as a latent factor, was measured by 12 variables, each on a five-point Likert scale with a Don’t Know option next to Strongly Disagree. The internal consistency, Alpha, was .89. Composite scores were used to represent the latent factor.

Then, the analysis was anticipated to continue to explain how the learner profile means in the context of IIT. The four identified, independent student groups were viewed as four levels of the independent variable. The average scores of three manifest variables represented the instructor overall integration of mobile technology, or ITT, the dependent variable. The three variables were related to instructor integrated use of (a) the tablet, (b) the smartphone, and (c) the laptop. Each variable was measured on a six-point semantic bipolar scale with More (or “5”) and Less (or “1”) noted at the ends, plus a “Don’t Know or N/A” option (or “0”) next to Less. Interval data were gathered. Therefore, a one-way analysis of variance (ANOVA) was selected for this part of the analysis.

Results and Discussions

Using two-step cluster analysis in SPSS 22, learners were profiled as four independent groups/clusters:

- **Group 1**: low USC, low IUC, low ICC, and low low AFF; hence, Group 1 is named, Lack of Total Locus of Control (LTLC) group.
- **Group 2**: average USC, low IUC, low ICC, and average AFF; hence, Group 2 is named, Lack of External Locus of Control (LELC) group.
- **Group 3**: low low USC, high IUC, high ICC, average AFF; hence, Group 3 is named, Total Confidence for Instructor (TCFI) group.
- **Group 4**: high USC, high IUC, high ICC, and high AFF; hence, Group 4 is named, Champions (CHMP) group.
This profiling above is based on average Silhouette = .4, which is considered fair, with the ratio of largest cluster to smallest cluster at 2.76 (<3). Cluster sizes vary. Respectively, they are 15.3%, 25.9%, 16.4%, and 42.4% of the total number of students surveyed.

We then used the four clusters previously identified Using one-way ANOVA, we found there is a significant mean difference, $F(3, 1641) = 64.107, p < .001, \eta^2 = .105$, in student perceived instructor overall integration of technology for the past year or IIT among the four profiled groups. The large effect size, .105, indicated a strong relationship between the learner profile factor and the change in student perceived instructor’s integrated use of mobile technology in the class. Missing data were not considered for the analysis.

Given the fact that the assumption of homogeneity of variances was violated ($< .05$), this finding is based on the significant results of Welch and Brown-Forsythe tests (both $<.001$). That is, as informed by the two robust tests of equality of means, the null hypothesis was rejected, suggesting there is a scientifically significant difference in the mean of IIT among the four groups.

Using the ANOVA procedure, the Games-Howell post hoc test indicated that (a) CHMP group significantly outperforms other three groups in IIT, (b) TCFI group significantly outperforms LTLC group in IIT, but not significantly does so with LELC group, and (c) LELC group significantly outperforms LTLC group in IIT. It is worth noting that Tukey HSD was not selected for this follow-up analysis due to the fact that the assumption of the homogeneity of variance was violated as mentioned previously.

To determine whether ownership of mobile devices (i.e., laptop, tablet/iPad, and smartphone) is related to learner profile, we first collapsed the four clusters into two, CHMP and non-CHMP, given the uneven distribution of the learners across the clusters. Next, we broke down the three ownership groups into two for each mobile technology for the sake of argument. Then, we performed a two-way contingency table analysis to examine the relationship of the ownership and learner profile on each of the three mobile technologies. Results suggested that (a) learner profile and laptop ownership are not significantly related, Pearson $X^2 (1, N = 1675) = .002, p = .961$, Cramér’s $V = .001$, (b) learner profile and tablet/iPad ownership are significantly related, Pearson $X^2 (1, N = 1675) = 7.684, p = .006$, Cramér’s $V = .068$, and (c) learner profile and smartphone ownership are also significantly related, Pearson $X^2 (1, N = 1675) = 4.432, p = .035$, Cramér’s $V = .051$.

Furthermore, the proportions of learners who were identified as part of CHMP with a tablet/iPad and those without were 46.6% and 39.7%, suggesting the probability of a college student being classified as a CHMP was about 1.17 times (46.6%/39.7%) more likely when the learner owned a tablet/iPad. The proportions of learners who were identified as part of CHMP with a smartphone and those without were 43.9% and 38.1%, suggesting the probability of a college student being classified as a CHMP was about 1.15 times (43.9%/38.1%) more likely when the learner owned a smartphone. Even though learner profile and laptop ownership were not found significantly related, our results showed the proportions of learners who were classified as part of CHMP with a laptop and those without were 42.4% and 42.2%, suggesting the probability of a college student being identified as a CHMP was about 1.01 times more likely when the learner owned a laptop.

Evidently, undergraduate students high in self-rated university support for CMS use from a mobile device (USC), high in expected instructor use of CMS for communications (ICC), and self-perceived affinity for technology (AFF) seemed to have expected their instructor to integrate mobile devices in the classroom the most, compared to three other learner groups in the studied elearning enterprise, a southern state university where each offered course was mandated to incorporate, at least, a Web component in the curriculum at all levels and across all disciplines. From a student perspective, the degree of expected use of mobile devices (e.g., tablets, smartphones, and laptops) varied from one learner group to another. While the institution is deciding to diversify its elearning portfolio by offering m-learning programs (e.g., BYOD or 1:1), the management should be taking into account their students’, or arguably, customer’s needs and expectations. This forward thinking, in favor of marketing orientation, as opposed to production orientation, can provide the institution with a competitive advantage in the future race.

Apparently, CHMP was the only learner group that expressed a strong need for mobile learning or m-learning. The learners in CHMP also reported a higher probability of owning a mobile device than their counterparts. Acknowledging the largest proportion of CHMP group and their higher chances of mobile technology ownership, one strategy that policy makers may consider initially is to single out CHMP from the others and provide those Champions with more resources in hopes to keep them satisfied with their college experience, sustain the satisfaction, and then afford a ripple effect on other elearning learners.

References


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