Exploring student learning profiles in algebra-based studio physics: A person-centered approach

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In this study, we explore the strategic self-regulatory and motivational characteristics of students in studio-mode physics courses at three universities with varying student populations and varying levels of success in their studio-mode courses. We survey students using questions compiled from several existing questionnaires designed to measure students' study strategies, attitudes toward and motivations for learning physics, organization of scientific knowledge, experiences outside the classroom, and demographics. Using a person-centered approach, we utilize cluster analysis methods to group students into learning profiles based on their individual responses to better understand the strategies and motives of algebra-based studio physics students. Previous studies have identified five distinct learning profiles across several student populations using similar methods. We present results from first-semester and second-semester studio-mode introductory physics courses across three universities. We identify these five distinct learning profiles found in previous studies to be present within our population of introductory physics students. In addition, we investigate interactions between these learning profiles and student demographics. We find significant interactions between a student's learning profile and their experience with high school physics, major, gender, grade expectation, and institution. Ultimately, we aim to use this method of analysis to take the characteristics of students into account in the investigation of successful strategies for using studio methods of physics instruction within and across institutions.

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I. INTRODUCTION

Despite their growing popularity, studio-mode introductory physics courses, which support an interactive student-centered learning environment, have seen variable success at different institutions as measured by student outcomes. We define a studio-mode introductory physics course as one that combines the lecture, laboratory, and recitation activities of a traditional introductory physics course and endeavors to reduce time spent on instructor-led lecture in favor of student-centered active learning opportunities. A variety of studio methods, which combine traditional lecture and recitation activities, have been developed for introductory physics, such as Workshop Physics [1,2], Rensselaer Polytechnic Institute's Studio Physics [3], and SCALE-UP [4]. These reforms typically prescribe a modified classroom structure, with tables that facilitate student collaboration rather than stadium-style lecture seating. SCALE-UP, a focus of this work, uses a reformed pedagogy that aims to minimize lecture time and maximize collaborative work time in a studio (large-enrollment) classroom environment.

Although many positive learning outcomes have been published for studio-mode courses [1,2,4–6], these benefits do not arise automatically from a reformed classroom. Instead, instructional practices and other factors can significantly influence success. Several instructor effects have been identified that may affect the success of a studio-mode course. As reported by Cummings *et al.* [3], conducting a course within a studio-mode classroom and adapting largely traditional activities to fit in with the studio environment was not enough to replicate the substantial student conceptual gains seen at other institutions adopting studio modes of instruction, such as SCALE-UP [7]. Along the same lines, Lasry *et al.* [8] found that an instructor's teaching methods are more important than the format of their room, such that teacher-centered pedagogies enacted in student-centered classrooms may have negative effects on students who have low physics knowledge prior to taking the course [8]. Furthermore, a recent study by Foote [9] found that even when the instructors adopting SCALE-UP have an interest in physics education research (PER) and are motivated to make the reform, difficulties in implementation of the research-based instructional material designed for SCALE-UP can lead to instructors creating their own materials which have the possibility of not being grounded in PER outcomes and thus may not fully support the SCALE-UP reforms. Ultimately, an increasing body of evidence supports the conclusion that building a studio-mode physics classroom

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and conducting class within it is not sufficient to make the implementation successful; there are nuances of studio-mode physics adoption and implementation that greatly affect the impact of such a learning space.

While previous research has explored instructor-level reasons for the variation in success of studio-mode physics courses, in this paper we explore how students' backgrounds, expectations, study strategies, and motivations may influence how they approach their learning in a studio setting. Prior work suggests these aspects vary across students and have the potential to influence their performance in a course. Elby demonstrated that students may select study strategies aligned with a performance orientation to get a good grade in a physics course despite understanding how to use study strategies aligned with a mastery orientation [10]. On the other hand, Kortemeyer found that students who tended to make physics-related comments on an online course discussion board had higher course grades and concept test scores compared to students who tended to make solution-oriented comments [11]. Stewart and colleagues found that students who earned high end-of-course grades were better able to self-regulate by changing their exam preparation time in reaction to their progress in the course compared to those who earned low end-of-course grades [12,13]. We expect that such behaviors may play an even more significant role in determining student success in studio-mode courses, which require active engagement of students both inside and outside of class.

While prior work has explored students' backgrounds, expectations, study strategies or motivations, in this paper we examine these constructs simultaneously. Specifically, we explore the utility of the "profile approach", which has been used in studies in educational psychology to identify five distinct learning profiles among several student populations [14]. We investigate the presence of these five previously identified learning profiles among students enrolled in algebra-based introductory studio-mode physics courses across three universities. To do this, we compiled a student characteristic survey from several published and validated questionnaires, similar to those used in Ref. [14], which probes students' strategic self-regulation and motivational characteristics and collects demographic information.

In this paper, we address the following three questions:

(i) Do the five learning profiles identified in prior research in the fields of educational psychology [14,15] and engineering education [16] describe the ways students approach learning in algebra-based, studio-mode introductory physics course?

(ii) Does learning profile adoption vary based on student demographics, such as gender, race or ethnicity, major, etc.?

(iii) Does learning profile adoption vary by institution?

We establish our survey's reliability and construct validity in our sample. We then use model-based cluster analysis to explore the presence of these five learning profiles among our students. This cluster analysis is "person centered," as it uses students' individual responses to find common, coherent groups among the students [14,17]. We start by discussing the five learning profiles found in previous studies using the profile approach, move to our survey construction and validation, and finish with our cluster analysis and learning profile results and their interpretation in relation to those found in the literature.

II. THEORETICAL FRAMEWORK

A. Self-regulated learning

The active attempt of a student to monitor and alter her or his approaches to a task is called self-regulation. Students engaged in ideal self-regulation are aware of their own thinking, can assess their current understanding and goals, and can change their strategies and thought processes as the need arises [18]. In educational psychology literature, a perspective that considers the various cognitive, motivational, behavioral, and contextual elements that guide student learning is termed the "self-regulated learning" (SRL) perspective [19]. We adopt the SRL perspective as it is important when looking at classroom environments such as the studio mode, where students are encouraged to learn on their own and in groups, to seek information from electronic sources, and to possess "personal initiative, perseverance, and adaptive skills" (p. 167) [20].

In the SRL model, students are assumed to be autonomous, active participants in their learning, able to make judgments about their learning processes in the context of their learning environments, and able to adapt to new goals and challenges, if they choose to do so. Further details of these assumptions are given by Pintrich [19]. Within the SRL perspective, there are four main areas in which self-regulation occurs: cognition, motivation or affect, behavior, and context [19,21]. Regulation of cognition refers to the active setting of goals and planning for studying the course material and the act of using metacognitive techniques to monitor studying and learning [19,22]. The regulation of motivation and affect encompasses how students regulate interest levels in the subject material, change ideas about the utility of the tasks involved, and alter goal orientations [19,20,22–24]. The regulation of behavior deals with how students decide to behave and how they control their behavior, including the links between planned behavior and subsequent actions [25–27] and the management of study time and the control of study effort [28,29]. The regulation of context refers to the extent that students interact with and shape elements of the course, such as designing experiments and working together in groups [19]. Although the nature and context of classroom activities are often controlled by the course instructor and out of the hands of the students, regulation of context becomes more important and relevant in student-centered classrooms, such as studio-mode courses [19].

The major motivational and self-regulatory characteristics that work together to explain the actions of a student are represented in the SRL perspective. While many studies look at one or two areas of SRL at a time, there is a method emerging in the field of educational psychology to better understand the interrelations between students' motivations and strategic self-regulatory behaviors which takes into account many of the different components of SRL simultaneously. This method is termed the "profile approach" and is detailed in the next section.

B. Profile approach

The profile approach is a relatively new and powerful method emerging from growing efforts in educational psychology research to better understand what motivates students and what self-regulated learning strategies students enact when studying [19,20,23,30–34]. This approach is distinguished from other methods by the use of person-centered techniques to group together individuals with similar motivations and strategic self-regulatory behaviors. Person-centered techniques take into consideration students' individual response patterns across multiple measures (or variables), looking for groups of individuals that share similar patterns. This is in contrast to variable-centered methods that are characterized by investigating the relationship between measures after averaging across students' responses, treating these measures as separate entities [17]. Some examples of techniques that utilize a person-centered approach are latent profile analysis [35,36], canonical correlation [15], and cluster analysis [14,16,37,38].

One of the most well-defined and reproducible sets of student groups was initially identified by Shell and Husman, who found five distinct student learning profiles among undergraduate educational psychology students in a study using canonical correlation to analyze a wide range of motivational, affective, and strategic self-regulatory measures [15]. The five profiles are described as follows: (i) a strategic profile of a student motivated to learn and retain the subject material, using whatever self-regulatory strategies are needed to do so; (ii) a knowledge building profile of a student intrinsically motivated to learn and understand the subject material, but less actively engaged with the course; (iii) a surface profile of a student who understands the course's usefulness, but is primarily concerned with passing the course with little engagement in the subject material; (iv) an apathetic profile of an unmotivated student who, though wanting to pass the class, invests minimal engagement and personal interest in learning the subject material; and (v) a learned helpless profile of a student putting in large amounts of time and effort to pass the course, but unable to optimize self-regulatory study strategies [14]. These five profiles, or some subset, have been found in several other studies using different types of analyses on varying student populations. Cluster analysis was used to identify the profiles among post-secondary computer science and engineering [14,16] and education students [39]. Latent profile analysis was used to identify them among German secondary and post-secondary students [36], middle school earth science and space science students and high school biology and chemistry students [35]. In this study, we aim to describe introductory algebra-based physics students based on the motivations and study strategies they adopt while enrolled in studio-mode courses.

Shell and Soh [14] investigated the prevalence of the five profiles among majors and nonmajors in a postsecondary computer science course and found that computer science majors more frequently adopted the strategic and knowledge building profiles while nonmajors more frequently adopted the surface and apathetic profiles. Additionally, they found that students in the strategic and knowledge building profiles demonstrated better retention of computational thinking knowledge than students in the other profiles. Since the algebra-based physics sequence is taken by nonphysics majors, we may expect to see a high rate of adoption of surface and apathetic profiles.

A growing catalog of literature suggests the profile approach to be a powerful and informative research methodology built upon a well-established theoretical framework of student learning. We thus adopt this strategy to not only investigate the existence of these five learning profiles among a population of undergraduate physics students (a population not yet investigated), but also to better understand the students in studio-mode physics courses and how their varying backgrounds, study strategies, and motivations may influence their success in these courses.

III. METHODOLOGY

To explore whether the five learning profiles identified by Shell and Husman [15] extend to students enrolled in an algebra-based, studio-mode introductory physics course, we distributed an online survey to students across three universities during the final month of the semester. We named this survey the Student Characteristics Survey, or SCS. In this section, we describe the development and validation of our survey, the cluster analysis method we used to analyze students' responses to the survey, and our study population.

A. Student Characteristics Survey

Based on the results of prior research, we sought to develop a survey with questions probing both motivational and strategic self-regulatory factors to identify all five learning profiles; studies that explored too few categories tended to identify only a subset of the five profiles [14,35,40]. We used the survey scales of Ref. [14] as a starting point and substituted comparable scales when specific ones were not readily available; these deviations are explained in the Supplemental Material [41]. Our strategic self-regulatory scales explore self-regulation, knowledge building, question asking, collaborative learning, learning approaches (deep, strategic, and surface), and study time and effort. Our motivational scales explore goal orientation, perceptions of instrumentality, and future time perspective. Additionally, we added an epistemological scale and demographic and academic experience questions. Information on the parent surveys and descriptions of the scales are given in the Supplemental Material [41].

To be confident that our set of survey items behaves together as expected, we evaluated both the reliability (the extent to which items collectively measure the same latent variable) and validity (if all of the scales put together into one survey act similarly as they did on their own) of our SCS for our population. We found that the ordinal α coefficients for all scales were above 0.70, indicating sufficient reliability to evaluate survey scales on a group level, and most were above 0.80, indicating sufficient reliability to evaluate survey scales on an individual level [42,43]. (The α for each scale is given in the Supplemental Material [41].) We used confirmatory factor analysis through the lavaan package in the open source statistical programming language, R, to test a proposed model where each item was associated with only the scale it came from and the scales were allowed to correlate [44,45]. The resulting fit statistics indicate the model is supported by the data, and we may use these scales together in one survey with confidence [$\chi^2(df = 2254) = 6639.966$, $p < 0.001$; SRMR = 0.063; RMSEA = 0.046] [46].

B. Cluster analysis

Cluster analysis is a method of creating groups, or clusters, such that individuals within a cluster are similar to each other and distinct from individuals in other clusters [47], allowing one to compare responses within and across groups [48]. Cluster analysis can be easily performed with R [44]. There are two main categories of cluster analysis algorithms: hard clustering and fuzzy clustering. When hard clustering methods are used, individuals are assumed to belong to one, and only one, of the resulting clusters [47]. On the other hand, when fuzzy clustering methods are used, each individual belongs to each cluster with a particular degree of membership [47]. We chose a model-based clustering method with mixture models in the present work because it allowed us to interpret an individual's cluster membership as a set of probabilities, analogous to the degrees of cluster membership resulting from fuzzy cluster analysis methods [49], instead of placing (or misplacing) an individual into a particular cluster. Additionally, it allowed us to conduct further analysis on the clusters with a population restricted to high probability (here, a minimum of 0.75 was chosen) of membership to only one cluster.

1. Model-based cluster analysis

We use model-based cluster analysis for the following three main reasons: (i) the use of likelihood measures of similarity in model-based clustering allow for one to interpret clustering in the data not just as collections of geometrically close points, but as probability distributions estimating populations of individuals from which one's sample was collected [47,50,51]; (ii) the likelihood similarity measures can easily be extended to account for mixing of these probability distributions (or clusters), allowing for a fuzzy interpretation of the clustering results [47,49,52]; and (iii) model-based clustering allows one to easily explore several different clustering solutions and provides a means to assess which solution is the best fit for one's data [52].

As with any cluster analysis method, a measure of proximity (or similarity) must be defined to quantify the distance between responses so that judgments can be made about the relationship between individuals. Model-based cluster analysis uses the probabilistic distance measure of likelihood rather than the more familiar Euclidean distance. With the likelihood distance measure, a set of data points is "closer" to each other if it is more likely that those points come from probability density functions with a shared set of parameters. In contrast to the Euclidian distance, where one looks for a minimum to find the closest points, one looks for the maximum likelihood to find the closest, or most similar, points. Furthermore, when using the probabilistic likelihood distance measure in model-based clustering, we make the assumption that the observed data come from a population comprised of subpopulations, or clusters; we then model each of these subpopulations separately and consider the total population as a mixture of these subpopulations [50,51]. This changes slightly the interpretation of our clustering results, as individuals placed in clusters are not simply close to each other in their numerical responses to our survey but are likely to belong to the same subpopulation of students (e.g., the same learning profile). The level of mixing of these subpopulations is interpreted as the probabilities that each individual belongs to a particular subpopulation, or cluster [47,50,51]. Thus, as a result of the model-based clustering, each individual is assigned a set of cluster membership probabilities: one value for each cluster, the set of which sum to 1.0. Such a set of values is analogous to degrees of cluster membership assigned to individuals as a result of fuzzy clustering techniques; thus, we consider our model-based cluster analysis with mixture models as a fuzzy cluster analysis [49].

In addition to a probabilistic distance measure, model-based cluster analysis allows one to propose different models that define the ways in which the volume, shape, and orientations of clusters are allowed to vary with respect to one another. Volume refers to whether the clusters are constrained to be roughly the same size (equal) or if they can vary in size across one another (variable). Shape refers to whether the clusters are constrained to be roughly the same ellipsoidal shape (equal) or if they can vary in ellipsoidal shape (i.e., vary in the sizes of their semi-major and semi-minor axes) across one another (variable). Orientation refers to whether the clusters are constrained to be roughly the same orientation (equal) or if they can vary in orientation across one another (variable). Analytically, the sizes and shapes of clusters are determined by the relative magnitudes of the clustering variable standard deviations, and the cluster orientations are determined by the correlations between clustering variables [53]. Ultimately, these different models constrain the covariance matrices of data within each cluster in different ways. For example, the model that returns the best solution in our analysis is the variable volume, variable shape, and equal orientation, or VVE, model. Thus, in our best solution, the clustering variable standard deviations are variable across clusters, but the correlations between clustering variables are the same across clusters. Gan *et al.* [47], Celeux and Govaert [49], and Everitt *et al.* [53] discuss the details and mathematics behind applying these models in model-based cluster analysis.

We chose the best solution by considering several measures of fit. The first of these measures is the Bayesian information criterion (BIC). The BIC "is a likelihood criterion penalized by the model complexity" (p. 646) [54]. The model and cluster number to give the highest BIC is likely the best solution [54]. In the learning profile research conducted by Shell and Soh [14] and Nelson *et al.* [16], they also use a likelihood-based similarity measure in their clustering process. Furthermore, Nelson *et al.* [16] considered several other fit statistics in conjunction with BIC values when choosing the best cluster solution: the sums of squares within (SSW), the sums of squares between (SSB), and the silhouette coefficient. SSW and SSB are defined in the same way as in a one-way ANOVA [55]. Similarly, we consider the SSW and SSB but also felt it appropriate to consider a validity index that takes into account not only the cohesion (compactness) and separation of the resulting clusters (as a silhouette coefficient does) but also the probabilistic and fuzzy nature of the cluster membership results (something the SSW, SSB, and silhouette do not). Such a validity index is the fuzzy index of Xie-Beni [47,56]. This validity index has been shown to perform well in validation of the results of model-based cluster analysis using mixture models [57,58]. Here, we denote this fuzzy validity index as S (the same notation used by Xie and Beni [56] and Gan *et al.* [47]); the smaller the S value, the more compact and separate the clusters are in the clustering solution. When evaluating the various cluster solutions produced by the model-based cluster analysis, we consider all four of these fit measures (BIC, SSW, SSB, and S) together, along with theoretical considerations, to choose the clustering solution that best fits our observations.

2. Variable reduction for cluster analysis

Though there is no consensus on the minimum sample size needed for cluster analysis, Formann [59] suggests a minimum sample size of 2^d, where d is the number of clustering variables; this minimum sample size condition is often referred to as Formann's criteria [59,60]. To use all of our 17 scales as potential clustering variables, we would need a minimum sample size of 131 072. Since our sample size is only 900, we wish to reduce the number of clustering variables (ideally to around 9 variables or less; $2^9 = 512$). Our goal of variable reduction is twofold: we are taking sample size restrictions into consideration, and we are working to identify the most informative variables and reduce the length of our survey for later distributions.

Sarstedt and Mooi [60] provide guidelines for selecting clustering variables to make the clustering results as meaningful as possible. We operationalized these guidelines into the following three rules to decide which variables to retain for clustering:

(i) We assess the quality of variables using the ordinal α reliability measure. Ordinal α values between 0.70 and 0.79 are sufficient to evaluate measures on a group level, while ordinal α values of 0.80 or greater are high enough to measure qualities of individuals [43]; thus, we retain only those variables with ordinal α values of 0.80 or higher for clustering, while variables with ordinal α values between 0.70 and 0.79 are considered for comparisons between clustered groups in follow-up analyses.

(ii) To reduce the possibility of overrepresented variables, we consider the correlation matrix between all variables retained after reliability considerations, and make note of those scales that possess both a moderate to strong ($r = 0.50$ to $r = 1.00$) correlation (statistical correlation) and considerable overlap in content assessed by the variables (theoretical correlation). As an additional constraint, since having distinct strategic self-regulatory and motivational variables are important to resolving the five learning profiles [14], we compare variables within their respective categories, so as to not convolve them.

(iii) We aim to select scales that will be the most informative to clustering and can give us the richest interpretation of resulting clusters. This rule can be used when deciding which of a pair of variables identified by step 2 to retain.

To apply our first rule, we examined the ordinal α values of each scale (listed in Table S1 of the Supplemental Material [41]), eliminating those with ordinal α values less than 0.80 and single-item scales for which an ordinal α could not be computed. This step eliminated seven scales from the cluster analysis. EBAPS: structure of scientific knowledge, future time perspective, performance approach, deep approach, and exogenous instrumentality (five total) were eliminated because their ordinal α values were less than 0.80. Furthermore, since study time and study effort are each based on a single item and their reliability cannot be calculated, they were also removed at this step.

Next, to apply our second rule, we considered statistical and theoretical correlations between the remaining ten scales to remove redundant information. Out of all the possible pairings, two pairs showed both considerable correlations and topical overlap among the constituent items. The low-level question asking and high-level question asking scales show a strong, significant correlation (Pearson's $r = 0.81$, $p < 0.001$). This indicates that a student's use of low-level questioning is a good predictor of their use of high-level questioning. Given low-level question asking's slightly higher reliability, we retained low-level question asking as a clustering variable. The self-regulation and strategic approach scales also showed a moderate, significant correlation (Pearson's $r = 0.62$, $p < 0.001$), and the topics of the items comprising these two scales overlap. Items in self-regulation address both students' study strategies and self-regulation, while items in strategic approach mainly focus on study strategies only. Hence, since self-regulation is a more informative scale [rule (iii)], we retained it as a clustering variable.

We note there are two scale pairs with Pearson's r values higher than 0.50, but that do not display substantial topical overlap: self-regulation and knowledge building (Pearson's $r = 0.56$, $p < 0.001$) and self-regulation and low-level question asking (Pearson's $r = 0.52$, $p < 0.001$). While these pairs have moderate correlations, there is little conceptual overlap between the core student characteristics probed by these scales. Thus, we chose to retain self-regulation, knowledge building, and low-level question asking as distinct clustering variables.

Concluding our variable reduction, we are left with eight clustering variables. We retained the strategic self-regulatory scales of self-regulation, knowledge building, low-level question asking, collaborative learning, and surface approach, and the motivational scales of learning approach, task or work avoid, and endogenous instrumentality. Using Formann's criteria, a set of eight clustering variables calls for a minimum sample size of $N = 2^8$ (256) students, which our data set exceeds. We can now proceed with these eight scales as cluster variables and use the remaining nine scales in postcluster analyses. To increase interpretability of the clustering results, scales are globally standardized to z scores prior to cluster analysis.

C. Institutional context and participants

Survey responses were collected from SCALE-UP-style [7] studio-mode courses at three large universities, described as "highest research activity" by the Carnegie classifications [61]. University A and University B are both public and primarily nonresidential, while University C is private not for profit and highly residential. All three universities have renovated classrooms specifically dedicated to SCALE-UP courses, featuring tables with movable chairs to facilitate small group interaction, whiteboards, and access to computers and lab equipment. The maximum class size varied from 54 at Institution B to 99 at Institution A. At the department level, the intention was for integrated course components at each of the three universities, although individual instructors had autonomy to decide how to spend class time, and some dedicated specific days to extended experiments. Additionally, the department-level intention was for reduced lecture time at all three universities, but individual instructors varied in how frequently they lectured. As described in our prior work, we conducted observations at Institutions A and C and found that lecture occurred with similar frequency across universities (22% versus 20%), but that individual instructors varied in their use, from 7% to 43% at University A and 7% to 36% at University C [62]. Instructors also had autonomy to decide how to structure groups and reported following a variety of practices. Some instructors carefully crafted groups, following recommendations that groups should have a student from the "top, middle, and bottom" of the class based on performance and/or that groups should not have a single woman or student from an under-represented racial or ethnic background. On the other hand, some instructors reported abandoning those practices and began randomly creating groups or allowing students to self-select groups. In this paper, our focus is at the department level; future work will explore instructor-level differences.

Survey responses were collected at all three institutions in the Spring 2015 semester, at Institution A in the Fall 2015 semester, and at both Institutions A and B in the Spring 2016 semester. Table I gives a breakdown by institution and semester of the number of course sections reporting data and the number of survey respondents. The survey was distributed online, and most students were offered a small amount of extra credit for their participation. Only those completing the survey, correctly answering two attention-check questions, and consenting to research participation are considered in the data analysis. Additionally, survey responses from students who took

TABLE I. Respondent breakdown by institution. (Percent of students participating is estimated by the maximum class size).

	A	B	C
		Spring 2015	
No. of Sections	3	4	2
Survey	199 (~67%)	119 (~51%)	123 (~75%)
		Fall 2015	
No. of Sections	4	…	…
Survey	121 (~30%)	…	…
		Spring 2016	
No. of Sections	4	3	…
Survey	246 (~62%)	92 (~57%)	…

the survey more than once were removed from the analysis so as to not violate any independence of observations assumptions in analyses conducted later. Ultimately, a total sample size of 900 valid responses to the SCS was collected.

IV. MODEL-BASED CLUTERING RESULTS

A. The best clustering solution: Five clusters in the VVE model

Figure 1 displays the BIC for models with various size, shape, and orientation restrictions for one through six clusters. Examining Fig. 1, we find that the VVE model results in the highest BIC value overall (at six clusters), in addition to giving relatively and consistently high BIC values. In addition, the VVE model gives the clustering algorithm the most freedom (allowing the shape and size of clusters to vary) while supplying enough constraint (in the cluster orientation) to allow for high BIC values. As one can see in Fig. 1, models with variable cluster orientation, those acronyms ending in a V, provide consistently low BIC values. Thus, in order to find an appropriate solution, we vary the number of clusters within the VVE model and compare the various measures of fit (BIC, SSW, SSB, and S). Table II gives these fit measures for several cluster solutions within the VVE model. Following the lead of previous researchers applying the profile approach (e.g., Shell and Soh [14] and Nelson *et al.* [16]), we compare solutions for two through six clusters.

The six-cluster solution gives the highest BIC; however, its SSW value is not the lowest, its SSB value is not the highest, and its S value is relatively large. Furthermore, while the two-cluster solution has the smallest S value, this

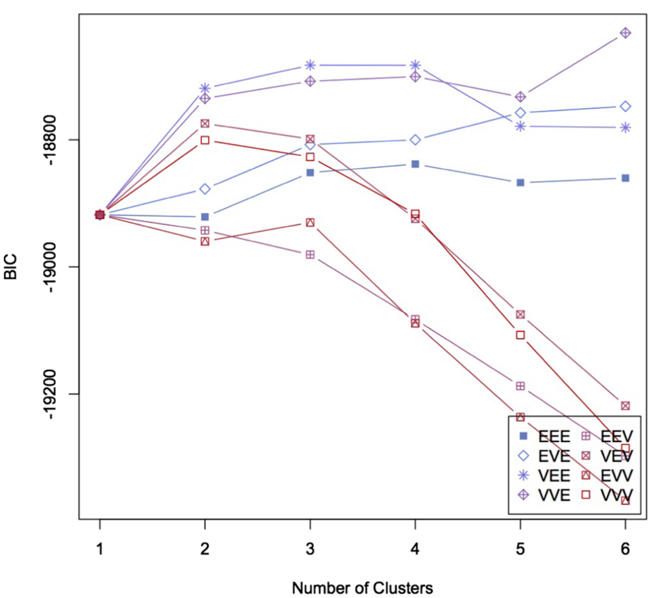

FIG. 1. Bayesian information criterion (BIC) values for various model-based clustering solutions.

TABLE II. Measures of fit for several cluster solutions in the VVE model.

Cluster number	BIC	SSW	SSB	S
2	−18 735	6381	810	1.4
3	−18 707	5771	1420	2.0
4	−18 700	5374	1817	2.3
5	−18 732	4751	2440	1.9
6	−18 631	5094	2097	2.2

solution's BIC, SSW, and SSB values are not desirable. Overall, the five-cluster solution possesses the best set of fit measures: the lowest SSW, the highest SSB, a relatively high BIC, and a relatively low S. The five-cluster solution also has the best theoretical backing, as it is supported by previous research also using survey instruments to probe a similar wide range of self-regulatory and motivational student characteristics [14–16]. Thus, we continue our analysis by interpreting the five-cluster solution, inspecting the resulting groups for similarities to the five learning profiles found in previous studies [14–16].

B. Interpreting the best clustering solution: Identification of the five learning profiles

Since we chose a model-based clustering method with mixture models, each respondent is given a probability of belonging to each cluster. In order to include only those students who have a high probability of possessing the characteristics necessary to be placed in one cluster over another, we retained only students with 0.75 or greater probability of being placed in a specific cluster. This reduced the sample size from $N = 900$ to 535. We chose to analyze data from students whose probability of membership in a particular cluster was 0.75 or greater as this level provided a balance of high similarity with others in a cluster and enough flexibility to retain the majority of our sample (60%). We explored this analysis with more restrictive (0.95 probability of membership, retaining just 20% of the population) and more flexible (0.50 probability of membership, retaining 92% of the population) cutoffs and did not observe changes in cluster interpretation. For example, comparing the means for the five profiles across the 17 scales with 0.50 and 0.75 cutoffs revealed only six (out of 85) changes in absolute ranking of clustering variables across clusters and all changes were within overlapping confidence intervals. Table III gives the cluster means and half-widths of their 95% confidence intervals for each standardized clustering and nonclustering variable for the five-cluster solution. For each cluster, these values were attained by calculating the averages and their 95% confidence intervals for each variable within each cluster using only those individuals placed in a cluster with 0.75 probability. In addition, for reference, the overall sample means used to globally standardize the scales prior

TABLE III. Standardized cluster means (and the half-width of their 95% confidence intervals) for the five-cluster solution. The overall sample means used to standardize data for each sale (and the half-width of their 95% confidence intervals) are given in the right column for reference.

Cluster number	1	2	3	4	5	Sample mean
Students in cluster	81	121	144	99	90	
Clustering variables						
Self-regulation	1.19 (0.10)	0.37 (0.11)	0.16 (0.11)	−0.45 (0.21)	−1.17 (0.25)	3.75 (0.05)
Knowledge building	1.30 (0.13)	0.59 (0.09)	−0.50 (0.13)	−0.15 (0.16)	−1.18 (0.20)	3.17 (0.06)
Low-level question asking	1.30 (0.10)	0.30 (0.12)	−0.22 (0.16)	−0.76 (0.17)	−0.69 (0.25)	3.36 (0.06)
Collaborative learning	1.01 (0.06)	0.27 (0.11)	0.57 (0.09)	−1.15 (0.22)	−0.80 (0.25)	4.10 (0.05)
Surface approach	−0.54 (0.23)	−0.96 (0.10)	0.48 (0.14)	0.40 (0.18)	0.31 (0.23)	2.94 (0.07)
Learning approach	0.51 (0.14)	0.74 (0.08)	−0.36 (0.10)	0.30 (0.15)	−1.71 (0.28)	3.94 (0.05)
Task or work avoid	−0.42 (0.24)	−0.28 (0.15)	0.01 (0.15)	−0.12 (0.19)	0.69 (0.25)	2.65 (0.06)
Endogenous instrumentality	0.59 (0.17)	0.79 (0.09)	−0.47 (0.13)	0.49 (0.13)	−1.45 (0.16)	3.30 (0.07)
Nonclustering variables						
High-level question asking	1.25 (0.12)	0.43 (0.13)	−0.27 (0.15)	−0.53 (0.17)	−0.77 (0.23)	3.29 (0.06)
Strategic approach	0.86 (0.14)	0.56 (0.13)	−0.13 (0.15)	−0.40 (0.21)	−0.79 (0.22)	3.62 (0.05)
Deep approach	0.71 (0.21)	0.40 (0.14)	−0.22 (0.15)	0.01 (0.20)	−0.89 (0.23)	3.49 (0.04)
Study time	0.45 (0.27)	−0.14 (0.15)	0.04 (0.17)	0.03 (0.21)	−0.52 (0.18)	2.00 (0.07)
Study effort	0.41 (0.20)	0.14 (0.17)	0.04 (0.14)	−0.01 (0.23)	−0.47 (0.25)	3.20 (0.07)
Performance approach	0.42 (0.21)	0.30 (0.18)	−0.13 (0.15)	0.01 (0.20)	−0.56 (0.24)	3.10 (0.06)
Exogenous instrumentality	0.53 (0.16)	0.38 (0.15)	−0.14 (0.17)	0.14 (0.19)	−0.86 (0.22)	4.12 (0.05)
Future	0.50 (0.18)	0.18 (0.16)	0.11 (0.15)	−0.08 (0.22)	−0.52 (0.25)	3.86 (0.04)
Structure of scientific knowledge	0.14 (0.23)	0.38 (0.19)	−0.22 (0.15)	0.07 (0.18)	−0.07 (0.23)	3.34 (0.05)

to cluster analysis (and the half-widths of their 95% confidence Intervals) are given in the right column of Table III. For example, the mean standardized self-regulation value for cluster 1 is 1.19 ± 0.10: meaning cluster 1's members possess, on average, a self-regulation scale value that is likely between 1.09 and 1.29 standard deviations above the overall sample mean of 3.75. Thus, members of cluster 1 have self-regulation scale values that are largely above average.

To assist in the interpretation of the clusters, within each scale, we compared the standardized cluster means (and their 95% confidence intervals) across the five clusters and ranked the clusters relative to each other. Table IV gives these ranking results. Clusters given "high" and "low" rankings within a scale possess relatively high and low means, respectively, compared to the other clusters; those given a "moderate" ranking have means somewhere in between. Clusters given the same ranking typically have overlapping confidence intervals.

Table IV also includes the learning profile interpretation for each of the clusters. Overall, the five clusters found in this study closely resemble the five learning profiles found by Shell and his colleagues [14–16]: the strategic, knowledge building, learned helpless, surface, and apathetic learning profiles.

Strategic students are characterized by high levels of self-regulated strategy use, knowledge building, and collaboration, in addition to low levels of task avoidance and relatively low levels of surface approach (the surface approach scale here is mainly a measure of students' inabilities to handle the course material and regulate their studying). Furthermore, strategic students possess desirable motivations, with high levels of learning (or mastery) approach and endogenous instrumentality. These are students who strongly feel that their current actions affect their future success, put much time and effort into the course, and want to understand the material on a deep level. Knowledge building students are similar to strategic students when it comes to their motivations; knowledge building students also feel that physics will be useful for their future. In contrast to strategic students, knowledge building students are less engaged with the course, having moderate levels of self-regulation, question asking, collaborative learning, study time, and study effort, but knowledge building students still tend to want to better understand the material (high learning approach) and use metacognitive techniques to do so (high deep and strategic approach). Thus, the knowledge building students appear to interact with their peers and instructors less, but are still intrinsically motivated to learn physics and excel at it. Strategic and knowledge building students also differ in their levels of surface approach, and this is a characteristic that makes the strategic profile here unique from that found by Shell and Soh [14] and Nelson *et al.* [16]. In the works of Shell and Soh [14] and Nelson *et al.* [16], students in the strategic profile have lack of regulation (or surface approach) levels that are just as low as the knowledge building students. Though strategic students in this sample exhibit excellent levels of self-regulated strategies and supportive motivations, they possess a moderate level of

TABLE IV. Comparative scale rankings across clusters and learning profile interpretations.

Cluster	1	2	3	4	5
Profile interpretation	Strategic	Knowledge building	Learned helpless	Surface	Apathetic
Students in cluster	81	121	144	99	90
Clustering variables					
Self-regulation	High	Moderate	Moderate	Low	Low
Knowledge-building	High	High	Low	Moderate	Low
Low-Level question asking	High	Moderate	Moderate	Low	Low
Collaborative learning	High	Moderate	Moderate	Low	Low
Surface approach	Moderate	Low	High	High	High
Learning approach	High	High	Moderate	High	Low
Task or work avoid	Low	Low	Moderate	Moderate	High
Endogenous instrumentality	High	High	Moderate	High	Low
Nonclustering variables					
High-level question asking	High	Moderate	Moderate	Low	Low
Strategic approach	High	High	Moderate	Moderate	Low
Deep approach	High	High	Moderate	Moderate	Low
Study time	High	Moderate	Moderate	Moderate	Low
Study effort	High	Moderate	Moderate	Moderate	Low
Performance approach	High	High	Moderate	Moderate	Low
Exogenous instrumentality	High	High	Moderate	Moderate	Low
Future	High	Moderate	Moderate	Moderate	Low
Structure of scientific knowledge	Moderate	High	Low	Moderate	Moderate

surface approach. Although this level of surface approach is still less than the overall global average, it is worth keeping in mind that the strategic students in this sample exhibit a slightly higher level of difficulty handling the course compared to the knowledge builders. Possibilities for this difference will be discussed in Sec. V.

Learned helpless students exhibit similar levels of engagement as knowledge building students; however, they possess high levels of surface approach and low levels of knowledge building, indicating that their attempts to engage with the course are at odds with their feelings of being unable to properly manage the material in the course. In addition, learned helpless students have some of the lowest levels of sophistication in views on the structure of scientific knowledge and exhibit only moderate levels of endogenous instrumentality and learning approach. This adoption of less than desirable motivations and views of physics knowledge could possibly be the cause for such struggling, or, conversely, the result of it.

Surface and apathetic learners have the lowest levels of engagement in the examined studio-mode, introductory physics courses. Both profiles have low levels of self-regulation, question asking, and collaborative learning, in addition to both having high levels of surface approach, showing that these students, like learned helpless students, may feel intimated by the course. Furthermore, apathetic students have the lowest levels of motivations, with low learning approach and low endogenous instrumentality. Also, apathetic students possess the lowest performance approach and exogenous instrumentality scores, indicating that these students care the least about looking intelligent and value their grade minimally. In addition, apathetic students have the highest of the task or work avoid levels and lowest study time and effort levels, indicating their desire to get through their physics courses with as little work as possible. In contrast, despite surface students' low engagement levels, they exhibit more desirable motivations for their physics courses, having high levels of endogenous instrumentality and learning approach. Hence, it appears that surface students do find the material in their physics classes to be useful to them, but they are not attempting to understand the material on a deeper level, as indicated by their low self-regulation and moderate strategic and deep approaches.

In summary, given the results of the model-based cluster analysis, the five-profile solution is the best fit for our population of algebra-based, studio-mode introductory physics students. Furthermore, this coherent set of learning profiles is similar to those found by Shell and Soh [14] and Nelson *et al.* [16]. Table V gives a synthesis of the key characteristics of the five learning profiles.

C. Interactions between learning profiles and demographics

1. Demographic information

In addition to strategic self-regulatory and motivational information about students, the SCS also collects demographic information. Table VI displays the levels and percentage of students within each level for the demographic variables.

TABLE V. Synthesis of learning profile key characteristics.

Learning profile	Key characteristics
• Strategic	• High levels of self-regulated strategy use, knowledge-building, and course engagement (i.e., time and effort spent on studying, asking questions, and working with classmates), and moderate levels of surface approach (i.e., lack of managing subject material). • Highly motivated to learn and feel physics is important for their future career.
• Knowledge building	• High levels of knowledge-building, but moderate levels of self-regulated strategy use and course engagement (levels lower compared to Strategic student), and low levels of surface approach. • Highly motivated to learn and feel physics in important for their future career.
• Learned helpless	• Moderate levels of self-regulated strategy use and course engagement, but low levels of knowledge-building and high levels of surface approach. This suggests that these students attempt to regulate learning, but have difficulties doing so. • Moderate levels of motivation to learn and moderate opinions of physics in as important for their future career.
• Surface	• Moderate levels of knowledge-building, but low levels of self-regulated strategy use and course engagement, accompanied by high levels of surface approach. • Motivated to learn and feel physics is important for their future career. This suggests that these students find physics useful, but do not attempt to understand it deeply.
• Apathetic	• The lowest levels of knowledge-building, self-regulated strategy use, and course engagement, accompanied by high levels of surface approach. • Not motivated to learn and feel physics is unimportant for their future career.

In addition, students were asked to report their SAT and/or ACT scores. Particularly, we are interested in students' math standardized test scores. Of the 900 students, $N = 481$ reported valid SAT math scores and $N = 344$ reported valid ACT math scores. The average SAT math score of these student respondents is 605 (out of 800) with a standard deviation of 103; the average ACT math score of these student respondents is 24 (out of 36) with a standard deviation of 7.

In the next section, we investigate the interactions between demographics and learning profile adoption to see how different demographic groups are distributed among the five learning profiles that emerged from the cluster analysis.

2. Interactions between learning profiles and demographics

We investigated interactions between learning profile and the demographic variables described in Table VI as well as student self-reported SAT or ACT scores. Since this involved running twelve statistical tests, we reduced our risk of type 1 error by applying a Bonferroni correction to our initial critical alpha value of $\alpha = 0.05$ and obtained a corrected critical alpha value of $\alpha^* = 4.17 \times 10^{-3}$. We ran a chi-square test [63] for association for each demographic variable in Table VI and learning profile. The results are given in Table VII. The four demographic variables showing significant associations with learning profile are gender, high school physics experience, major, and grade expectation.

Table VIII displays contingency tables for learning profile and the significant variables identified in Table VII. Row percentages are given in each cell, indicating the percentage of students within a demographic level belonging to a learning profile. In addition, within each cell, the adjusted residuals are given in parentheses. We examine the adjusted residuals to understand which cells contributed to the significant difference in profile adoption among the levels of each variable. Adjusted residuals are a measure of the difference between the observed and expected values for a cell, similar to a z score but standardized by the square root of the expected cell value; the larger the magnitude of a cell's adjusted residual, the larger its contribution to the overall chi-squared value for the contingency table [64]. The sign of the adjusted residual indicates if the observed value is above or below expected. For comparisons with ten or fewer cells (here, gender and high school physics experience), we consider adjusted residual values of ± 2 or greater to indicate a significant deviation from expectation. Following Sharpe [64], when the comparison involves more than ten cells (here, major and grade expectation), we increase the level for significance to ± 3 or greater to lower our type 1 error rate.

For gender, we find that men are more likely to adopt the apathetic and knowledge building profiles and less likely to adopt the learned helpless profile compared to women. This suggests men are somewhat more likely to adopt one of the adaptive and one of the very maladaptive profiles and that women are more likely to experience difficulties regulating their learning in this course.

For high school experience, we find that students with prior high school experience with physics are more likely to adopt a knowledge building profile and less likely to adopt

TABLE VI. Overall demographics breakdown of SCS sample.

Demographic variable	Levels within variable	Number of students	Percentage	Additional details
Gender	Woman	587	65.3%	
	Man	310	34.4%	
	No response	3	0.30%	
Ethnicity or race	Majority (MAJ)	531	59.0%	Students identifying as White ($N = 402$) or Asian ($N = 129$)
	Underrepresented (UR)	307	34.1%	Students identifying as American Indian or Alaskan Native ($N = 4$), Native Hawaiian or Other Pacific Islander ($N = 2$), Black or African American ($N = 139$), and Hispanic or Latino ($N = 162$)
	Not categorized	62	6.90%	Students identifying as nonresident aliens ($N = 3$) or multiple ethnicities or other ($N = 59$)
High school physics experience (HPSE)	HSPE	380	42.2%	
	No HSPE	520	57.8%	
First generation (1st Gen)[a]	1st gen	267	41.8%	Neither of student's parents or guardians attained a bachelor's degree
	Not 1st gen	192	58.2%	One or more of student's parents or guardians attained a bachelor's degree
Employment	Employed	580	64.4%	
	Not employed	320	35.6%	
Residence	On campus	200	22.2%	
	Off campus	700	77.8%	
Math background (Math BG)	Calculus experience	465	54.0%	
	No calculus experience	396	46.0%	
Grade expectation (Grade Exp)	A	364	40.4%	
	B	376	41.8%	
	C	150	16.7%	
	D or F	10	1.1%	
Major	Health science	308	34.2%	E.g., health sciences-preclinical track, sport and exercise science, athletic training
	Life sciences	311	34.6%	E.g., biology, biomedical sciences, biotechnology
	Life sciences–pre health	117	13.0%	E.g., biology or biomedical sciences majors preparing for medical careers
	Social sciences	49	5.4%	E.g., psychology, sociology
	Other category	115	12.8%	

[a]Only asked in Fall 2015 and Spring 2016 surveys.

TABLE VII. Results of chi-squared tests for learning profile interactions with other categorical variables.

Variable	χ^2 Statistic	Degrees of freedom	p value	Cramer's V (95% CI)	Size of effect
Employment	0.63	4	0.960	0.034 (0.032–0.155)	Small
1st gen	1.00	4	0.911	0.060 (0.048–0.221)	Small
Residence	2.55	4	0.636	0.069 (0.041–0.175)	Small
Ethnicity	5.83	4	0.212	0.108 (0.059–0.214)	Small
Math BG	6.54	4	0.162	0.113 (0.062–0.216)	Small
HSPE[a]	15.46	4	3.84×10^{-3}	0.170 (0.104–0.267)	Small
Major[a]	30.62	12	2.25×10^{-3}	0.148 (0.125–0.218)	Small
Gender[a]	17.11	4	1.85×10^{-3}	0.179 (0.117–0.272)	Small
Grade exp[a]	74.08	12	5.48×10^{-11}	0.215 (0.180–0.274)	Medium

[a]Significant after Bonferroni correction.

TABLE VIII. Contingency tables for demographic variables with significant interactions with learning profile. Row percentages and adjusted residuals (in parentheses) given in each cell.

		Strategic	Knowledge building	Learned helpless	Surface	Apathetic
Overall	$N = 535$	15.2%	22.7%	26.9%	18.4%	16.7%
Gender	Man ($N = 190$)	16.3% (.5)	27.9% (2.1)[a]	17.4% (−3.7)[a]	17.4% (−.5)	21.1% (2.0)[a]
	Woman ($N = 342$)	14.6% (−.5)	19.9% (−2.1)[a]	32.2% (3.7)[a]	19.0% (.5)	14.3% (−2.0)[a]
HSPE	Yes HSPE ($N = 215$)	11.2% (−2.1)[a]	30.2% (3.5)[a]	23.3% (−1.6)	17.2% (−.6)	18.1% (.7)
	No HSPE ($N = 320$)	17.8% (2.1)[a]	17.5% (−3.5)[a]	29.4% (1.6)	19.4% (.6)	15.9% (0.7)
Major	Health Science ($N = 200$)	17.0% (.4)	13.5% (−3.9)[a]	34.5% (3.2)[a]	17.0% (−.9)	18.0% (1.1)
	Life Sciences ($N = 177$)	14.1% (−1.0)	27.1% (2.0)	22.0% (−1.9)	23.2% (1.9)	13.6% (−1.0)
	Life Sciences–Pre Health ($N = 68$)	22.1% (1.4)	27.9% (1.2)	22.1% (−1.0)	11.8% (−1.6)	16.2% (.1)
	Social Sciences ($N = 23$)	8.7% (−1.0)	43.5% (2.5)	13.0% (−1.5)	21.8% (.4)	13.0% (−.4)
Grade expectation	A ($N = 226$)	18.1% (1.7)	36.7% (6.7)[a]	17.3% (−4.3)[a]	13.7% (−2.4)	14.2% (−1.4)
	B ($N = 214$)	13.1% (−1.1)	14.5% (−3.7)[a]	35.5% (3.7)[a]	21.0% (1.2)	15.9% (−.5)
	C ($N = 88$)	13.6% (−0.4)	8.0% (−3.6)[a]	31.8% (1.1)	20.5% (.5)	26.1% (2.6)
	D or F ($N = 7$)	0% (−1.1)	0% (−1.4)	14.3% (−.8)	71.4% (3.6)[a]	14.3% (−.2)

[a]Significant deviation from expectation.

a strategic profile than students who did not take a physics course in high school. This result may suggest that these studio-mode physics courses are supportive of students who did not take physics in high school, as adoption of the strategic profile suggests good use of metacognitive techniques and high motivation to learn physics. Students who have taken a physics course in high school may be more likely to adopt a knowledge building profile if they maintain intrinsic motivation to learn physics but do not have to put in as much time and effort as their peers to learn the material because they have already been exposed to it.

For Major, only the adjusted residuals for health science majors rise to the corrected level of ± 3. We find that students in the health sciences majors are more likely to adopt a learned helpless profile and less likely to adopt a knowledge building profile than their peers in other majors. To try to understand potential reasons for this difference, we explored the curricular requirements across these majors. We found that students in the health sciences category are not required to take as many credits in upper-level physical and life sciences compared to students in the life sciences and life sciences–prehealth categories. Such courses (including organic chemistry, biochemistry, and immunology) are suggested as electives for health science students, but are required for life sciences and life sciences–prehealth students. Additionally, students in the health sciences category are not required to take as many credits of statistical and research methods courses compared to students in the social sciences category. Thus, this introductory physics course, which is required for the health sciences majors, may be one of the more challenging courses that these students take. Since the students are required to take it, they likely feel the need to perform well, but may not be intrinsically motivated or understand how the course will connect to their future. These feelings combined with the difficulty of the physics course compared to their other required courses may combine and lead to the higher adoption of the learned helpless profile and lower adoption of the knowledge building profile.

For grade expectation, the main differences we find are within the learned helpless and knowledge building profiles. Students in the learned helpless profile are more likely to expect to earn a B and less likely to expect to earn an A compared to their peers. Students in the knowledge building profile are much more likely to expect to earn an A and less likely to expect to earn a B or C compared to their peers. Overall, these results suggest that those adopting the knowledge building profile are more likely to be confident in their performance in the course. This result is consistent with the other results found thus far and with the description of the knowledge building profile; students in this profile are more intrinsically motivated and likely to have had previous physics experience in high school, possibly leading to self-evaluations of performing well in the course. Furthermore, the result that those students expecting to achieve a B in the course are more likely to be in the learned helpless profile suggests that these students are less likely to be confident in their performance in the course. From the description of learned helpless students, who attempt to regulate themselves but have difficulty in doing so, it follows that such individuals may struggle with the course, leading to lower self-evaluations with respect to course grade achievement. Given the more confident and motivated characterization of the knowledge building profile, it makes sense that those students expecting to achieve a C in the course are not well represented in this profile, as these students are likely encountering issues in the course that affect their ability to perform. We also find that students expecting to fail the course (achieving a D or F) adopt the surface profile more often than expected; however, this result should be interpreted with caution, as there are very

TABLE IX. Frequency of learning profiles across institutions. Row percentages and adjusted residuals (in parentheses) given in each cell.

	Strategic	Knowledge building	Learned helpless	Surface	Apathetic
Inst. A ($N = 346$)	15.6% (.4)	16.2% (−4.8)[a]	31.8% (3.4)[a]	17.3% (−.9)	19.1% (1.9)
Inst. B ($N = 124$)	16.9% (.6)	40.3% (5.4)[a]	16.9% (−2.9)[a]	14.5% (−1.3)	11.3% (−1.9)
Inst. C ($N = 65$)	9.2% (−1.4)	23.1% (.1)	20.0% (−1.3)	32.3% (3.1)[a]	15.4% (−.3)

[a]Significant deviation from expectation.

few individuals expecting to fail. Conducting this test after the removal of those expecting to fail does not affect our other results.

To explore whether students within different learning profiles share similar standardized test scores (a continuous variable), we utilize the Kruskal-Wallis test [65], which is a nonparametric version of the analysis of variance (ANOVA) test. We do not find a statistically significant relationship between learning profile adoption and either SAT math score [$H(4) = 6.5,\ p = 0.16$] or ACT Math score [$H(4) = 7.4,\ p = 0.12$]. Thus, students' performance on standardized tests does not appear to predict the way they are engaging with their studio-mode introductory physics course.

D. Interactions between learning profiles and institution

Since the goal of our overarching project is to explain the variable success of studio-mode physics across institutions, we also explored whether the rate of profile adoption varied across the three institutions. A chi-squared test finds a significant association with a small to medium effect size between institution and learning profile [$\chi^2(8) = 45.5$, $p = 2.92 \times 10^{-7}$, $V = 0.21$ (0.16, 0.28)]. Table IX displays the contingency table for institution and learning profile. We find that Institution A has more students adopting the learned helpless profile and fewer adopting the knowledge building profile, which may indicate that more students at Institution A are struggling to regulate their learning in the course. We find the opposite at Institution B, where more students have adopted the knowledge building profile and fewer have adopted the learned helpless profile, suggesting that the students at Institution B are more motivated to learn, but are still not engaging or self-regulating to the highest degree. As seen in Table VIII, difference in adoption of the knowledge building versus learned helpless profiles may be explained by gender and major. Comparing demographics across institutions, we find no significant association between gender and institution [$\chi^2(2) = 1.1,\ p = 0.58$]. However, we do find differences in major across institutions [$\chi^2(6) = 177.8,\ p = 9.83 \times 10^{-36}$], with students at Institution A more likely to declare a health sciences major (53.3%) and less likely to declare a life sciences (28.2%) or social sciences (2.1%) major, and the converse is true for Institution B (health sciences, 11.0%; life sciences, 65.9%; social sciences, 11.0%). Thus, it is unclear whether the difference in profile adoption is more likely due to differences in student population or the actual instructional methods used in the studio course. Finally, we find that students at Institution C are more likely to adopt the surface profile, possibly indicating students are less engaged with the course. It seems likely that this difference is due to the instructional methods used at Institution C since surface profile adoption was not significantly associated with the other demographic variables measured (with the exception of grade expectation).

V. DISCUSSION AND IMPLICATIONS

We find that the five learning profiles found in previous studies in other disciplines [14–16] are also useful in describing how students in algebra-based, studio-mode physics courses approach this class. We note that there is a difference between the description of the strategic profile in our study compared to that of prior studies, in that students in our strategic profile exhibit a higher level of surface approach as compared to students in the knowledge building profile. The surface approach scale in this study assesses the difficulty students have managing the material in the course. We hypothesize that this increased difficulty handling the course material could be due to the student-centered nature of studio-mode courses and may suggest that even students with an effective approach to the course would benefit from better support in planning their study approach.

Two of the five profiles, knowledge building and strategic, are considered "adaptive," as students in these profiles exhibit high levels of motivation and connection building. A major difference between these two adaptive profiles is their level of engagement with the course, with students in the knowledge building profile exhibiting lower levels of question asking, collaborative learning, time spent studying, and self-regulating but retaining the high levels of intrinsic motivation for building connections between physics and other subject material (compared to students in the strategic profile). The interaction of previous high school physics experience with profile adoption suggests a possible explanation for these differences. Students who had previous experience in high school with physics were more likely to be in the knowledge building profile; it is possible these students' prior exposure to the content reduced their need to engage at the highest level while still succeeding in the course. This hypothesis is further supported by the finding that students in the knowledge building profile were more likely than their peers to expect to earn an A in the course. We found that students without prior experience with physics in high school were more likely to adopt the strategic profile. We interpret this as possible support for the studio-mode course for algebra-based students as this adaptive profile is accessible to students without prior experience who are enrolled in this type of course. However, we also find that this is the least populated profile, describing only 15% of our students (in the reduced population of students with high probability of placement in only one profile). Overall, only 38% of students were identified as adopting either of the two adaptive profiles. This suggests that instructors of algebra-based studio-mode physics courses may need to offer more support to help students appropriately approach learning in the course.

The remaining three profiles, surface, learned helpless, and apathetic, are considered "maladaptive." However, there are important differences between these profiles. We find that the Learned Helpless profile is the most highly populated, with 27% of our reduced population and 43% of those adopting a maladaptive profile. Students in this profile are putting in nearly as much study time and study effort as those in the adaptive profiles, but are marked by a lack of connection building, as seen by low scores on the knowledge building and structure of scientific knowledge scales and high scores on the surface approach scale. This implies that learned helpless students are trying to study for their physics courses, but they are not using the best strategies and are often left overwhelmed by the amount of material present in the course. It seems likely that these students would benefit from and be open to an intervention helping them understand how to approach learning in this course. We find that adoption of the learned helpless profile correlates with major, with students in a health sciences major more likely to adopt this profile and less likely to adopt a knowledge building profile compared to their peers. Anecdotally, we have heard colleagues discuss students with health sciences majors struggling in studio-mode courses; this profile analysis suggests a reason for this enhanced struggle may be a lack of appropriate strategies for more independent learning in a challenging course.

Additionally, we find that women are more likely to adopt the learned helpless profile in their studio-mode physics course. This is a somewhat surprising result, as previous research on SCALE-UP physics has found that it is more supportive for women than traditional lectures, with women 4 to 5 times less likely to fail a SCALE-UP than traditional physics course [4]. Beichner has argued that women may benefit from SCALE-UP instruction since research has shown women's confidence may increase when clear expectations are presented and from collaborative learning, which he reasons is consistent with Bandura's theory of social cognition [66], which predicts increased confidence will lead to improved performance and resilience. On the other hand, an attitude survey and follow-up interviews by Laws revealed that junior and senior women in a Workshop Physics course had more negative attitudes towards required collaborative work due to time demands and personal departures from their instructor's understanding of the nature of learning [2]. Laws also found that women students reported more involvement in extracurricular activities compared to men, which may influence the amount of time women can devote to out of class activities. A meta-analysis on gender effects in introductory physics found that most approaches to decreasing the gap between men and women's performance had varied success across implementations [67]. One reason for this variable success, supported by the profile approach, is the extent to which instruction encourages use of metacognitive techniques and addresses students' perceptions of the utility of physics, as these strategies have the potential to decrease the adoption of the learned helpless and apathetic profiles. Future work should investigate the frequency of learned helpless profile adoption in more traditional courses to establish a baseline for comparison. It is possible that the frequency observed here is actually a reduction from that which would be observed in a more traditional course.

VI. LIMITATIONS AND FUTURE WORK

We point out notes of caution in interpreting and extending these results. The 900 student database collected in this study is large enough to serve as a reference for further cluster analyses on similar populations of algebra-based, studio-mode introductory physics courses. However, when attempting to extend the model-based cluster analysis to different student populations, such as those in a different course context, like a traditional lecture course, or a different discipline, such as a studio-mode biology course, it is likely that a new reference database must be collected, in addition to validity and reliability of the SCS being reevaluated for that particular course context. Additionally, we caution instructors against "labeling" individual students in a particular way, since a student's approach to a course is likely to be context dependent and fluid. However, the cross section of the ways students are approaching a course and the frequency of adoption of the various approaches should provide valuable feedback to instructors about the types of support that may help their students approach the class productively.

This work is part of a project to investigate the nuances of and model success in algebra-based, studio-mode introductory physics courses across universities. In future studies, we will investigate how learning profiles and demographic data collected by the SCS affect student outcomes measured in algebra-based, studio-mode introductory physics courses. Additionally, we will expand the institutions where we collect SCS data to further investigate the predictive power of student characteristics within and across various institutions. Ultimately, we aim to describe how students differ within an institution and across institutions and to identify which characteristics are better predictors for studio success at one institution compared to another, if such differential behavior exists. Overall, the person-centered profile approach presented here helps to characterize students and gives a basis to investigate what students themselves bring to the classroom. Identifying learning profiles and their adoptions among different types of students gives insight into students' classroom motivations and study behaviors and allow us, as educators, to better understand and respond to their needs.

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[1] P. W. Laws, Calculus-based physics without lectures, Phys. Today **44**, No. 12, 24 (1991).
[2] P. W. Laws, P. J. Rosborough, and F. J. Poodry, Women's responses to an activity-based introductory physics program, Am. J. Phys. **67**, S32 (1999).
[3] K. Cummings, J. Marx, R. Thornton, and D. Kuhl, Evaluating innovation in studio physics, Am. J. Phys. **67**, S38 (1999).
[4] R. J. Beichner, J. M. Saul, D. S. Abbott, J. J. Morse, D. Deardorff, R. J. Allain, S. W. Bonham, M. H. Dancy, and J. S. Risley, The student-centered activities for large enrollment undergraduate programs (SCALE-UP) project, *Research-Based Reform of University Physics* edited by E. F. Redish and P. J. Cooney (American Association of Physics Teachers, College Park, MD, 2007), Vol. 1.
[5] P. B. Kohl and V. H. Kuo, Chronicling a successful secondary implementation of Studio Physics, Am. J. Phys. **80**, 832 (2012).
[6] J. Saul and E. Redish, Evaluation of the Workshop Physics Dissemination Project, http://www.per-central.org/items/detail.cfm?ID=11797.
[7] R. Beichner, The student-centered activities for large enrollment undergraduate programs (SCALE-UP) project, in Research-Based Reform of University Physics (2007), http://sites.nationalacademies.org/cs/groups/dbassesite/documents/webpage/dbasse_072628.pdf.
[8] N. Lasry, E. Charles, and C. Whittaker, When teacher-centered instructors are assigned to student-centered classrooms, Phys. Rev. ST Phys. Educ. Res. **10**, 010116 (2014).
[9] K. T. Foote, Curriculum development in studio-style university physics and implications for dissemination of research-based reforms, Phys. Rev. Phys. Educ. Res. **12**, 010127 (2016).
[10] A. Elby, Another reason that physics students learn by rote, Am. J. Phys. **67**, S52 (1999).
[11] G. Kortemeyer, Correlations between student discussion behavior, attitudes, and learning, Phys. Rev. ST Phys. Educ. Res. **3**, 010101 (2007).
[12] J. Stewart, S. DeVore, G. Stewart, and L. Michaluk, Behavioral self-regulation in a physics class, Phys. Rev. Phys. Educ. Res. **12**, 010125 (2016).
[13] J. Stewart, G. Stewart, and J. Taylor, Using time-on-task measurements to understand student performance in a physics class: A four-year study, Phys. Rev. ST Phys. Educ. Res. **8**, 010114 (2012).
[14] D. F. Shell and L.-K. Soh, Profiles of motivated self-regulation in college computer science courses: differences in major versus required non-major courses, J. Sci. Educ. Technol. **22**, 899 (2013).
[15] D. F. Shell and J. Husman, Control, motivation, affect, and strategic self-regulation in the college classroom: A multidimensional phenomenon, J. Educ. Psychol. **100**, 443 (2008).
[16] K. G. Nelson, D. F. Shell, J. Husman, E. J. Fishman, and L.-K. Soh, Motivational and self-regulated learning profiles of students taking a foundational engineering course, J. Eng. Educ. **104**, 74 (2015).
[17] L. R. Bergman and H. Andersson, The person and the variable in developmental psychology, Z. Psych. **218**, 155 (2010).
[18] M. Boekaerts, S. Maes, and P. Karoly, Self-regulation across domains of applied psychology: is there an emerging consensus?, Applied psychology **54**, 149 (2005).
[19] P. R. Pintrich, A conceptual framework for assessing motivation and self-regulated learning in college students, Educational Psychology Review **16**, 385 (2004).
[20] B. J. Zimmerman, Investigating self-regulation and motivation: historical background, methodological developments, and future prospects, Am. Educ. Res. J. **45**, 166 (2008).
[21] R. E. Snow, L. Corno, and D. Jackson III, in *Handbook of Educational Psychology*, edited by D. C. Berliner *et al.* (Macmillan Library Reference USA, Prentice Hall International, New York, NY, London, 1996), p. 243.
[22] P. R. Pintrich, The role of goal orientation in self-regulated learning, in *Handbook of Self-Regulation* (Academic Press, San Diego, 2000), p. 451.
[23] P. R. Pintrich, A motivational science perspective on the role of student motivation in learning and teaching contexts, J. Educ. Psychol. **95**, 667 (2003).
[24] A. Wigfield, J. S. Eccles, U. Schiefele, R. W. Roeser, and P. Davis-Kean, *Development of Achievement Motivation*

Handbook of Child Psychology (John Wiley & Sons, Hoboken, NJ, 2006), Vol. 3.
[25] I. Ajzen, *Attitudes, Personality, and Behavior*, Mapping social psychology, 2nd ed. (Open University Press, Maidenhead, Berkshire, England; New York, 2005).
[26] J. M. Diefendorff and R. G. Lord, The volitional and strategic effects of planning on task performance and goal commitment, Human Performance **16**, 365 (2003).
[27] P. M. Gollwitzer, The volitional benefits of planning, in *The Psychology of Action: Linking Cognition, and Motivation to Behavior*, edited by P. M. Gollwitzer *et al.* (Guilford Press, New York, 1996), p. 287.
[28] A. Koriat and R. Nussinson, Attributing study effort to data-driven and goal-driven effects: Implications for metacognitive judgments, J. Exp. Psychol. Appl. **35**, 1338 (2009).
[29] S. A. Nonis and G. I. Hudson, Performance of college students: Impact of study time and study habits, J. Educ. Bus. **85**, 229 (2010).
[30] A. Bandura, *Self-Efficacy: The Exercise of Control* (W. H. Freeman, New York, 1997).
[31] M. Boekaerts and E. Cascallar, How Far Have We Moved Toward the Integration of Theory and Practice in Self-Regulation?, Educational Psychology Review **18**, 199 (2006).
[32] J. S. Eccles and A. Wigfield, Motivational beliefs, values, and goals, Annu. Rev. Psychol., **53** 109 (2002).
[33] P. R. Pintrich, The role of motivation in promoting and sustaining self-regulated learning, Int. J. Educ. Res. **31**, 459 (1999).
[34] B. J. Zimmerman and D. H. Schunk, *Handbook of Self-Regulation of Learning and Performance*, Educational Psychology Handbook Series (Routledge, New York, 2011).
[35] J. A. Chen, Implicit theories, epistemic beliefs, and science motivation: A person-centered approach, Learn. Individ. Differ. **22**, 724 (2012).
[36] M. Schwinger, R. Steinmayr, and B. Spinath, Not all roads lead to Rome–Comparing different types of motivational regulation profiles, Learn. Individ. Differ. **22**, 269 (2012).
[37] A. M. Conley, Patterns of motivation beliefs: Combining achievement goal and expectancy-value perspectives, J. Educ. Psychol. **104**, 32 (2012).
[38] J. Pond and J. Chini, Exploring student learning profiles in algebra-based studio physics: A person-centered approach, in *Proceedings of the 2015 Physics Education Research Conference, College Park, MD* (AIP, New York, 2015), p. 263.
[39] P. A. Alexander and P. K. Murphy, Profiling the differences in students' knowledge, interest, and strategic processing, J. Educ. Psychol. **90**, 435 (1998).
[40] H. Tuominen-Soini, K. Salmela-Aro, and M. Niemivirta, Stability and change in achievement goal orientations: A person-centered approach, Contemp. Educ. Psychol. **36**, 82 (2011).
[41] See Supplemental Material at http://link.aps.org/supplemental/10.1103/PhysRevPhysEducRes.13.010119 for information on the Student Characteristics Survey contents and validation.
[42] A. M. Gadermann, M. Guhn, and B. D. Zumbo, Estimating ordinal reliability for Likert-type and ordinal item response data: A conceptual, empirical, and practical guide, Pract. Assess., Res. Eval. **17**, 1 (2012).
[43] R. L. Doran, *Basic Measurement and Evaluation of Science Instruction* (National Science Teachers Association, Arlington, VA, 1980).
[44] R Development (Core Team), R: A language and environment for statistical computing (*R Foundation for Statistical Computing*, Washington, DC, 2010).
[45] Y. Rosseel, lavaan: An R package for structural equation modeling, J. Stat. Softw. **48**, 1 (2012).
[46] L. Hu and P. M. Bentler, Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives, Struct. Eq. Modeling **6**, 1 (1999).
[47] G. Gan, C. Ma, and J. Wu, *Data Clustering: Theory, Algorithms, and Applications* ASA-SIAM Series on Statistics and Applied Probability (Society for Industrial and Applied Mathematics, Philadelphia, PA; American Statistical Association, Alexandria, VA, 2007).
[48] L. Ding and R. Beichner, Approaches to data analysis of multiple-choice questions, Phys. Rev. ST Phys. Educ. Res. **5**, 020103 (2009).
[49] C. Celeux and G. Govaert, Fuzzy custing and misture models, in *Compstat: Proceedings in Computational Statistics 11th Symposium Held in Vienna, Austria, 1994*, edited by R. Dutter and W. Grossmann (Physica, Heidelberg, Germany, 1994).
[50] E. Y. Mun, A. von Eye, M. E. Bates, and E. G. Vaschillo, Finding groups using model-based cluster analysis: heterogeneous emotional self-regulatory processes and heavy alcohol use risk, Dev. Psychol. **44**, 481 (2008).
[51] A. E. Raftery and N. Dean, Variable selection for model-based clustering, J. Am. Stat. Assoc. **101**, 168 (2006).
[52] C. Fraley, A. E. Raftery, and L. Scrucca, University of Washington Report No. 597 2012.
[53] B. S. Everitt, S. Landau, M. Leese, and D. Stahl, *Cluster Analysis*,5th ed. (John Wiley & Sons, Chichester, UK, 2011).
[54] S. S. Chen and P. S. Gopalakrishnan, Clustering via the Bayesian information criterion with applications in speech recognition, in *Proceedings of the 1998 IEEE International Conference on Acoustics, Speech and Signal Processing* (IEEE, 1998), p. 645.
[55] One-way ANOVA, http://www.upa.pdx.edu/IOA/newsom/da1/ho_ANOVA.pdf (accessed June 20 2016).
[56] X. L. Xie and G. Beni, A validity measure for fuzzy clustering, IEEE Trans. Pattern Anal. Mach. Intell. **13**, 841 (1991).
[57] J. C. Bezdek, W. Li, Y. Attikiouzel, and M. Windham, A geometric approach to cluster validity for normal mixtures, Soft Computing **1**, 166 (1997).
[58] J. R. Fonseca and M. G. Cardoso, Mixture-model cluster analysis using information theoretical criteria, Intelligent Data Analysis **11**, 155 (2007).
[59] A. K. Formann, *Die Latent-Class-Analyse: Einführung in Theorie und Anwendung* (Beltz, 20.
Weinheim, Germany, 1984).
[60] M. Sarstedt and E. Mooi, *A Concise Guide to Market Research: The Process, Data, and Methods Using IBM SPSS Statistics* (Springer, New York, 2014).
[61] The Carnegie Classification of Institutions of Higher Education (n.d.). About Carnegie Classification, retrieved from http://carnegieclassifications.iu.edu/.

[62] M. Wilcox, G. Feldman, J. Von Korff, N. Klinger, O. Sengul, and J. Chini, Characterizing studio physics instruction across instructors and institutions, in *Proceedings of the 2016 Physics Education Research Conference, Sacramento, CA* (AIP, New York, 2016), p. 392.

[63] R. Rana and R. Singhal, Chi-square test and its application in hypothesis testing, J. Pract. Cardiovasc. Sci. **1**, 69 (2015).

[64] D. Sharpe, Your chi-square test is statistically significant: Now what?, Pract. Assess., Res. Eval. **20**, 2 (2015).

[65] P. E. McKight and J. Najab, Kruskal-wallis test, in *The Corsini Encyclopedia of Psychology* (John Wiley & Sons, Inc., New York, 2010).

[66] A. Bandura, *Social Foundations of Thought and Action: A Social Cognitive Theory* (Prentice-Hall, Englewood Cliffs, NJ, 1986).

[67] A. Madsen, S. B. McKagan, and E. C. Sayre, Gender gap on concept inventories in physics: What is consistent, what is inconsistent, and what factors influence the gap?, Phys. Rev. ST Phys. Educ. Res. **9**, 020121 (2013).