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Engineering Students Engagement Profiles while Using Low-Cost Desktop Learning Modules*

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There is overwhelming research evidence showing that students often struggle with learning key engineering concepts. The Low-Cost Desktop Learning Modules (LCDLMs) are model prototypes of standard industry equipment designed for students to learn some fundamental but abstract engineering concepts in the classrooms. Previous results have shown that students who interact with LCDLMs tend to outperform those who engage in traditional lectures. However, little is known about student profiles and their forms of engagement with this tool. Hence, the present study seeks to investigate the different student profiles that emerge from students working with the LCDLM and the demographic factors that influence student engagement with the tool. Participants (N = 1,288) responded to an engagement survey after working with LCDLMs in engineering classrooms in several states around the United States. We then used a latent profile analysis (LPA) – an advanced statistical approach – to better understand the representation of learner engagement profiles resulting from their self-reported learning engagement beliefs as they reflect on their experience in using LCDLMs. The LPA revealed five distinct profile types – disengaged, somewhat engaged, moderately engaged, highly engaged, and fluctuating engagement. Results showed that those who are more interactive and actively engaged with the LCDLM scored higher on their questionnaire compared to those who passively engaged with the LCDLM. We conclude with a discussion of the theoretical and practical implications of our findings.

Keywords: low-cost desktop learning module; student engagement; hands-on learning

1. Introduction

Recent years have seen a growing interest in Latent Profile Analysis (LPA) in organizational sciences (e.g., [1, 2]). LPA uses categorical latent variables to identify latent subpopulations within a target population. It assumes that people can be classified by varying degrees into different groupings (subpopulations) based on their personal and/or environmental characteristics. A categorical latent variable model can be used to represent structures by using groupings, as Woo et al. indicated [2]. Developing and incorporating typologies based on data can be conceptually meaningful and methodologically feasible through categorical latent variable models [3]. Leveraging on LPA methodological features and underlying assumptions, we used LPA to better understand and establish the representation of learner engagement profiles resulting from their self-reported learning engagement beliefs as they reflect on their experience in using hands-on learning equipment in engineering classrooms in several states around the United States.

Science, Technology, Engineering, and Mathematics (STEM) instructors in higher education have touted active learning as a promising way to positively transform STEM education [4–7]. Specifically, proponents of active learning in STEM suggest that such active learning strategies increase student engagement in and interaction with their learning environments [8, 9]. As engagement increases, positive outcomes such as learning performance, interest, attention, and self-regulation are likely to follow [10–13].

To better understand student roles in active learning environments, we draw upon Lombardi et al.'s definition of active learning [6]. According to Lombardi et al., "[active] learning is a classroom situation in which the instructor and instructional activities explicitly afford students agency for their learning" (p. 17). This suggests that instructors are responsible for offering instructional activities that

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provide specific affordances in learning, however, students are similarly responsible for their learning. Lombardi et al.'s definition also delineates that within undergraduate STEM instruction, active learning should focus on increasing learner engagement by offering opportunities for "direct experiences of phenomena," using scientific data and models that both provide and represent said phenomena, and "domain-specific practices that guide the scientific interpretation" [6].

An example of an instructional activity that aligns with Lombardi et al.'s definition of active learning [6] is the Low-Cost Desktop Learning Modules (LCDLMs) designed by an engineering education research team at the Washington State University, Pullman campus [14]. LCDLMs were designed to offer postsecondary students (i.e., undergraduates) a robust active learning experience in learning engineering topics. Specifically, students can use these LCDLMs to conduct direct investigations of hydraulic loss, flow measurement, and heat transfer phenomena [15]. Yet, while LCDLMs were designed to increase learner engagement in the engineering classroom, preliminary analyses indicate LCDLMs are not always more effective than traditional approaches especially when learning engineering concepts at lower levels of Bloom's taxonomy [14]. To better understand for whom and when the LCDLMs are more beneficial for learning, in this study, we take on a person-centered approach by examining the effects of the individual learner's engagement level as they interact with LCDLMs during a typical engineering learning activity.

While activities may be designated as being active learning modes to increase engagement in the classroom and afford student agency for learning, actual student engagement, specifically cognitive engagement, during the learning task, may still vary [10]. For example, an instructor might intend for students to work collaboratively with the LCDLM for an engineering lab assignment. However, students who simply sit with their group members but do not contribute to the assignment will have a much lower level of cognitive engagement than their group members who are actively contributing to the group discussion. In a different scenario, a student might instruct others on how to use the LCDLM, answer questions raised by other group members, and mentally formulate questions to ask the instructor. Although the student is not physically interacting with the LCDLM, they are still highly engaged in the learning activity. These two scenarios illustrate how the same learning activity might elicit different levels of engagement for students. More specifically, while the learning activity was designed to promote a specific level of engagement, students may approach these activities differently resulting in differential learning outcomes. This leads to the need to answer an overarching research question: what individual characteristics should researchers consider to determine whether active learning activities are effective for promoting positive learning outcomes?

To address the above question, in this paper, we aim to (1) establish a representation of learner engagement profiles resulting from their self-reported learning engagement beliefs, (2) establish differences in profile membership based on gender, race, and class standing, and (3) investigate the relationship between profile membership and learning performance on a posttest.

2. Background

2.1 Low-Cost Desktop Learning Modules (LCDLMs)

The Low-Cost Desktop Learning Modules (LCDLMs) were developed so that engineering students can conduct investigations to learn fundamental principles in fluid mechanics and heat transfer [14, 16, 17]. One key advantage of learning with the LCDLM is that it provides visual representations of engineering phenomena that would otherwise be difficult to comprehend without such visual representation (see Fig. 1) [8]. Such visual representations promote a better understanding of specific concepts in engineering, such as identifying the system boundary for computing a heat transfer rate in a heat exchanger [17] and predicting fluid velocity in a pipe [18]. The potential benefits of the LCDLMs are far-reaching. A recent study showed that the effects of learning with the LCDLMs are not just limited to a specific learning environment or implementation procedure [15]. Notably, findings in the study show that LCDLMs have been implemented in a wide variety of learning environments

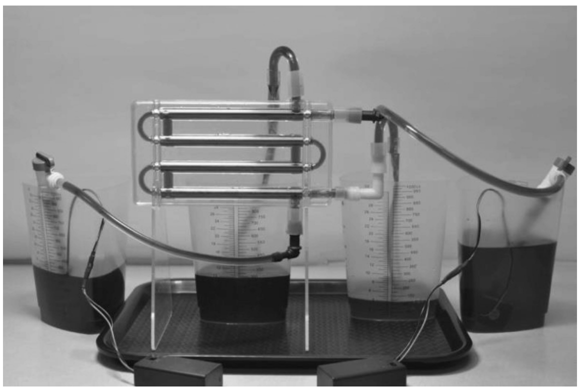

Fig. 1. Photo of the Double Pipe Heat Exchanger LCDLM used in Reynolds et al's study [8].

and their deployment by engineering faculty at universities across the US leads to well-documented effectiveness.

2.2 Interactive, Constructive, Active, and Passive (ICAP) Framework

Because in this study we seek to examine the impact of the individual learner engagement profile on learning achievement, we used the ICAP framework as observed by their overt learning behaviors [10]. Specifically, *I* stands for interactive, *C* for constructive, *A* for active, and *P* for passive. Based on the framework, learning activities that require a deeper level of engagement, i.e., constructive, and interactive, are better for learning than activities requiring little to no engagement (i.e., active and passive). More specifically, the ICAP framework predicts that interactive engagement provides better cognitive engagement than constructive engagement and other modes of engagement. In turn, constructive engagement is better than active engagement, which is better than passive engagement.

Under the interactive mode of engagement, activities are structured such that learners are actively interacting with each other to address a common learning objective. As such, interactive learning activities promote the deepest level of understanding as supported by the work of Chi and Wylie [10] because learners exchange information beneficial for strengthening each other's knowledge structures. Additionally, learners at this level of cognitive engagement are more likely to arrive at solutions for novel problems [10]. In the ICAP framework, an instructional dialogue between the teacher and student is also considered an interactive engagement.

Under the constructive mode of engagement, learners generate or produce additional externalized outputs or products beyond what was provided in the learning materials [10]. Unlike the interactive mode of engagement, learners work on tasks individually to construct or generate knowledge that goes beyond the information given. Constructive activities include drawing concept maps, taking notes, asking questions, comparing and contrasting, integrating text and diagrams, reflecting and monitoring one's understanding, and other self-regulatory activities. Thus, a characteristic descriptor of the constructive mode is generative. To meet the criteria for constructive engagement, the outputs of generative behaviors should contain new ideas that go beyond the information given; otherwise, such behaviors are merely active/manipulative [10].

We operationalize active students as those who manipulate some parts of the instructional materials such as pointing or gesturing, pausing or rewinding, underlining, copying, hands-on, or choosing an option [9]. By restricting active activities to mean those that require some form of motoric behavior that causes focused attention while performing a physical manipulation, we are distinguishing them from overt activities that are carried out mindlessly, such as reading a book out loud.

Finally, we define a passive mode of engagement as learners being oriented toward and receiving information from instructional materials without overtly doing anything else related to learning besides listening [10]. Essentially, learners are passive recipients of information. Outwardly, they do not look like they are doing anything to interact with the information. This might look like a student sitting in a lecture and simply listening to the information, or a student sitting with a group of other students but who is not involved in any discussions or activity with the group. Although the passive level is described as the lowest of the four modes of engagement, the authors acknowledge it is possible for students to covertly process the materials while listening or observing a video, even though they may appear to be passively engaged.

Based on the ICAP framework and the definitions of the different modes of engagement, a psychometrically-validated survey was adapted to reflect learning opportunities with the LCDLM that maps onto the four different modes of engagement. The ICAP hypothesis predicts that as students become more engaged with the learning materials, they progressively move from passive to active to constructive, and finally to interactive learning. Literature on active learning typically encourages students to participate in classrooms during instruction. Research at the post-secondary level has been the most prominent in promoting and using active learning in college classrooms. Indeed, it has been shown to be effective by many scholars including Harvard physics instructors [20, 21] and more recently promoted by Nobel Laureate in physics, Carl Wieman [22]. Researchers have also looked at other predictors of success, such as the status as an international student, student standing in the university, gender, and age [23], and learning during the COVID-19 pandemic .

3. Purpose of Study

Learning environments and interactions play a pivotal role in higher-education learning outcomes. Students use of learning strategies is also likely to differ across contexts and learning environments. Regardless, students who interact with hands-on modules and course-related materials tend to outperform those in the traditional face-to-face lecture format [22]. Given this, we ask three fundamental research questions: (Research Question 1) what are the different student profiles that emerge from students working with the LCDLM; (Research Question 2) is the LCDLM successful in improving learning outcomes; and (Research Question 3) how do students respond to the LCDLM based on their demographic information and academic standing?

With regard to Research Question 1, we examined how learner profiles varied based on LCCLM scores. Specifically, we expect to see a difference in responses to the survey based on learner profiles. For example, we expect highly engaged students to report high interactivity and low passivity on the survey. Similarly, we expect the reverse for those with low engagement. We also postulate that using the LCDLM in class will increase learning outcomes at the base level, which is consistent with prior literature outcomes [8, 15]. Specifically, we postulate that highly interactive and highly engaged students will outperform those in the group with lower engagement. Finally, we expect to see characteristics such as year in school, gender, race, etc., influence responses on the survey and their performance on the LCDLM-related tests.

4. Methods

4.1 Participants

Participants were 1,288 postsecondary engineering heat transfer and fluid mechanics students from both undergraduate and graduate engineering classes from 25 universities, and 41 classes in total, across the United States. Universities were recruited based on the region of operation and included both private and public universities. These universities were categorized into "hubs" to facilitate data collection and management. There were seven national hubs and each consisted of five to eight universities. Student participants were recruited for the study in class by their instructor. Instructors and their respective teaching assistants at the universities underwent training before implementation. Participation in the study was voluntary. Students were also told that their responses would be kept confidential. The study was approved by the second author's University Institutional Review Board.

4.2 Equipment and Implementation

The Low-Cost Desktop Learning Modules (LCDLMs) are model prototypes of standard industry equipment designed to achieve different purposes, and a past study reported that these miniaturized industrial-scale equipment produce data that align with large-scale industrial equipment [19]. These LCDLMs are hands-on instructional aids that simulate engineering concepts. These are helpful tools for learning abstract engineering concepts in the classroom since students can manipulate and observe them. The LCDLM versions used in our studies are simple, inexpensive to construct, and made from low-cost materials. Fig. 2 shows a picture of a shell and tube exchanger. By adjusting the valves, students can quantify the impact of the flow rate on temperature. By using shell and tube model equations, they may explore different scenarios to understand shell and tube concepts better. Through their interactions with an LCDLM, students can substantiate many abstract concepts taught in the classroom.

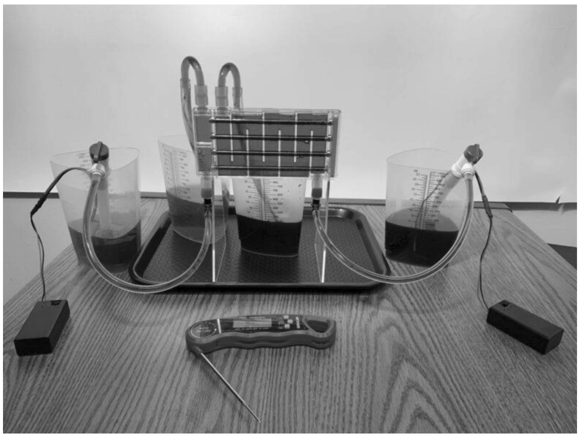

Fig. 2. Sample of a Shell and Tube LCDLM.

4.3 Measurement

4.3.1 Measures of Learning Performance

Measures of learning performance were constructed by the research team for each of the LCDLM learning topics (i.e., hydraulic loss, venturi meter, double pipe, shell, and tube). To examine prior knowledge, topic-specific pre-tests were administered to students before they participated in the LCDLM learning activities. The number of questions on the pre-test ranged from six to nine questions, depending on the topic. A posttest, identical to the pre-test, was administered to assess learning following the completion of the LCDLM activities. The tests comprised a mix of conceptual multiple-choice questions, true/false questions, and open-ended questions.

4.3.2 ICAP Survey

To establish learning profiles, the research team adapted a survey to assess perceptions of engagement when learning with the LCDLMs. There were 16 items on the survey to assess the level of engagement when learning with the LCDLMs. There were four items for each of the four modes of engagement based on Chi and Wylie's framework [10]. Participants responded to the survey items using a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree), self-reporting how the LCDLM influenced their learning experience. Engagement modes were assessed to reflect participant learning activity. Based on their experiences with LCDLM-facilitated instruction, participants were asked to express how LCDLM instruction helped them engage. Example items for each mode of engagement are provided below:

Interactive: The use of the LCDLMs helped me discuss with a peer about the Double Pipe Heat Exchanger concepts more than I could with a lecture.
Constructive: The use of the LCDLMs can help me to self-explain the concepts to myself better than lectures.
Active: The use of the LCDLMs helped me see Double Pipe Heat Exchanger concepts better than lectures.
Passive: The use of the LCDLMs made me idle.

Six items about the usefulness of specific features of the LCDLM were also included in the survey. For example, students were asked whether the see-through plastic in the LCDLM helped them understand specific concepts relevant to heat exchange. Similarly, participants responded to these items using a 5-point Likert scale (1 = strongly disagree and 5 = strongly agree), reporting how these features influenced their learning experience.

4.4 Scoring

4.4.1 Change in Learning Score

The pre- and posttests were graded by the instructors and teaching assistants of the respective classes. Each item on the test was worth one point. The pre- and posttests for each respective topic were identical. The total score on the tests ranged from six to nine points, depending on the topic. To examine the change in learning score, we calculate the difference between posttest and pre-test scores. We subsequently developed two categories for learning performance: scores increased, where posttest scores were higher than the pre-test, and scores decreased/remained the same, where posttest scores were lower than the pre-test or the same.

4.4.2 ICAP Survey Scores

For this study, we were primarily interested in responses to the 16 ICAP items on how the LCDLM engaged and influenced students. There were four items for each of the four modes of engagement (Interactive, Constructive, Active, and Passive). To calculate self-reported engagement, we summed up responses for the respective subscales. The highest possible score for each subscale is 20 points (i.e., a response of “Strongly Agree” for all four items on a particular subscale), and the lowest possible score is 4 (i.e., a response of “Strongly Disagree” for all four items on the particular subscale).

4.5 Procedure

The instructors who participated in this study were given the LCDLMs and asked to incorporate the module into the class sessions to facilitate instruction while teaching heat transfer and fluid mechanics concepts. All participants had at least 50 minutes of weekly instruction on these engineering concepts of heat transfer and fluid mechanics taught using the LCDLMs at each implementation site. The consent form was administered to all students in the respective classes. Students who consented to release their data for the study were redirected to a demographic survey via Qualtrics. Students in the experimental group received links to an online survey administered via Qualtrics at the end of the LCDLM sessions. The pre-test and posttest were both administered via Qualtrics. The pre-test was administered before students started working on the LCDLMs and the posttest was administered after completion of LCDLM learning activities. Data analyzed in the present study were collected from face-to-face and online settings.

4.6 Data Analysis Plan

4.6.1 Covariates

Age, gender, race, college standing, international student status, classroom size, and academic year were included in the logistic regression model as covariates to control their effects on the score differences before and after exposure to the LCDLM activities. Gender was coded as male, female, and others, and race was included as dummy binary variables.

4.6.2 Statistical Analysis

To establish measurement models of key constructs of ICAP, we conducted confirmatory factor analysis using Mplus 8.4 [25] to ensure that subscale scores within the ICAP framework could be distinguished and thus reported separately. The measurement model for incentivized self-learning – a possible key predictor of ICAP profiles – was also examined. We tested model fit by using the root mean square error of approximation (RMSEA), the standardized root mean square residual (SRMR), and the Tucker-Lewis index (TLI) / comparative fit index (CFI). The model fit was considered appropriate if the RMSEA and SRMR values were below

0.08, and the CFI and TLI values were close to or higher than 0.95 [26].

We performed latent profile analysis (LPA) [27] to group individuals into homogenous profiles with regard to their ICAP score. LPA is a special case of mixture models in which it assumes that the population consists of unobserved subgroups or profiles. The number and nature of the profiles are unknown and have to be inferred from the data; that is, it is hypothesized that the scores of individuals on several continuous scales can be explained by their membership within latent profiles. LPA seeks to find a solution with a sufficient number of profiles that reveal a distinctive pattern of responses between the different profiles but relatively homogeneous responses within each profile.

LPA was chosen as our modeling technique given the advantages over standard cluster analysis methods such as agglomerative hierarchical cluster analysis or k-means clustering. LPA has the advantage of being a model-based approach, allowing a quantitative comparison of models with solutions varying in the number of profiles to select the one best fitting the data. Because the number of expected profiles is unknown, we conduct an exploratory analysis by investigating models for one to seven profiles. To obtain stable solutions, the variances were constrained to be equal across clusters [28]. Using MPlus 8.4 we generated several model fit criteria to help decide which latent profile model best fits the data. More specifically, the Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC) were checked. Smaller values for the BIC and AIC are favored as they indicate a better model fit [29, 30], Furthermore, a significant p-value for the Lo-Mendell-Rubin likelihood ratio test implied that the k-profile model fit better than the model with k-1 profiles [31]. Next, the entropy was examined, which indicated the clear delineation of clusters. The entropy values should be greater than 0.7 to indicate an acceptable classification accuracy [32]. Finally, the sizes of the profiles and their interpretability were used as further selection criteria [33]. We are mindful in our analysis of models that present groups with less than 5% of the total students (i.e., which in our case would be less than 60 students in a profile), to avoid groups that provide statistical differences, but insignificant theoretical differences. After the best solution is determined, a profile of performance in each group is plotted, and a detailed description of each group is provided.

4.7 Predicting Performance with Profile Membership

We used multivariate logistic regression to describe whether the membership of LCDLM interaction profiles is associated with increased academic performance. We conducted an initial bivariate logistic regression and a more complex model with all the related covariates included. The logistic regression outcome is binary, with scores increases coded as 1 and score remaining the same or decreasing coded as 0. The analysis was used to answer the research question regarding profile membership in predicting student success in engineering concepts. Specifically, this analysis was conducted to answer Research Questions 2 and 3, to explore the extent to which personal background characteristics and academic profile of adult students predict their profile membership, and whether profile membership increases or decreases the odds of successful academic performance.

5. Results

Table 1 provides the general descriptions of the population sampled. Data from 1,288 participants were analyzed in this study. Caucasian population represented the largest group in racial diversity (41.4%), followed by Asian and Pacific Islanders (28.4%), African American (20.3%), and Native American (7.1%) Due to COVID-19, we observed an increase in the number of individuals participating in online classes or hybrids (37.9%) as colleges adjusted to prevent the spread of the pandemic and remain in session. Additionally, there was a small variation in the grouping of each regional hub, with the Northwest hub having the highest recruitment as it was the first site for LCDLM implementation and represents over 35.8% of the total population.

5.1 Class Choice

To establish a representation of learner engagement profiles based on their self-reported learning engagement beliefs (Research Question 1), fit indices and criteria are used for the selection of the model with the optimal number of clusters. The fit indices performed on the LPA are located on Table 2, specifically looking at the AIC, BIC, LMR, G^2 statistics, entropy, and the smallest group size. The AIC and BIC, decreased as the number of groups increased, but only marginally from more than seven group solutions onward. The *p* values of the LMR for K versus K-1 classes were also significant for each higher group, except for six-, seven-, and eight-classes profiles. Yet, log-likelihood for AIC and BIC indicates that the model progressively improves until the nine-model, with the lowest score being nine-class (Negative-LL; –23333.1; AIC: 47002.12; BIC: 47881.7), but entropy is highest for the seven-profiles model (0.95). The Lo-Mendell-Ruben likelihood-ratio test indicates the model was progressive until the

Table 1. Descriptive Analysis of the Total Population Included in the Analysis

Variable	LCDLM
Total Count	1288
Academic Year/Semester	
2018 Fall	180 (14.0%)
2019 Spring	295 (22.9%)
2019 Fall	253 (19.6%)
2020 Spring	210 (16.3%)
2021 Fall	350 (27.2%)
Race	
Caucasian	533 (41.4%)
Black or African American	262 (20.3%)
Asian and Pacific Islander	366 (28.4%)
Native American	91 (7.1%)
Others	36 (2.8%)
Median Age (S.D.)	19.71
Gender (Female)	492 (38.2%)
International Student (yes)	392 (30.4%)
Class Standing	
Freshman	321 (24.9%)
Sophomore	536 (41.6%)
Junior	217 (16.8%)
Senior	152 (11.8%)
Graduate and Others	62 (4.8%)
Learning Setting	
In-Person	291 (22.6%)
Online	509 (39.5%)
Hybrid	488 (37.9%)
Learning Score	
Score increased	830 (64.4%)
Score remained or decreased	388 (30.1%)
Regions and Hubs	
Northwest	461 (35.8%)
Southwest	186 (14.4%)
Northeast	192 (14.9%)
Southeast	274 (21.3%)
Central	175 (13.6%)

6-class model, where the seven-class model is not optimal compared to the six-class model ($p = 0.08$). Examining the group size, only the 5-class model has an acceptable group size that is over 5% of the total study population. The final class selected based on the metrics is the five-class model, with acceptable group size, LMR test, and grouping.

5.2 Class Description

Fig. 3 provides a visual representation of responses to the 16 items on the ICAP survey, sorted by student profiles. In this section, we explore the level of engagement based on their profiles. Overall, most students do not differentiate significantly from interactive learning, constructive learning, and active learning within the same profile, meaning that their score on interactive learning is similar to their constructive and active learning scores. Moreover, the four questions that are used to classify each group also depict similar scores within the same group. Below we discuss more in detail regarding the different classes.

5.3 Latent Profiles

5.3.1 Profile 1: Disengaged (138 individuals)

The first profile is called the 'Disengaged profile' ($n = 147$). Disengaged students are characterized by the lowest response scores on most of the ICAP items. The profiles here reveal lower interactive, constructive, and active engagement scores, contrasted with higher passive learning scores. Compared to other groups, the Disengaged students mostly exhibit higher-than-average passive scores (2.90), and extremely low interactive (1.52), active (1.61), and constructive learning (1.59).

5.3.2 Profile 2: Somewhat Engaged (271 individuals)

Somewhat Engaged students reported higher interactive, constructive, and active levels than those with the disengaged profiles, but lower levels than

Table 2. Fit Statistics of LPA

Model	*N*	LL (model)	*df*	AIC	BIC	LMR (K class to K-1 class)	G^2	Entropy	Smallest group size
Two class	1,288	–27535.1	49	55168.11	55424.66	0.001	0.06	0.92	640
Three class	1,288	–26311.4	66	52754.77	53100.33	0.001	0.07	0.93	212
Four class	1,288	–25197.9	83	50561.8	50996.35	0.001	0.07	0.92	70
Five class	1,288	–24424.8	100	49049.58	49573.14	0.001	0.09	0.92	77
Six class	1,288	–23893.1	117	48020.26	48632.82	0.001	0.1	0.95	46
Seven class	1,288	–23688.1	134	47644.24	48345.82	0.08	0.07	0.95	37
Eight class	1,288	–23496.5	151	47294.99	48085.57	0.1	0.096	0.90	37
Nine class	1,288	–23333.1	168	47002.12	47881.7	0.07	0.4	0.94	35

Note: Log-Likelihood (LL) Akaike's Information Criterion (AIC), Bayesian Information Criterion (BIC), Lo-Mendell-Rubin likelihood ratio test (LMR), G-test, entropy, and the smallest group size are listed for each model built.

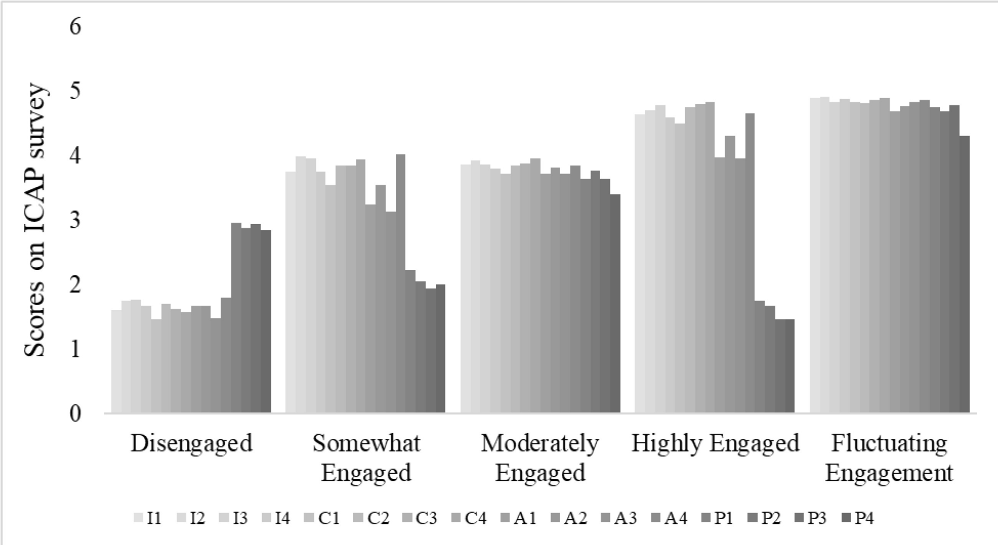

Fig. 3. The output of the LPA found five unique profiles in the study sample.

those in the stronger profiles. Contrasting with these higher scores are the lower score for passive. On average, this class has an average score in interactive score (3.82), constructive score (3.73), and active score (3.50). Compared with the disengaged profile, Somewhat-Engaged students have a lower score on passive learning (1.98), which indicates that this group may experience a more beneficial interactive effect while interacting with the LCDLM.

5.3.3 Profile 3: Moderately Engaged (615 individuals)

Moderately Engaged profiles (Profile 3 or Group 3) are similar to the profiles of group 2 (Profile 2), but with a statistically significantly higher score than group 2 in terms of their interactive score (3.87), constructive learning score (3.85), and active learning score (3.76). However, students that are members of this profile also reported a higher level of passive learning, deviating from the theoretical construct.

Comparing groups 2 to 3, we can conclude that both groups share similar scores on the ICAP scale, aside from the difference on the passive subscale – differing in approximately 1.5–1.7 points (26%). One possible explanation for the quantitative difference observed between Profiles 2 and 3 is the effort required for these students to succeed may be different in the LCDLM model. In Profile 3, more students have higher learning scores. For example, some students, especially those who have prior exposure to related engineering concepts, may exhibit more passive learning. This is consistent with the Expertise Reversal Principle, where instructional material becomes redundant for more knowledgeable learners [34]. It may be the case that students in Profile 3 who have high prior knowledge do not feel the LCDLM can help them engage and learn engineering concepts better because they already have some level of prior knowledge brought into the learning scenario.

5.3.4 Profile 4: Highly Engaged (192 individuals)

This profile demonstrated the highest level of interactive, constructive, and active learning. Additionally, this group had the lowest score in terms of passive learning, which is ideal for formulating critical thinking. Consistent with the ICAP framework, the higher scores on the interactive learning (4.76) and constructive learning (4.69) subscales are associated with lower passive learning scores (1.51) and resulting in the formulation of critical thinking while engaged with the DLM model.

5.3.5 Profile 5: Fluctuating Engagement (72 individuals)

Students assigned to Profile 5 reported high scores on all ICAP subscales, which deviates farthest from the ICAP framework. This suggests that not only do these 77 students exhibit high scores in interactive, constructive, and active learning; but the students in this particular profile group also have a moderately high score on the passive subscale. We will discuss this further in the discussion section because the students may have fluctuated between actively and attentively interacting with the modules, and passively learning. Additionally, COVID-19 may have introduced further complications where the line between active and passive learning is further blurred.

Table 3. Results from Simple Logistic Regression Analysis

Variable	Bivariable Regression	Multivariable Regression
Academic Year	0.65**	0.96
Race		
Caucasian	Reference	Reference
Black or African American	0.28**	0.32**
Asian and Pacific Islander	1.63***	1.42**
Native American	0.80	0.70*
Age	1.03	1.07
Gender (female)	1.32*	1.18*
International Student (yes)	0.7	1.0
Class Standing	1.63**	1.35*
LCDLM Medium		
In-Person	Reference	Reference
Hybrid	0.93	0.86
Online	0.56**	0.52**
Regions and Hubs		
Northwest	0.88	0.92
Southwest	1.10	1.03
Northeast	1.03	1.03
Southeast	1.01	1.01
Central	Reference	Reference
Latent Groups		
Disengaged	0.53**	0.47*
Somewhat Engaged	Reference	Reference
Moderately Engaged	1.26**	1.24**
Highly Engaged	2.78***	2.61**
Fluctuating Engagement	0.77	1.02

Note. $^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

5.4 Predicting Performance with Profile Membership

The result for the multivariate logistic regression is shown in Table 3. Two different logistic regressions were used to answer Research Questions 2 and 3, respectively. The multivariate logistic regression describes whether the membership of LCDLM-interaction profiles is associated with increased academic performance (Research Question 2), while the multinomial logistic regression determines if specific demographic and academic background increases the odds of specific membership (Research Question 3). The logistic regression outcome is binary, with score increases coded as 1 and scores remaining the same or decreasing coded as 0. The analysis was used to answer the research question regarding profile membership in predicting student success in engineering concepts. Specifically, this analysis was conducted to answer Research Question 3, which explores the extent to which personal background characteristics and academic profile of adult students predict their profile membership, and whether profile membership increases or decreases the odds of successful academic performance.

In Table 4, we used odds ratio to present the results for the multivariate logistic regression models, a bivariate model, and a final model including the predictor class and covariates in the equation. The logistic regression showed that different covariates impacted academic performance. When comparing only racial differences, Blacks and African American students had lower odds of scoring

Table 4. Means (Standard Deviations) of the Main Variables by Cluster

Student Profiles	Disengaged (n= 147)	Somewhat Engaged (n = 290)	Moderately Engaged (n = 658)	Highly Engaged (n = 205)	Fluctuating Engagement (n = 77)
I1	1.61 (0.04)	3.74 (0.03)	3.86 (0.04)	4.63 (0.05)	4.90 (0.07)
I2	1.75 (0.05)	3.98 (0.03)	3.92 (0.06)	4.71 (0.05)	4.91 (0.08)
I3	1.76 (0.05)	3.95 (0.03)	3.85 (0.05)	4.78 (0.05)	4.82 (0.08)
I4	1.67 (0.05)	3.74 (0.03)	3.80 (0.06)	4.59 (0.05)	4.88 (0.09)
C1	1.47 (0.04)	3.55 (0.03)	3.71 (0.05)	4.49 (0.05)	4.82 (0.08)
C2	1.70 (0.04)	3.84 (0.03)	3.85 (0.05)	4.74 (0.05)	4.82 (0.08)
C3	1.61 (0.04)	3.85 (0.03)	3.87 (0.05)	4.80 (0.05)	4.86 (0.07)
C4	1.57 (0.04)	3.95 (0.03)	3.96 (0.05)	4.83 (0.04)	4.89 (0.07)
A1	1.66 (0.05)	3.24 (0.03)	3.72 (0.06)	3.98 (0.06)	4.69 (0.10)
A2	1.67 (0.05)	3.54 (0.03)	3.82 (0.06)	4.30 (0.05)	4.77 (0.08)
A3	1.47 (0.06)	3.13 (0.04)	3.71 (0.07)	3.96 (0.07)	4.84 (0.11)
A4	1.79 (0.04)	4.02 (0.03)	3.84 (0.05)	4.65 (0.05)	4.86 (0.08)
P1	2.96 (0.05)	2.23 (0.03)	3.63 (0.06)	1.75 (0.05)	4.76 (0.09)
P2	2.87 (0.05)	2.05 (0.03)	3.77 (0.06)	1.67 (0.05)	4.69 (0.09)
P3	2.93 (0.05)	1.95 (0.03)	3.63 (0.06)	1.46 (0.05)	4.78 (0.08)
P4	2.84 (0.05)	2.01 (0.03)	3.41 (0.07)	1.46 (0.06)	4.30 (0.10)

Note. I = Interactive, C = Constructive, A = Active, P = Passive.

higher on their posttest compared to Caucasian students after interacting with the LCDLM (OR = 0.32, 95% CI = [0.22, 0.4]). Conversely, Asian and Pacific Islanders had higher odds of scoring higher on their posttest after interacting with the DLM (OR = 1.42, 95% CI = [1.20, 5.51]). Although female-identifying students represented a smaller percentage of students, they had higher odds of learning the concepts taught by LCDLMs compared to male-identifying students (OR = 1.18, 95% CI = [1.04, 1.46]). College class standing also significantly affected posttest performance, with upper-class college students performing better (OR = 1.35, 95% CL = [1.51, 1.78]). More specifically, as indicated by the odds ratios, students are 1.4 times more likely to perform better on the posttest with every year spent in college. The latent groups, after controlling for the medium in which participants worked with LCDLM, class standing, year of enrollment, gender, race, age, and location-hub, still accurately predicted the posttest performance. The reference groups were picked based on the theoretically acceptable group, with "Somewhat Engaged" chosen for this model. The "Somewhat Engaged" profile is used as the reference category, as this is the expected group with median performance. As expected, the disengaged group performed poorly, with roughly two times increased odds of doing poorer on the post-DLM model compared to the "Somewhat Engaged" profile (OR = 0.47, 95% CI = [0.3, 0.7]), while "Moderately Engaged" performed better (OR = 1.24, 95% CI [1.21, 1.35]). The highly engaged group outperformed most groups (OR = 2.61, 95% CI = [1.8, 3.74]). In the final model, some relationships were diluted, such as gender, race, and class standing. However, no relationships were found to be insignificant after including them in the multivariable logistic regression.

6. Discussion

In the present study, we explored different groups of students who interacted with the LCDLM based on ICAP questionnaire responses. We found that following the ICAP framework, those who are more interactive and actively engaged with the LCDLM scored higher on their questionnaire compared to those who passively engaged with the LCDLM. The LPA revealed five distinct profile types and the validation process resulted in a differentiation of group academic success. Given this, we provide a discussion of the unexpected results.

Students assigned to Profile 4 (Highly Engaged, 205 students) exhibited relatively high scores on Interactive, Constructive, and Active forms of engagement. They also reported relatively low levels of skills for idle learning, which is the least effective style of learning. Even when controlled for race, ethnicity, gender, and other academic information, students in this group outperformed other groups in terms of test score improvement. More notably, the students that are in this group are generally more likely to succeed in using the LCDLM. Altogether, these results are suggestive of a group of students characterized by their commitment to the engineering lab modules.

The other profile, namely the profile in which students score lowest for all questionnaires in the ICAP is called the "Disengaged" profile (n = 147). Students in this profile are characterized by lower scores on all subscales, which is associated with poorer outcomes as exhibited in the logistic regression output. When comparing the different profiles in terms of the trend in the scores for the various subscales, the disengaged profile shows a greater amount of passive learning in comparison to the other ICAP profiles, while other profiles have lower or moderate passive learning outcomes. Furthermore, the fluctuating profile was associated with high ICAP scores across the subscales but exhibited test score outcomes similar to those that are of the moderately engaged profile.

Having higher interactive and constructive scores indicates a higher likelihood of optimal learning performance. Additionally, a positive view of working with the LCDLM leads to more effective learning (e.g., high satisfaction with the teaching lab or instructor). Thus, there appears to be an effect of positive perception of the learning environment rather than the direct effect of LCDLM modules themselves on learning [35–37].

Based on student ratings on the ICAP subscales and other demographic information (e.g., class standing, international student, or US region), the moderately-engaged profile had higher odds of performing better on tests compared to the somewhat engaged profile. Among these profiles, the fluctuating engagement profile performed similarly to the somewhat-engaged profile in terms of testing outcome after controlling for demographic and academic backgrounds. This suggests that the LCDLM is in itself useful for learning.

The demographic information suggests that there are still barriers to learning effectively with the LCDLMs. Those who are African American and Native American are still left behind in terms of positive educational outcomes, and in our study, students of those demographics still performed more poorly than their Caucasian and Asian American counterparts. In addition, results from our study show that first-year college students tended to do worse than those who had been in college for more years, with each year consecutively performing better. Lastly, those who interacted with LCDLMs benefited more. This is in line with the copious literature explicating the deleterious effects of COVID-19 and the forced remote/online learning during that period [38, 39].

6.1 Limitations

Although we were successful in generating and characterizing five types of profiles in LCDLM users, there are a couple of limitations of the study. First, some of the obtained results may be explained better by soliciting additional information from participants about their reasons for endorsing any particular form of engagement. Alternatively, future studies may include conducting interviews with selected participants.

Second, because our search for the types of LCDLM-user profiles was exploratory, future studies must replicate and further validate our results. This is needed to better explicate the robustness of our findings. In addition, future studies should investigate whether the reasons that we used to generate the types of LCDLM users are indeed stable or that they vary over situations or time. It is also important to examine student retention of information over time with the continuous use of LCDLMs. In addition, it is suggested that active and engaged learning will improve student learning, leading to better student outcomes. Thus, future studies may also include student course grades and or course pass/fail rates as potential covariates.

7. Conclusion

In this paper, we examined students' engagement profiles in the context of learning with low-cost desktop learning modules (LCDLM). Students completed an ICAP questionnaire consisting of four ICAP subscales, interactive, constructive, active, and passive. Based on students' responses to the questionnaire, the LPA identified five distinct engagement profiles – disengaged, somewhat engaged, moderately engaged, highly engaged, and fluctuating engagement. Specifically, students in the highly engaged and moderately engaged profiles expressed greater engagement with the LCDLM, as indicated by their higher interactive and constructive subscale scores on the ICAP questionnaire. Importantly, the results also indicated that students in the highly engaged and moderately engaged profiles were more likely to succeed while working with the LCDLM than those in the other categories, after controlling for other student and demographic factors. This finding aligns with existing work on the impact of engagement in the classroom on learning, and draws instructors' attention to the need of identifying engineering education learning activities that increase engagement.

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