Student Profiling, Instructor Use of Mobile Devices, and Device Ownership

Cheng-Chang Pan, Jeffrey A. Graham, and Eunice Luyegu

Background and Introduction

Profiling college students has become a common practice in education (e.g., Finney, Barry, Horst, & Johnson, 2018; O'Donnell, 2017; Olivera-Aguilar, Rikoon, & Robbins, 2017; Primack et al., 2012; Sulak, Massey, & Thomson, 2017; Yu, DiGangi, Jannasch-Pennell, & Kaprolet, 2008; Yukselturk & Top, 2013) in a broader effort to promote student well-being and academic success. Using a web survey or questionnaire for rapid distribution to target population, an increasing number of learner characteristics and demographics can be studied and accessed in some form of data. Given the easy access to the collected data, researchers have attempted to take into account multiple (i.e., two-way or more) profiling variables at once, in lieu of dealing with one variable at a time. This attempt makes the design of their research, arguably, more sophisticated and more versatile, partially thanks to the advanced survey technologies (e.g., branching logic). The deliberate effort also assists the researchers in finding hidden

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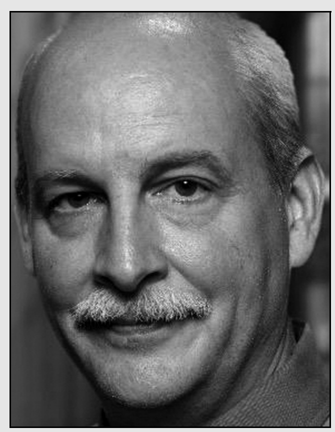

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patterns of the learners and their behaviors (Shih, Jheng, & Lai, 2010). Most importantly, their study results empower the top management team to make informed decisions. One major advantage of two-step cluster analysis is it allows researchers to 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 Șchiopu (2010) claimed. The claim is also endorsed by Filho et al. (2014), and Primack et al. (2012).

The two purposes of this phase of the investigation are to (a) follow up on some of the results of a multiple regression study by Pan, Sivo, and Goldsmith (2016) on learner perceived success in eLearning that is explained by four factors: perceived course management system 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 mLearning student success.

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Use of mobile devices in teaching and learning has been much documented in the literature. Through the lens of Fred Davis's (1989) technology acceptance model, Iqbal and Bhatti (2015) studied college students' intention to use smartphones for school-related activities (e.g., reading assignments or articles on the phone) and found direct and indirect causal relationships between student perceived ease of use, perceived usefulness, and their intention to use smartphones for mLearning. The results of their structural equation modeling study also confirmed two exogenous variables: students' readiness and their psychological readiness, suggesting student perception of smartphone use in terms of ease and usefulness be affected by variables, including college students' technical skills, self-reported confidence, and preferences.

Laptops appear to be one mobile device college students use the most for learning. A 2015 Pearson Student Mobile Device Survey (Pearson, 2015) reported (a) overall college students' use of mobile devices for school continues to grow, (b) even though college students use smartphones more than tablets, the growth of tablet use seems faster, (c) students use laptops for school the most, smartphones next, and then tablets, and (d) the majority of surveyed college students use one mobile device (likely a laptop) per school day on average. The 2018 EDUCAUSE ECAR Study of Undergraduate Students and Information Technology (Galanek, Gierdowski, & Brooks, 2018) revealed that (a) access to mobile devices is nearly universal as the majority of surveyed students reported some type of access to smartphones (95%) and laptops (91%), (b) non-White students are more likely than White students to think mobile devices are important to their success, (c) approximately a third of students reported use of mobile devices is discouraged in the classroom, and when used, laptops are more encouraged than smartphones, and (d) laptops are the most used device and are associated the most with perceived importance to student success.

Surrounded by prospective and present competitors in the same market or across markets that provide online program management services at lower fixed costs (Becker & Toutkoushian, 2013), 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 one can, the schools will unlikely survive the intense competition against other eLearning service providers, both nonprofit and for-profit, on the market. The management shall attend to the customers' or learners' needs and expectations while adhering to the organization's mission statement. Given the notion that student university experience is highly affected by their instructors' integration of technology in the curriculum, as noted in the survey research by Pan et al. (2016), we intended to answer this follow-up 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?" This is the goal of this study. The present stage of the investigation is supposed to benefit university distance education management team and related policy or decision makers.

Three research questions were framed and studied.

- To what degree do eLearning students' USC, IUC, ICC, and AFF contribute to the most plausible learner profile?
- What does the sought learner profile mean in the context of instructor integration of mobile technology in learning (IIT)?
- To what degree do USC, IUC, ICC, AFF, and learner profile predict mobile device ownership?

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 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.

The 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 in which they learned most; 85% perceived that the course management system (CMS) is a very or extremely important tool to achieve their academic success.

Drawn from the research by 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 (versus non-eLearning courses), the two-step cluster analysis procedure 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 5-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 6-point sematic 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 5-point Likert scale with a "Don't Know" option next to "Strongly Disagree." The internal consistency, Alpha, was .89. Composite scores (continuous data) were used to represent the latent factor.

Next, the analysis continued to explain what 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 expected by students, or IIT, as 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 6-point sematic 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.

Then, given a potential nexus between student use of technology for school and student ownership of the technology (Pan & Graham, 2018), we further studied the causal relationship between the four learner success factors and students' ownership of mobile technology, using logistic regression analysis. Students' ownership of laptops, tablets/iPads, and smartphones were treated as three separate, binary dependent variables.

Results and Discussion

To answer the first research question, we conducted a two-step cluster analysis in SPSS 22. Learners were profiled as four independent groups/clusters:

- Group 1: high ICC, low USC, high IUC, and average AFF; hence, Group 1 is named High Technology Expectation for Instructor (HTEI) group.
- Group 2: average ICC, average USC, average IUC, and average AFF; hence, Group 2 is named Ordinary Joes (ORDI) group.
- Group 3: high ICC, high USC, high IUC, and high AFF; hence, Group 3 is named Champions (CHMP) group.
- Group 4: low ICC, average USC, low IUC, and average AFF; hence, Group 4 is named Low Technology Expectation for Instructor (LTEI) group.

Figure 1 gives a visual representation of four clusters cohesive (within clusters), yet distant (between clusters).

On the X-axis are four student clusters, HTEI, ORDI, CHMP, and LTEI. The Y-axis indicates the range of mean scores (1–5). This profiling result is based on average Silhouette = .4, which is considered fair, with the ratio of largest cluster to smallest cluster at 2.77, smaller than the acceptable cut-off value of 3. Cluster sizes vary. Respectively, they are 15.2%, 27.2%, 42%, and 15.6% of the total number of students surveyed. Figure 2 shows the SPSS output of cluster sizes and the ratio.

To answer the second research question, we then used the four clusters previously identified for factorial analysis. Using one-way ANOVA, we found there is a significant mean difference, $F(3, 1631) = 61.44$, $p < .001$, $\eta^2 = .102$, in student perceived instructor overall integration of technology for the past year or IIT among the four pro-

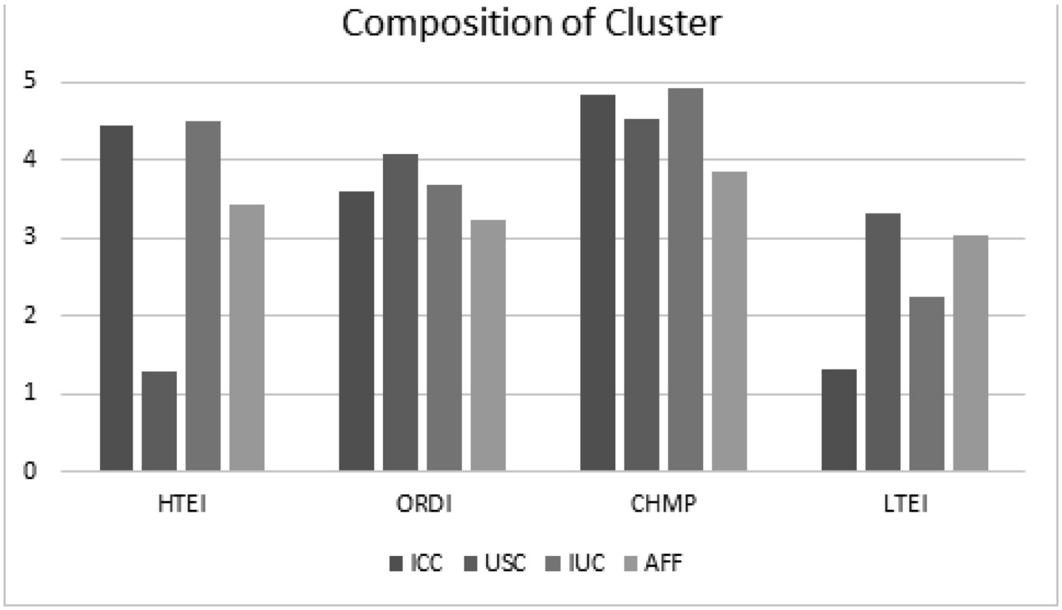
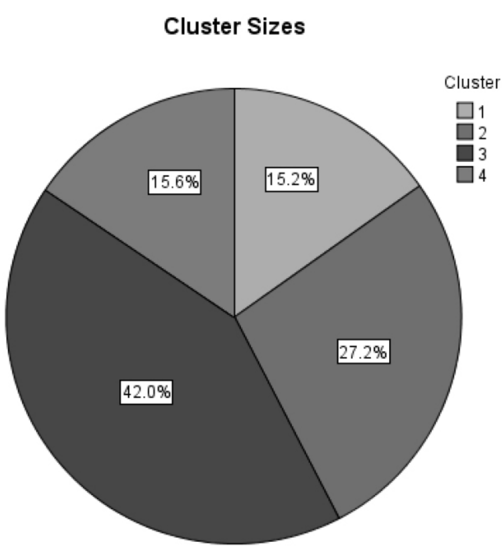


Figure 1. Bar chart comparing four clusters composed by four types of learner perceptions.



Size of Smallest Cluster	253 (15.2%)
Size of Largest Cluster	700 (42%)
Ratio of Sizes: Largest Cluster to Smallest Cluster	2.77

Figure 2. SPSS 22 output of cluster sizes and the ratio of largest cluster to smallest cluster.

filed groups. The medium-large effect size, .102, 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. Table 1 shows the means and standard deviations on IIT as a function of learner profile. Table 2 indicates the output of one-way ANOVA of IIT by learner profile.

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 < .05). 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) LTEI group significantly performs less than three other groups in IIT, and (c) HTEI

Table 1. Means and Standard Deviations on IIT as a Function of Learner Profile

Learner Profile	*n*	*M*	*SD*
HTEI	250	2.72	1.66
ORDI	442	2.63	1.44
CHMP	688	3.38	1.62
LTEI	255	1.86	1.70

Note: The maximum score is 5.

Table 2. One-Way Analysis of Variance of Perceived Instructor Integrated Use of Mobile Technology by Learner Profile

Source	*df*	*SS*	*MS*	*F*	*P*
Between groups	3	470.62	156.87	61.44	.000
Within groups	1,631	4,164.06	2.55		
Total	1,634	4,634.68			

does not significantly outperform ORDI 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.

Given the results above, we continued to answer the third research question by treating three types of mobile devices (i.e., laptops, tablets, and smartphones) separately and adding CHMP to the further analysis as a binary independent variable. Using logistic regression analysis, we found the logistic regression model was statistically significant, $X^2(5) = 12.54$, $p < .05$. The model explained 1.3% (Nagelkerke R^2) of the variance in laptop ownership and correctly classified 84.5% of cases. Of all the five predictors, only USC and AFF are statistically significant ones. Per unit increase in USC, the log odds of laptop ownership increases by .12 or 12%; per unit increase in AFF, the log odds of tablet ownership increases by .19 or 19%. We also found the logistic regression model was statistically significant, $X^2(5) = 23.23$, $p < .0005$. The model explained 1.9% (Nagelkerke R^2) of the variance in tablet/iPad ownership and correctly classified 61% of cases. Of all the five predictors, only ICC and AFF are statistically significant ones. Per unit increase in ICC, the log odds of tablet/iPad ownership increases by 10%; per unit increase in AFF, the log odds of tablet ownership increases by 18%. Using smartphone ownership as the criterion variable, we performed another logistic regression analysis. Results showed that the tested logistic regression model was again statistically significant, $X^2(5) = 19.79$, $p = .001$. The model explained 1.7% (Nagelkerke R^2) of the variance in smartphone ownership and correctly classified 73.6% of cases. Of all the five predictors, only USC and AFF are statistically significant ones. Per unit increase in USC, the log odds of smartphone ownership increases by 12%; per unit increase in AFF, the log odds of smartphone ownership increases by 22%.

Evidently, the degree of perceived instructor integration of mobile devices (e.g., laptops, tablets/iPads, and smartphones) in the curriculum varied from one learner group to another. Undergraduate students high in self-rated university support for CMS use from a mobile device (USC), high in expected instructor use of CMS (IUC), 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. The studied setting was 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.

We continued to explore whether the ownership of a mobile device can be predicted by the four learner success factors: USC, IUC, ICC, and AFF, and whether the ownership is predicted by CHMP or not. Our findings suggested that whether CHMP or not does not predict the ownership of any sort of mobile device. When it comes to laptop and smartphone ownership, increasing rating on institution's support for the course management system and that on student affinity for technology both were associated with an increase in the likelihood of owning a laptop. Regarding the likelihood of owning a tablet or iPad, it is associated with an increasing expectation of students on instructor use of the CMS for the communications purposes and also an increase in student affinity for technology. Overall, student affinity for technology and university support for CMS appeared to predict student ownership of all the mobile technologies, except tablets/iPads. This means that (a) students who express a higher level of attraction to technology in general, there is more likelihood that they own mobile technology and (b) students who are satisfied with university's support for CMS tend to own mobile technologies (i.e., laptops and smartphones). One of our earlier studies (Pan et al., 2016) also revealed that student affinity for technology and university support for CMS both cause student success through the adopted course management system.

While the institution is deciding to diversify its eLearning portfolio by offering mLearning programs (e.g., bring your own device or 1:1) as a pilot program, the management should be taking into account their students', or arguably, customers' 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.

In this study, CHMP was the only learner group that expressed a strong need for mobile learning or mLearning. This finding seemed to go against the cliché of "one size fits all." Acknowledging the largest proportion of CHMP group, one strategy that policy or decision makers may consider *initially* is to single out CHMP from the others and provide these 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 mLearning learners. Yet, this CHMP group is not able to predict any student ownership of the mobile device(s). This could add another layer of challenge to the mLearning programs as being a champion in the context of this paper hardly guarantees his/her mobile device ownership.

Recommendations for future research include further research on (a) profiling mlearning students using gathered demographics (e.g., gender, class standing, and college), (b) examining the predictability of mobile device ownership for desired learning environments, and (c) replicating the present investigation using multiple-year datasets.

One of the limitations of the study is that because the data were collected through a student self-reported survey, the students may respond in a socially acceptable manner. Surveys are an efficient and effective way to collect data, but they are only proximities of actual behavior (Carrell & Willmington, 1996). Also, a growing maturation threat is likely to affect internal validity of the study as the surveyed students continue to finish college. Another limitation lies in the fact that the survey study is quantitative in nature, which could benefit from some form of qualitative inquiry.

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