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Major differences: modeling profiles of community college persisters in career clusters

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Abstract The purpose is to explore factors associated with community college student persistence in academic program areas through the modeling of student profiles (i.e., classes) using selected variables from the Education Longitudinal Study of 2002 (ELS:2002) conducted by the National Center for Education Statistics that has followed a national sample of students from the tenth grade with follow-ups 2 and 4 years later. To this end, we used multiple-group latent class analysis in order to identify underlying classes of students and to evaluate the equivalence of the latent class solution across those students who persisted and those who did not. A four-class solution was identified that was determined to be invariant across student groups although the proportions of persisters and nonpersisters were different across classes. Using the final class solution for persisting students, we found that class membership was moderately associated with which Career Cluster students pursued.

Keywords Latent class analysis · Measurement invariance · Community college student success · Career clusters

1 Introduction

In this era of higher education accountability when student completion is paramount and there is greater emphasis on employment and earnings of graduating college students, community colleges have risen to the forefront of the postsecondary conversation. The 2-year public college sector is a place where approximately eight million students engage in credit-bearing

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courses each year (AACC 2013) for many reasons, not the least of which is gaining the skills needed for employment and improved wages. By 2018, it is projected that 63 % of available jobs will require some level of postsecondary education (Carnevale et al. 2010), and the level and field of education matter.

Grubb (1997) documented the connection between levels of higher education and the economic benefits, finding that credentials typically earned at community colleges (i.e., certificates and associate's degrees) yielded increased earnings. While these increases were not at the same level as 4-year degrees, they were significant. Grubb also found that persisting through the attainment of a credential was very important since earning a certificate or degree paid off more than completing some college. Additionally, the study noted differences in benefits by fields of study. This understanding of the connection among education, employment, and earnings can help to inform local and state priorities. Rosenfeld (1998), for example, notes the benefits of an industry-specific strategy that sets educational priorities based on targeted industry clusters. This industry-focused approach provides a way to target specific programs that support the local or regional economy.

It is this connection between education and industry needs that informed some of our previous work (D'Amico et al. 2011), where we explored one state's approach to cluster-based workforce development and its student success efforts. We found that students in the five workforce cluster priority areas (advanced manufacturing, energy, health care, tourism, and transportation and logistics) were successful at different rates. Also, we found that different variables were more influential for some program areas than others. For example, while lower academic preparation, as measured by a requirement to complete developmental studies, was relatively consistent as a negative predictor of success, gender, age, ethnicity, and Pell Grant receipt were statistically significant in only some of the clusters. Essentially, we recommended that "a one-size-fits-all approach" (D'Amico et al. 2011, p. 788) to student success across clusters may not be the best strategy.

Our intent through the present study is to expand on our previous work to explore factors associated with community college student persistence in academic program areas through the modeling of student profiles (i.e., classes) by employing selected variables from the Education Longitudinal Study of 2002 (ELS:2002) conducted by the National Center for Education Statistics that has followed a national sample of students from the tenth grade with follow-ups 2 and 4 years later. After the modeling and identification of profiles, the analysis will look at persisters, defined as those who maintain four semesters of continuous enrollment at public 2-year colleges, and the alignment of profiles and other variables of interest with community college programs of study. For the purpose of this inquiry, programs of study will be operationalized as the 16 Career Clusters. The Career Clusters provide a structure for career and technical education programs in K-12 and higher education to categorize programs and Pathways into program areas that are relevant to the professional environment. The Career Clusters include: Agriculture, Food, and Natural Resources; Architecture and Construction; Arts, A/V Technology and Communications; Business, Management and Administration; Education and Training; Finance; Government and Public Administration; Health Science; Hospitality and Tourism; Human Services; Information Technology (IT); Law, Public Safety, Corrections, and Security; Manufacturing; Marketing; Science, Technology, Engineering, and Mathematics (STEM); and, Transportation, Distribution, and Logistics (National Association of State Directors of Career Technical Education Consortium 2013). Our intent through this work is to jointly explore community college student profiles, variables of interest that may be associated with improved student outcomes, and enrollment in specific program areas (i.e., majors) through the Career Clusters.

2 Review of literature

In an effort to understand the context of this study that explores the success of students in community college programs of study, there are three relevant themes in the literature: the economic benefits of community college students in specific programs of study, which we call the "economics of major"; the importance of selecting a major and success within program areas, which we call "clustered success"; and the methodological discussion of modeling classes of community college enrollees through a nationally representative sample of traditional-aged college students.

2.1 Economics of major

As documented by Grubb (1997), associate degree attainment is economically beneficial to community college students. Bailey et al. (2004) also noted that associate degree attainment had a positive impact on earnings for men and women, more so in occupational programs. Overall, it is important to note that level of education does matter for employment and wages; however, the benefit may vary by demographic groups and also by program of study.

Dadgar and Weiss' (2012) one-state study of economic returns based on wages looking at level of community college credential and programs of study/Career Clusters showed that financial returns on associate degrees are significant in nearly all program fields. Also, the high return for associate degrees is unlike that of short-term and long-term certificates that yielded improved wages in only a portion of program areas. Thus, longer-term enrollment is advantageous for community college students, which demonstrates the need to study continuous enrollment over a multi-year period as done in the present study.

Compton et al. (2010) conducted a study of students in the Business Management and Administration, IT, and Marketing Career Clusters and found that few students earn credentials with male, minority, and non-Pell recipients less likely to complete programs. In addition, they found that earning an associate's degree was important in influencing higher wages in IT and Marketing, but not in Business. In a later study of STEM, Manufacturing, and Arts, A/V Technology and Communications Career Clusters, Maguire et al. (2012) conducted a demographic review of Iowa students in those clusters and compared those who earned a credential and those to departed the institution prior to completion. They found that older students, women, minority, and non-Pell recipients in Manufacturing and STEM clusters were more likely to leave without a credential. However, women and minority students were a very small percentage of the Manufacturing/STEM sample (11.7 and 3.9 % respectively). The picture is somewhat different for the Arts, A/V Technology, and Communications cluster, where older students, male, minority, and Pell students were more likely to leave. They went on to find that gender (being male) was significant in predicting higher earnings, but that women could lessen or eliminate the gender pay gap by earning an associate's degree. Pertinent to the present study is that Compton et al. (2010) and Maguire et al. (2012) found differences between the profiles of cluster groupings and/or earnings for degree completers. These differences illustrate how an in-depth look into student profiles related to specific clusters is warranted.

Carnevale et al. (2011) conducted an analysis of earnings and employment opportunities by Career Cluster and education level. They found that a combination of education level and career area influence earnings. Among associate's degrees holders, those in STEM and Information Technology clusters yield the highest earnings followed by Architecture and Construction; Law, Public Safety, Corrections, and Security; Manufacturing; and, Business, Management, and Administration. Additionally, the report listed employment projections by education level and Career Cluster. For those with associate's degrees, top demand will be in Health Science, followed by Business, Management, and Administration; Marketing, Sales, and Service; Hospitality and Tourism; and, Manufacturing.

Most recently, in a look at the recovering economy, Carnevale and Cheah (2013) reported unemployment rates in program specific areas. They found that areas such as recreation, education, health, and agriculture and natural resources had the lowest unemployment rates in 2010–2011 for recent college graduates. Conversely, architecture, social science, arts, and law and public policy had the highest unemployment rates for new college graduates. Although this report noted employment by major at the baccalaureate level, what this analysis tells us is the great variability in employment by program of study. Perhaps the most significant lesson learned from previous work connecting employment and wages to programs of study is that *major matters*.

2.2 Clustered success

Understanding the importance of one's community college major in terms of potential economic benefits, the next consideration for educational leaders is student success in career-focused programs. Alfonso et al. (2005) found that among associate degree seekers, those who are male, Black, enrolling part-time, interrupt their enrollment, and enrolled in a career-focused (i.e., occupational) program area are less likely to earn a degree. Among their explanations, they suggest that perhaps "community colleges work less effectively with occupational students" (p. 210). This further justifies the need to better understand who persists in each Career Cluster.

In a comparison of students in terminal majors, those seeking transfer, and the undeclared at colleges that participate in the Achieving the Dream national initiative, Lee (2007) determined that older students and those with financial need (i.e., Pell Grant recipients) were more likely to be enrolled in career focused, terminal degrees. Then it was found that undeclared and terminal degree-seeking students were less likely to persist. By comparison, a later study of Achieving the Dream students (Clery 2011) uncovered that those with terminal majors were more likely than prospective transfers to complete a credential or transfer, while undeclared students were least likely to demonstrate success. In addition, Clery (2011) reported that those who declare a program of study in their first term had a greater likelihood of success than those who did not enter a program.

A sub-theme in the literature is also the importance of selecting a major, which is consistent with one of the key purposes behind the initiation of Career Clusters in the secondary and postsecondary settings. So, why does selecting a major matter? In a study looking at 3-year graduation rates of community college students in career programs, Gantt (2010) found that younger students were more likely to be successful than older students, but gender, marital status, family education, number of dependents, and annual income were not statistically significant. On the academic side, creating a degree plan and selecting a major were positively associated with successful outcomes, while access to faculty and previous college experience were not. Finally, non-academic factors such as career counseling, student activities, distance from campus, and number of years employed in a career field were not statistically significant. However, the key finding is that those students with plans of study and declared majors were more likely to be successful.

Through a qualitative study of students at an urban community college enrolled in early childhood and paralegal programs, Nitecki (2011) found that "positive program culture" (p. 114) contributed to student success and acknowledged that the culture was quite different for each program area. Early childhood was more nurturing while paralegal was more professionally focused; however, it was the presence of this culture reflecting the career fields that influenced student outcomes.

Jenkins and Cho (2012) found that students who enter a program of study earlier, as demonstrated by taking related courses, were more likely to earn a credential or transfer to a 4-year college or university. Using a similar related course completion approach to describe those who enter a program of study, Moore and Shulock (2011) reported that White and Asian students were more likely to enter a program than Black and Latino students, and entering a program of study earlier is related to the likelihood of transferring or earning a credential.

However, the interpretation of completion findings for career-focused programs, such as those related to many of the Career Clusters, can be complicated. Lohman and Dingerson (2005) studied those from career programs who did not complete. They found that withdraws among this group occur for several work-related reasons such as taking skills learned in courses and entering the workforce, gaining work-based incentives, or entering programs for displaced workers. Essentially, students leave because they have met their objectives related to employment that do not necessarily include earning a credential. What these studies show is that the commitment to a major can indeed be associated with student success, but those in career-focused programs at community colleges may also be vulnerable to competing interests, employment concerns, and other barriers to completion; thus, additional exploration of success in specific program areas is necessary.

2.3 Multiple-group latent class analysis (LCA)

Finite mixture modeling is a model-based approach that can be used to identify groups of cases underlying a multivariate dataset. The term finite mixture model is used because the analysis assumes that an observed dataset is a mixture of observations collected from a finite number of mutually exclusive classes, each with its own characteristics. These procedures have been referred to in the literature under many different names, such as mixture likelihood approach to clustering (McLachlan and Basford 1988; Everitt 1993) and model-based clustering (Banfield and Raferty 1993). Depending on the metric level of the variables included in the study, other terms used to describe this methodology are LCA, latent profiles analysis, latent class clustering, or model-based clustering. Under the general mixture modeling approach, membership in one of the underlying populations conceptualized as a latent, categorical variable that is not directly observed. Instead, class membership must be measured indirectly using two or more observed, or indicator, variables, which are subject to measurement error. Models that contain at least one categorical indicator are most commonly referred to as LCA models (Morgan in press), which is the terminology used in this paper. The goal of LCA is the classification of similar objects into one of K groups, or classes, of unknown form and frequency. The form of the classes refers to parameters which distinguish the groups, such as cluster-specific means, variances, and covariances (Vermunt and Magidson 2002), and the frequency refers to the number of underlying groups.

Not only can LCA be used for examining the existence of unobserved, underlying populations (i.e., classes), but it can also be implemented to examine whether the underlying latent class structure is the same across multiple observed groups. That is, one can employ a multiple-group LCA approach to determine the extent to which the latent class structure is invariant between groups by fitting a series of increasingly restrictive models. This approach is commonly used for examining factorial invariance, or more generally, measurement invariance (Meredith 1993; Raykov et al. 2012; Reise et al. 1993; Vandenberg and Lance 2000; Widaman and Reise 1997), in which the latent variable is continuous instead of categorical as is the case in this study. Given the nature of the guiding research questions (discussed below), we demonstrate the use of the multiple-group LCA approach for examining measurement invariance across two groups of observed community college students. Invariance testing via multiple-group LCA offers significant benefits for educational and psychological researchers. Furthermore, we are unaware of any applications of multiple-group LCA invariance testing using this population of students. Therefore, this study makes an important methodological and substantive contribution to the literature.

3 Conceptual framework and research questions

In addition to employing Career Clusters as a central piece of the design of the present study, we also consider the 2-year public college population and students who enroll in such program areas. Therefore, our conceptual framework is based on Hirschy et al.'s (2011) "conceptual model for student success in community college occupational programs" (p. 310). Informed by other models on student success, Hirschy and colleagues consider the specific needs, backgrounds, and experiences of career program students and propose a model that includes the following primary and secondary components: student characteristics (sociodemographic, academic preparation/aptitude/performance, commitments and responsibilities, dispositions and skills, educational intentions/goals, employment intentions/goals), college environment (academic/social integration, campus support, career integration), local community environment (career integration, community support), and student success (attain educational goals) (p. 310). While the present study does not include variables under all secondary components of the Hirschy model, those selected from the dataset fit under each of the primary constructs (see Table 1).

Based on the importance of major as discussed in the literature, the application of the FFM approach to identifying classes of public 2-year college students, and the conceptual model for the study of career-focused students, the following research questions guided this study:

1. What are the profiles/classes of traditional-aged community college students?
2. Are the latent class configurations the same for students who persisted and those who did not?
3. How are the profiles/classes of persisting community college students aligned with Career Clusters?

4 Methods

4.1 Sample

The analytic sample used in this study came from the Educational Longitudinal Study of 2002 (ELS:2002), which was "designed to monitor the transition of a national sample of young people as they progress from tenth grade through high school and on to postsecondary education and/or the world of work" (U.S. Department of Education 2004). Interested readers should visit the ELS:2002 section of the Institute of Educational Sciences website for more information on the design of the ELS:2002 (www.nces.ed.gov/surveys/els2002). Permission to use the data was granted to the authors by IES, and the "restricted-

Table 1 Conceptual framework and variables of interest

Construct[a]	Variable of interest	Sub-construct[a]
Student characteristics	Ethnicity	Sociodemographic
	Gender	Sociodemographic
	Socioeconomic status	Sociodemographic
	Carnegie Units completed in high school	Academic preparation/ aptitude/performance
	High school GPA	Academic preparation/ aptitude/performance
	Requirement to complete dev. courses	Academic preparation /aptitude/performance
	Employment earnings	Commitments and responsibilities
	Student educational expectations	Educational intentions/goals
College environment	Enrollment by Career Cluster/program type	Academic/social integration, career integration
	Full-time or part-time attendance	Academic/social integration
	Extracurricular activity participation	Academic/social integration
	Engagement with faculty and advisors	Academic/social integration and campus support
	Student loan attainment	Campus support
Local community environment	Enrollment by Career Cluster/program type	Career integration
Student success	Continuous enrollment at public 2-year college (persistence)	Attain educational goals

[a] The constructs and sub-constructs are from Hirschy et al. (2011) "Conceptual model for student success in community college occupational programs"

use" data were loaded and housed on a secured computer in accordance with the IES security requirements.

It should be noted that the ELS:2002 survey design used a two-stage sample selection process. First, schools were selected by sampling within specified strata. Second, a sample of ∼30 students was selected from each participating school. In order to increase the representativeness of the sample to national population of sophomores, sampling weights were applied to each student's data. In the current study, we elected not to use the sampling weights because they are not applicable to the target population (i.e., 2-year college students). That is, the sampling weights were developed to yield a nationally representative sample of high school sophomores. The current study focused squarely on traditional-aged community college students. We subset the ELS:2002 dataset based on those students who attended public 2-year institution following high school. We further disaggregated those students who reported continuous enrollment at a public 2-year college for four consecutive semesters (2004 to 2006) (i.e., persisters) and those who reported noncontinuous enrollment during that same time period (i.e., nonpersisters) as indicated by the follow-up survey responses. Students who transferred to a 4-year college or university were excluded from the analysis. The final sample consisted of 1,540 students, 780 of which had continuous enrollment and 770 of which were not continuously enrolled. The full demographic summaries of this analytic sample are presented in Table 2.

Table 2 Student demographic composition

Variable	Frequency (n)	%
Sex		
Female	950	55.0
Male	780	45.0
Race		
Other	100	5.7
Asian	180	10.3
Black or African American	180	10.4
Hispanic	260	15.2
White	1010	58.8
Job		
No job	160	9.4
$1–7,500	850	49.2
More than $7,500	710	41.4
Loan		
No loan	190	10.8
$1–3,000	150	8.6
More than $3,000	1390	80.6
Educational aspirations		
No clear aspirations	200	11.7
Complete High School or some college	190	11
Complete college	1330	77.2
Remedial courses		
None	870	50.4
One or more	860	49.6
Extracurricular activity		
None	1050	60.9
Some	380	22
Often	300	17.1
Interacted with faculty		
Not at all	230	13.1
Some	990	57.6
Often	510	29.3
College enrolment		
Part-time	1500	87.1
Full-time	220	12.9

Note All frequencies have been rounded to the nearest 10 per Institute of Education Sciences publication policy

4.2 Analysis

Given the research questions under investigation, we used multiple-group LCA in order to identify underlying classes of students based on a host of variables (discussed in Sect. 4.3). As a classification approach, mixture modeling offers significant improvement over traditional, distance-based procedures. Three important benefits of mixture modeling in the current study are (1) the ease with which the model can simultaneously accommodate continuous and discrete variables (Morgan in press), (2) probabilistic class assignment, and (3) the availability of fit indices to aid in model selection. Mixture models that contain only discrete class membership indicators are commonly referred to as latent class models, and those that contain only continuous class membership indicators are commonly referred to as latent profile models. The current study used a combination of discrete and continuous indicators, and the model can be expressed as:

$$f\left(y_i|\boldsymbol{\Phi}\right) = \sum_{k=1}^{K} \pi_k \prod_{j=1}^{J} f_k\left(\boldsymbol{y}_i|\boldsymbol{\theta}_{jk}\right),$$

where $\boldsymbol{y}_i$ denotes the profile of scores for case i across the set of variables, Φ is a mixture of the class-specific joint distributions of the indicators, K is the number of underlying classes, J is total number of indicators, π_k denotes the prior probability of belonging to class k (i.e., class prevalence), and $\boldsymbol{\theta}_{jk}$ is the set of model parameters (Vermunt and Magidson 2002).

With regard to probabilistic class assignment, each person in the dataset is given a probability of belonging to each class based on the alignment between the person's characteristics and the characteristics of each class. The person is then classified into the class too which she or he has the highest probability of belonging (i.e, modal assignment). The fit indices examined were Akaike information criterion (AIC), Bayesian information criterion (BIC), adjusted BIC (aBIC), Lo-Mendell-Rubin likelihood ratio test (LMR), and, where available, bootstrapped likelihood ratio test (BLRT). Numerous studies have found the BIC and aBIC tend to outperform other fit indices at identifying mixture model solutions (Henson et al. 2007; Morgan in press; Nylund et al. 2007; Tofighi and Enders 2008; Yang 2006). At the time of this writing, the BLRT was only available in M*plus* for mixture model solutions conducted separately for persisters or nonpersisters. These fit indices are used to identify which of the tested models fit the data best.

In order to identify the best approximating model, we took the following steps. First, we compared the fit of a two- through five-class solution for the nonpersisters. Second, we compared the fit of a two- through five-class solution for the persisters. Third, we fit two- through five-class solutions to the combined sample and only required that the number of classes be the same for persisters and nonpersisters. Thus, each class was allowed to have its own characteristics and a different proportion of persisters and nonpersisters. Fourth, we fit two- through five-class solutions to the combined sample and required that the number of classes and characteristics of each class be the same for persisters and nonpersisters. Based on the model selected in the previous step, we concluded by fitting a solution that required the number of classes and class-specific characteristics to be the same for persisters and nonpersisters as well as requiring the same proportion of persisters and nonpersisters to be in each class. Within each step outlined above, the fit indices were compared between the competing solutions. Solution with relatively lower AIC, BIC, and aBIC values indicate better model-data fit. The LMR and BLRT test the hypothesis that the k-class solution fits better than a solution with $k-1$ classes, and it yields a p value. Using a maximum Type I error rate of 5 %, the best fitting solution is the one where k class yields of p value greater than 0.05. These steps are recommended for multiple-group LCA (Collins and Lanza 2010).

After the multiple-group LCA was complete, the final class solution was compared with the available Career Cluster information to determine whether students in different classes differentially pursued programs in certain Career Clusters. All mixture analysis was conducted using M*plus* (version 6.12, Muthén and Muthén 2012). The number of random starting values was increased from 10 to 2,000 in an effort to avoid local solutions. Subsequent analysis between class membership and Career Clusters was conducted using SAS software (version 9.2, SAS Institute 2008).

4.3 Variables

The identification of classes is based on the distribution of variables used as indicators of class membership. The ELS:2002 variables we used were: student sex composite [BYSEX], student race/ethnic composite [BYRACE_R], respondent's 2005 job earnings [F2ERN05R], amount borrowed for undergraduate loans [F2B226R], reported student educational aspirations [BYSTEXP], required remedial coursework in reading [F2B16A], writing [F2B16B], or math [F2B16C], participation in postsecondary extracurricular activities [F2B18E, F2B18F, F2B18G], interaction with faculty and/or academic advisor [F2B18A, F2B18B], enrollment intensity [F2IFTPT], socioeconomic status composite version 2 [F1SES2R], total Carnegie units [F1RHTUN], and high school GPA for academic courses [F1RAGP]. To aid in model interpretability, several of these variables were recoded to produce dummy vectors. Dummy variables were created to serve as indicators for female, African American, Asian, Hispanic, other racial/ethnic background, job earning between $1 and $7,500 while in college, job earning more than $7,500 while in college, no student loans, student loans between $1 and $3,000, student aspirations of high school diploma to 2-year degree completion, student aspirations of 4-year degree completion or higher, required developmental coursework, occasional postsecondary extracurricular activity, frequent postsecondary extracurricular activity, occasional interaction with faculty, frequent interaction with faculty, and part-time enrollment. The reference categories for these variables are male, White, job earning $0 while enrolled in college, students loans greater than $3,000, no reported student educational aspirations, no remedial coursework, no involvement in postsecondary extracurricular activity, no reported interaction with faculty, and enrolled full-time about half of the time or more. The recoding resulted in 20 variables (17 dichotomous, 3 continuous) as indicators of class membership. Class membership was determined by differences in proportions on dichotomous variables and means on continuous variables.

In an effort to classify students according to their programs of study grouped by Career Cluster, we conducted a multi-step process. First, the ELS:2002 dataset includes program codes, which were mapped to Classification of Instructional Programs (CIP) Codes which are higher education program codes that have been used by the U.S. Department of Education since 1980 (NCES, n.d.). While there have been many versions of CIP Codes since 1980, we employed the CIP-2000 version, which is consistent with the timeframe of original ELS:2002 data collection. Second, once all records in the sample had assigned CIP Codes relevant to program of study in college, we used the *Perkins IV Crosswalk*, which is a guide for classifying all CIP Codes into the 16 Career Clusters (Perkins Collaborative Resource Network 2007). Following the crosswalk guidelines, all records in the sample were then assigned to a Career Cluster driven by their reported program of study at the community college.

To date, there have been several studies that used the ELS:2002. For example, Chen (2009) explored college students in STEM majors; Lee and Judy (2011) also looked at STEM students, but were investigating academic patterns in high school; and, Kim et al. (2012) looked at 4-year college students and how financial aid is related to departure. To our knowledge, previous inquiry has not looked comprehensively at public 2-year college students across the 16 Career Clusters, nor has any employed multiple-group LCA.

5 Results

The results of the analysis described above are presented in the same order as outlined. First, we examined the class enumeration separately for persisters and nonpersisters. We began

Table 3 Summary of the fit indices for all models

Classes	LL	AIC	BIC	aBIC	LMR p value	BLRT p value
Continuously enrolled (persisting) subsample						
2	−9978.7	20045.4	20249.7	20110.0	<0.001	<0.001
3	−9824.2	19778.5	20080.3	19873.9	<0.001	<0.001
4	−9697.4	19566.9[a]	19966.2[a]	19693.1[a]	<0.001[a]	<0.001[a]
5	Not well-identified					
Noncontinuously enrolled (nonpersisting) subsample						
2	−9484.5	19057.0	19261.7	19122.0	<0.001	<0.001
3	−9252.6	18635.3	18937.7	18731.3	<0.001[a]	<0.001
4	−9137.5	18447.0[a]	18847.1[a]	18574.0[a]	0.07	<0.001[a]
5	Not well-identified					
Combined sample—equal number of classes						
2	−20557.1	41286.2	41745.6	41472.4		
3	−20171.0	40598.0	41281.7	40875.1		
4	−19948.4	40236.8[a]	41144.9[a]	40604.9[a]		
5	Not well-identified					
Combined sample—equal number of classes and class characteristics						
2	−20780.8	41653.6	41899.3	41753.2		
3	−20370.5	40877.1	41240.3	41024.3		
4	−20140.0	40460.1[a]	40940.8[a]	40654.9[a]		
5	Not well-identified					
Combined sample—equal number of classes, class characteristics, and proportions of each student group in each class						
4	−20162.4	40498.8	40963.5	40687.1		

[a] Denotes best fitting model according to each fit index

by fitting a two-class solution and increased the number of classes up to five in subsequent solutions. In both subsamples, we identified four underlying classes of students. Second, we fit a series of models (i.e., two-to-five-class models) that required only that the number of classes be the same for persisters and nonpersisters. Under this model specification, the four-class solution was identified as the best fitting model of those tested. Third, we fit a series of models (i.e., two-to-five-class models) that required that the number of classes and characteristics of each class were the same for persisters and nonpersisters. Under this model specification, the four-class solution was again identified as the best fitting model of those tested. Based on all evidence collected, we concluded that there were four underlying classes of students in the sample. Finally, we fit a model that required that the number of classes, class characteristics, and proportion of students in each class were the same for persisters and nonpersisters. This additional constraint resulted in slightly worse fit. Therefore, the solution with four classes and equal class characteristics but unequal proportions of persisters and nonpersisters in each class was selected as the best fitting model. The summary of the fit indices for all models is presented in Table 3. The following is a presentation of the final selected model ordered by class size.

Table 4 Class-specific percentages and means

Class membership indicator	Class 1	Class 2	Class 3	Class 4
Female	61.9	65.5	39.5	46.4
African American	11.9	13.7	11.5	7.1
Asian	14.2	8.4	8.0	9.1
Hispanic	13.0	14.7	14.5	19.1
Other	4.0	5.8	5.5	5.8
Job ($1–$7,500)	93.5	51.6	39.5	0.0
Job ($7,500+)	0.0	39.3	46.5	89.6
Loans ($0)	81.2	81.5	79.5	88.9
Loans ($1–$3,000)	9.8	7.2	11.0	6.4
Student aspirations (2-year college completion or less)	0.0	0.0	93.0	0.0
Student aspirations (4-year degree or more)	83.26	90.8	0.0	87.3
Developmental course	51.46	53.3	55.5	44.7
Occasional extracurricular participation	21.3	29.2	20.5	18.9
Frequent extracurricular participation	15.5	27.2	13.5	11.1
Occasional interaction with faculty	86.4	0.0	58.0	80.2
Frequent interaction with faculty	0.0	100.0	22.5	0.0
Enrolled part-time	9.2	7.1	23.5	17.6
SES	−0.01	−0.04	−0.20	−0.04
Carnegie Units	25.5	25.2	24.2	25.7
Academic GPA	2.6	2.5	2.7	2.5
Proportion in each class				
Combined sample	0.31	0.27	0.14	0.29
Continuously enrolled (persisting) subsample	0.34	0.32	0.10	0.24
Noncontinuously enrolled (nonpersisting) subsample	0.28	0.21	0.17	0.33

6 Class 1

The largest class of students was Class 1 for the combined sample (31 %) and the persister subsample (34 %). Among the nonpersister subsample, Class 1 was the second largest class (28 %). In mixture modeling, each person was assigned a probability of belonging to each class, and people were then assigned to the class to which they have the highest probability of belonging. The average classification probability for Class 1 was 0.95 of persisters and 0.96 for nonpersisters. Therefore, the classification certainty of students into this class was high. Relative to the other classes, Class 1 was characterized by the highest proportion of students who are Asian students (0.14), with job earning between $1 and $7,500 (0.94), and with occasional interaction with faculty (0.86). Class 1 had the lowest proportion of students who are Hispanic (0.13) and other racial/ethnic background (0.04). No students in Class 1 reported aspirations of completing a 2-year degree or less. Class 1 did not differ greatly from the other classes on SES, number of Carnegie units, or academic GPA. The class-specific percentages and means are presented in Table 4.

6.1 Class 4

The second largest class in the combined sample was Class 4 (29 %), and it was the third largest among persisters (24 %) and the largest among nonpersisters (33 %). The average classification probability for Class 4 was 0.96 of persisters and 0.95 for nonpersisters. Therefore, the classification certainty of students into this class was high. Relative to the other classes, Class 4 was characterized by the highest proportion of students who are Hispanic (0.19), with jobs earning more than $7,500 (0.90), and with no loans (0.89). Class 1 had the lowest proportion of students who are African American (0.07), with loans between $1 and $3,000 (0.06), were required to take development courses (0.45), and with occasionally (0.19) or frequently (0.11) participating in extracurricular activities. No students in Class 1 reported aspirations of a 2-year degree or less or frequent interaction with faculty. Class 4 did not differ greatly from the other classes on SES, number of Carnegie units, or academic GPA. The class-specific percentages and means are presented in Table 4.

6.2 Class 2

The third largest class in the combined sample was Class 2 (27 %), and it was the second largest among persisters (32 %) and the third largest among nonpersisters (21 %). The average classification probability for Class 2 was 1.00 of persisters and 0.99 for nonpersisters. Therefore, the classification certainty of students into this class was high. Relative to the other classes, Class 2 was characterized by the highest proportion of students who are female (0.66), African American (0.14), have reported aspirations of 4-year degree or higher (0.91), and occasionally (0.29) or frequently (0.27) participated in extracurricular activities. Class 2 had the lowest proportion of students who were enrolled part-time (0.07). No students in Class 2 reported aspirations of completing a 2-year degree or lower, and all students in Class 2 reported frequent interaction with faculty. Class 2 did not differ greatly from the other classes on SES, number of Carnegie units, or academic GPA. The class-specific percentages and means are presented in Table 4.

6.3 Class 3

The smallest class in the combined sample was Class 3 (14 %), and it was also the smallest class among persisters (10 %) and the nonpersisters (17 %). The average classification probability for Class 3 was 0.99 of persisters and 0.97 for nonpersisters. Therefore, the classification certainty of students into this class was high. Relative to the other classes, Class 3 was characterized by the highest proportion of students who reported student loans between $1 and $3,000 (0.11), reported educational aspirations of a 2-year degree or less (0.93), required development coursework (0.56), and were enrolled part-time (0.24). Class 3 had the lowest proportion of students who are female (0.40) and Asian (0.08). No students in Class 3 reported aspirations of completing a 4-year degree or higher. Class 3 had considerably lower SES composite mean but did not differ greatly from the other classes on number of Carnegie units or academic GPA. The class-specific percentages and means are presented in Table 4.

6.4 Analysis with class variable

Based on the model results presented above the class proportions differed based on the enrollment continuity of students. Thus, these classes have the same the meaning in each group, but students in each group are not equally likely to be in each class. This provided preliminary evidence of a relationship between the class variable and student grouping variable. We estimated the strength of this relationship using Cramer's V; this estimate was 0.18, which was considered a moderate effect size. In this sample, students who persisted were more likely to be in Classes 1 and 2, and students who did not persist were more likely to be in Classes 3 and 4.

Next, we examined the relationship between the class and Career Cluster to which each student belonged. In all, there were 16 identified clusters, and one category that was used to classify programs that did not fit into one of the 16 identified clusters. Of the 780 students who persisted, three were missing academic program information. Of the 770 students who did not persist, most (84 %) were missing academic program information, and we excluded the nonpersisting students from this analysis. Therefore, the examination of class membership and Career Clusters was informed by the persisters. The estimated correlation between class membership and Career Cluster was 0.20 as measured by Cramer's V. This estimate was considered a moderate effect size. Among persisting students, the largest clusters represented were Health Science ($n = 190$), Education and Training ($n = 130$), and Business, Management, and Administration ($n = 130$). The Health Science cluster had the largest representation of students from Class 1 (27.9 %) and Class 4 (26.4 %) followed by Class 2 (24.4 %) and Class 3 (13.3 %). The Education and Training cluster had the largest representation of students from Class 1 (19.6 %) and Class 2 (24.4 %) followed by Class 4 (15.4 %) and Class 3 (9.3 %). The Business, Management, and Administration cluster had the largest representation of students from Class 4 (20.9 %) and Class 1 (17.0 %) followed by Class 2 (15.2 %) and Class 3 (10.7 %). The cluster that was most represented in Classes 1, 2, and 4 was the Health Science cluster. In Class 3, the Health Science and Arts, A/V Technology, and Communications clusters were most represented.

7 Discussion

In this study, we found that the latent class characteristics were invariant across the persisters and nonpersisters. Therefore, differences in class membership probabilities could be interpreted with confidence because the classes have exactly the same meaning for persisters and nonpersisters. Given that students in Classes 1 and 2 were more likely to persist, and students in Classes 3 and 4 were more likely not to persist, we employed the conceptual framework (Hirschy et al. 2011) to further discuss the findings in terms of student success along the three key constructs of student characteristics and college environment. The key variable for local community environment construct is cluster alignment, which will be discussed later in this section.

8 Student characteristics and college environment

Following the conceptual framework for this study, student characteristics include sex, ethnicity, socioeconomic status (SES), academic preparation (HS GPA, Carnegie units completed, and requirement to complete developmental studies), employment, and student aspirations. The organization of the present study is unlike a more typical study that considers variables that may be directly related one's likelihood of success. The present approach that utilizes classes provides opportunities to discuss items associated with student success as well as the alignment of variables and relationships with particular Career Clusters. In the following paragraphs, we discuss the prevalence of values aligned with a greater likelihood of persistence (Classes 1 and 2) and less likelihood of persistence (Classes 3 and 4).

Women had majority representation in Classes 1 and 2, the higher persisting clusters, while males held majority representation in Classes 3 and 4. Since we know that students in the latter classes had less likelihood of persistence, these findings are consistent with Alfonso et al. (2005), who noted that males in associate degree programs were less likely to earn degrees than females. They also found that Black students were less likely to be successful, which is different than the present study. The proportion of white student enrollment in each class ranged from ~57 to 61 %; thus, there was not great variation in terms of White students as compared with all "minority" groups combined. However, there was some variability in terms of specific minority groups per class. For example, Asian students had greater representation in Class 1 than the other classes. Hispanic/Latina/o students had the greatest representation in Class 4, a lower-persisting group. Finally, African-American students had the greatest representation in Class 2, a higher persisting class, and their lowest representation in Class 4, a lower-persisting group. Thus, it appears that being Asian holds greater alignment with one of the persisting classes, Hispanic/Latina/o was more aligned with nonpersisting classes, and the findings were mixed for African-American students.

SES status was relatively consistent for Classes 1, 2, and 4; however, Class 3 tended to have lower SES status and greater numbers of students who did not persist. This finding as well as the mixed findings for ethnicity further support the emergence of four classes, since there is not a direct alignment between the higher-persisting classes (1 and 2) and the lower-persisting classes (3 and 4).

Carnegie units earned and high school GPA were consistent across classes, while Class 4 had the lowest percentage of students required to complete developmental studies. This finding is interesting since Class 4 is a lower-persisting group, and the requirement to complete developmental studies is often discussed in terms of challenges related to student success (see, e.g., Illich et al. 2004; Kolajo 2004).

Regarding employment, those earning more were in the lower-persisting groups (Classes 3 and 4), and those earning less were in higher-persisting groups (Classes 1 and 2). We suspect these findings are about more than just earnings, but also reflect the commitment to something other than school. Whether this is based on financial need or desire to enter a particular career area, it may signal interests that compete with a focus on college persistence. This could perhaps be understood in light of Lohman and Dingerson's (2005) finding that students in career-focused programs may depart because they have met educational objectives and leave for work-related reasons. Lastly, only Class 3 contained students who aspired to a 2-year degree or less, and this is one of the lower-persisting groups, which shows a potential connection between lower aspirations and nonpersistence.

Institutional environment variables also tell a compelling story about the links among variables of interest, classes, and persistence. Students in the lower-persisting classes (3 and 4) were more likely to be enrolled part-time, which is consistent with pervious literature (e.g., Alfonso et al. 2005). Students in Classes 1 and 2 had more interaction with faculty and more extracurricular participation in college with all students in Class 2 having frequent interaction with faculty and the greatest levels of extracurricular participation. This could be related to Nitecki's (2011) finding that program culture may contribute to student success. At the least, faculty interaction and extracurricular participation creates the conditions whereby students can interact with the culture.

8.1 Cluster alignment

Understanding that program enrollment and completion in Career Cluster areas has potential implications for employment and earnings (Carnevale et al. 2011; Carnevale and Cheah

2013), and mapping out the profiles of students in specific clusters could potentially inform institutional practice around facilitating completion. For example, Table 5 shows that the Career Clusters with the greatest representation of persisting students in Class 1 included: Business, Management, & Administration; Education & Training; Health Science; Information Technology; Science, Technology, Engineering, & Mathematics; and Other. The Career Clusters with greatest representation in Class 2 included: Arts, A/V Technology, & Communications; Finance, Hospitality & Tourism; Law, Public Safety, Corrections, & Security; Manufacturing; and, Marketing. Human Services is equally represented in Classes 1 and 2. Class 3 holds top representation for Agriculture, Food, & Natural Resources; Architecture & Construction; and, Transportation, Distribution, & Logistics. Finally, Government & Public Administration is best aligned with Class 4. In addition, Table 6 shows top ranking Career Clusters for numbers of persisters in each class.

One of the takeaways that becomes clear is that the majority of Career Clusters have at least half of their persister enrollment in Classes 1 and 2. However, four Career Clusters have their greatest number of persisters in Classes 3 and 4, which in the analysis of the full dataset was comprised of students more likely not to persist. In summary, these findings show that (a) students with specific profiles may be more likely to persist and (b) students in all four classes may be able to succeed despite being profiled in classes marked by lower persistence rates.

We suggest that institutions consider two potential ways of using these findings. First, gaining a better understanding of predominant profiles aligned with each Career Cluster allows for considerations within cluster-specific programs to enhance student success. For example, persisters in Health Science are mostly in Classes 1 and 2 (70 %). This informa-

Table 5 Percentage of persisting students in each class by Career Cluster

Career Cluster	Class 1	Class 2	Class 3	Class 4
Agriculture, Food & Natural Resources	25.0	25.0	33.3	16.7
Architecture & Construction	26.1	26.1	30.4	17.4
Arts, A/V Technology & Communications	25.8	34.9	15.2	24.2
Business Management & Administration	34.9	29.5	6.2	29.5
Education & Training	38.8	35.1	5.2	20.9
Finance	25.0	50.0	0.0	25.0
Government & Public Administration	0.0	33.3	0.0	66.7
Health Science	38.3	31.6	5.2	24.9
Hospitality & Tourism	25.0	50.0	12.5	12.5
Human Services	30.0	30.0	15.0	25.0
IT	42.3	23.1	7.7	26.9
Law, Public Safety, Corrections & Security	25.0	42.3	15.4	17.3
Manufacturing	20.0	60.0	0.0	20.0
Marketing	25.0	66.7	0.0	8.3
Science, Technology, Engineering & Mathematics	37.7	28.3	11.3	22.6
Transportation, Distribution & Logistics	28.6	9.5	42.9	19.1
Other	45.5	27.3	0.0	27.3

Note The percentages reflect the distribution of students in each class by Career Cluster. Therefore, the sum of the rows should total 100 within rounding error

Table 6 Top five clusters of persisting students in each class

Rank	Class 1	Class 2	Class 3	Class 4
1	Health Sciences (27.9 %)	Health Sciences (24.4 %)	Arts, A/V Technology, & Communications (13.3 %)	Health Sciences (26.4 %)
2	Education & Training (19.6 %)	Education & Training (18.8 %)	Health Sciences (13.3 %)	Business, Management, & Administration (20.9 %)
3	Business, Management, & Administration (17.0 %)	Business, Management, & Administration (15.2 %)	Transportation, Distribution, & Logistics (12.0 %)	Education & Training (15.4 %)
4	Science, Technology, Engineering, & Mathematics (7.6 %)	Arts, A/V Technology, & Communications (9.2 %)	Business, Management, & Administration (10.7 %)	Arts, A/V Technology, & Communications (8.8 %)
5	Arts, A/V Technology, & Communications (6.4 %)	Law, Public Safety, Corrections, & Security (8.8 %)	Law, Public Safety, Corrections, & Security (10.7 %)	Science, Technology, Engineering, & Mathematics (6.6 %)

tion gives institutional leaders in those program areas a good understanding of predominant characteristics of their persisting students. However, looking into their low numbers of students in Class 3 (5.2 %) and Class 4 (24.9 %) can also provide insights into why there are lower numbers of persisters in the latter classes. Another example is Transportation, Distribution, & Logistics, where 43 % of persisting enrollees were in Class 3, one of the typically low-persistence classes which is more likely to have students with lower aspirations, less frequent extra curricular participation, less interaction with faculty, and greater likelihood of enrolling part-time. Leaders could ask why so many persisting students are aligned with that class. Ultimately, institutional leaders could use this information consider ways to engage specific cluster-based student populations for improved outcomes.

Second, colleges could consider characteristics of students in the most prevalent classes by Career Cluster areas as they work to facilitate success among their students. For example, Business, Management, & Administration and Education & Training have similar representation among classes. Academic and student service professionals working with students in those programs could potentially work to provide similar interventions to those groups of students who share many of the variables related to student characteristics and college environment. These similarities could even inform alignment with organizational structures, assigned advisors, orientations, and other considerations to facilitate connections among Career Cluster programs with similar student profiles.

In this era when the majority of available jobs will require postsecondary education (Carnevale et al. 2010) and associate degree attainment is important for future earnings (Bailey et al. 2004; Dadgar and Weiss 2012; Grubb 1997), helping to facilitate success among students in specific Career Clusters could serve as an important strategy to enhancing the economic competitiveness of individuals and communities. Perhaps a better understanding of student profiles and alignment among Career Cluster programs can inform thinking toward improved student outcomes.

9 Contribution to mixture modeling

Methodologically, this study demonstrates the use of multiple-group LCA for examining subgroup classification among those students who persist or do not persist among public 2-year college students. By using this approach, we recognize that there is variability within those students who do or do not persist. In procedures traditionally used for making group comparisons (e.g., analysis of variance, multiple regression), those members of each group are treated the same. Not only does multiple-group LCA allow for examination of within group variability and classification into unobserved classes each with specific characteristics, but it also provides researchers with the ability to examine the equivalence of subgroup characteristics across classes. The examination of across group equivalence is often referred to as measurement invariance although some readers may be more familiar with invariance within the context of multi-group confirmatory factor analysis or item response theory (i.e., differential item functioning). This study further shows how invariance may be examined with a categorical latent variable and mixed metric indicators, which may be of interest for many educational and/or psychological researchers. In education, for example, a researcher may be interested in modeling latent class membership as a function of whether students receive special education services, receive free/reduced price lunch, or participate in after-school programs as well as their standardized reading, mathematics, and science scores. In psychology, for example, one might choose to examine latent class differences between youths on the basis of their smoking, alcohol consumption, drug use, and sex practices in addition to scores on personality inventories or another instrument. Finally, methods that recognize within group variation may be more appropriate when studying people, such as 2-year college students, who have well-documented diversity of backgrounds and experiences.

10 Suggestions for future research

One suggestion for future research involves a cluster-specific study involving a sample with greater age diversity. While there is value in using the ELS:2002 as a nationally representative sample, the traditional-aged population does not necessarily reflect other interesting aspects of community college student characteristics, an important element of the conceptual framework of this study. It may also be of interest to methodologically to investigate the accuracy of various fit indices for studying invariance testing via multi-group LCA. It may be inferred from previous mixture modeling studies that certain fit indices (e.g., BIC, aBIC) might perform well, but further Monte Carlo investigation would provide support for or against these inferences.

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