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# An Empirical Typology of the Latent Programmatic Structure of Community College Student Success Programs

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## Abstract

The definition and description of student success programs in the literature (e.g., orientation, first-year seminars, learning communities, etc.) suggest underlying programmatic similarities. Yet researchers to date typically depend on ambiguous labels to delimit studies, resulting in loosely related but separate research lines and few generalizable findings. To demonstrate whether or how certain programs are effective there is need for more coherent conceptualizations to identify and describe programs. This is particularly problematic for community colleges where success programs are uniquely tailored relative to other sectors. The study's purpose is to derive an empirical typology of community college student success programs based on their curricular and programmatic features. Data come from 1047 success programs at 336 U.S.-based respondents to the Community College Institutional Survey. Because programs might be characterized by their focus in different curricular areas and combinations of foci, we used factor mixture modeling, a hybrid of factor analysis and latent class analysis, which provides a model-based classification method that simultaneously accounts for dimensional and categorical data structures. Descriptive findings revealed extensive commonalities among nominal program types. Inferential analysis revealed five factors (types) of program elements, combined in unique ways among four latent program types: success skills programs, comprehensive programs, collaborative academic programs, and minimalist programs. We illustrate how the typology deconstructs nominal categories, may help unify different bodies of research, and affords a common framework and language for researchers and practitioners to identify and conceptualize programs based on what they do rather than by their names.

**Keywords:** Community college, First-year programs, Promising practices, Program design, Latent class analysis, Factor mixture model

## Introduction

The prominent college student completion agenda of the last several years has led to, among other activities, a renewed policy and research focus on identifying and scaling up practices in higher education which “appear to engage participants at levels that elevate their performance across multiple engagement and desired-outcomes measures” (Kuh 2008, p. 14; cf. Kuh and O’Donnell 2013) frequently referred to as *high-impact practices*, or more guardedly *promising practices*. In the community college sector, practitioners and organizations have redoubled efforts to verify the impact of, and explore the potential to scale up, promising practices such as first-year seminars, learning communities, student success courses, orientation, and accelerated developmental education programs (Brock et al. 2007; Center for Community College Student Engagement [CCCSE] 2012). These are designed to equip incoming students with skills, knowledge, and support networks for successful college-going (CCCSE 2012; Levin et al. 2010; Price and Tovar 2014). There is growing evidence these practices have the potential to impact a number of desirable student outcomes (see reviews by Brownell and Swaner 2009; Crisp and Taggart 2013; Kulik et al. 1983; Karp 2011; Swaner and Brownell 2009). However, most related research is conducted in the 4-year sector. While these programs in the 2-year sector share many characteristics with similarly-named programs in the 4-year sector, students at community colleges are different in important ways from students attending 4-year institutions leading these programs to be tailored to the community college context (Young and Hopp 2014). Additionally, participation remains low overall (Hatch and Bohlig 2015; CCCSE 2012) and questions remain as to what extent additional investment in them might foster student completion in equitable ways (Lester 2014).

Unfortunately, evidence of program effectiveness is still largely based on studies of single institutions or programs, and most publications include few details about program design and implementation preventing researchers and practitioners from being able to replicate the intervention or to know if different programs by the same labels in the literature are truly comparable. Even where studies pay close attention to implementation details and use experimental methods to discern causal effects, there are still questions as to the generalizability of findings. For instance, recent research by MDRC at the City University of New York (Scrivener et al. 2015) found that a completely re-envisioned accelerated community college experience with intensive financial, academic, and career support, among other features, resulted in dramatic gains in retention and graduation for the experimental group. What is not clear from the study, however, is an understanding of which program elements were responsible for the outcomes (Mangan 2015).

Explication of programmatic details is important for practitioners tasked with identifying and deploying programs for student success so that they can make informed decisions about the appropriateness and potential effectiveness of a program at their institution. To date, evaluation researchers have mainly focused on the average effects of programs but have, for the most part, struggled to answer “why some programs are more effective than others and what it might take to design and operate more successful programs” (Weiss et al. 2013, p. 2). Researchers studying student success programs in community colleges agree

that the field needs substantially more details about program components, more rigorous research designs, and more multi-institutional studies in order to more clearly demonstrate whether and why interventions may contribute to differential student outcomes (Bailey and Alfonso 2005; Brownell and Swaner 2009; Crisp and Taggart 2013; Karp 2011). Along with a scarcity of methodologically sophisticated and large-scale studies, there is an absence of conceptual frameworks to operationalize program environments in the first place. Research suggests that promising practices implemented at community colleges under different labels often have more features in common than features that distinguish them (Hatch and Bohlig 2015; Young and Hopp 2014). Yet the literature to date typically depends on ambiguous labels and equally ambiguous descriptions of program content to delimit studies and lines of research. If it is true that “before one may explain why something happens or does not happen one must be able to identify the thing itself and its kind” (Bahr 2010, p. 725) the lack of conceptual frameworks to define student success programs partially explains limited progress toward generalizable findings. For the field to clearly demonstrate whether programs are effective, and if so, why, there is need for a coherent way to conceptualize programs across sites and across studies based on their programmatic and curricular features rather than based on their local names or idiosyncratic features.

## **Purpose and Research Questions**

This paper addresses the lack of a conceptual framework for operationalizing the features of various related student success programs. Our purpose is to uncover latent patterns of program design that have previously been mostly overlooked and unexplored. The degree to which programs may share features suggests they may be comparable in ways that could bridge previously separate lines of research. Such a typology may provide a framework for researchers and practitioners to define programs across multiple sites and studies to determine not only whether program design matters, but if so why, for whom, and under what circumstances. We first review the literature to demonstrate the shortcomings of current conceptualizations of programs which ignore their shared programmatic and curricular features. Then, using national data on program descriptions, we aim to derive a typological conceptual framework based on latent patterns of program features. The following research questions guided this portion of the analysis:

1. Cutting across nominal categories of student success programs, which kinds of curricular and programmatic elements tend to be implemented together?
2. Given latent groupings or types of elements, what are the latent classes of programs that implement these elements in various combinations?

Finally, we investigate both dimensions of latent patterns of program design in terms of nominal program labels to illustrate the implication of the typology for the research agendas proposed in the literature.

## **Framework Building Through Typology**

Rather than implementing a study that tests hypotheses, this study proposes a conceptual framework to describe student success programs in an effort to facilitate comparisons of like-programs across institutions and studies. Typologies fit within the battery of approaches

available in the social sciences as a bridge between systematic substantive theory and relatively unstructured empirical data. In typological analysis, as in Weber's (1949) methodology of *ideal type*, the analytical task is the derivation, rather than the application, of a model or analytical construct which captures the features of a given set of phenomena and their systemic variation as found through empirical observations (Ayres and Knaf 2008; Bahr 2010; Kim 2012). That is, while theory can be employed to interrogate data, data can just as often be used in a complementary process to develop theory (Trowler 2012). This study does the latter in an attempt to provide a framework to operationalize descriptions of programs in multi-site research.

Typologies are typically derived through either conceptual or empirical methods. In conceptual typological studies, authors propose new or reconcile previous conceptualizations through a heuristic reading of the literature. Few studies have considered at length the underlying similarities and dissimilarities of programs. Two exceptions are literature reviews by Beatty-Guenter (1994) and Karp (2011) who considered formal programs and more general strategies, in the former case for fostering student retention, and in the latter case for providing nonacademic support. Beatty-Guenter interpreted the literature on retention strategies to reveal four types, whether an intervention (a) sorted students, (b) supported students, (c) connected students (to each other and the institution), or (d) transformed students. Karp delved into the details of how interventions operate and found that interventions described as effective are characterized by four main *mechanisms* of nonacademic support: (a) creating social relationships, (b) clarifying aspirations and enhancing commitment, (c) developing college know-how, and (d) making college life feasible. Karp reports that the aim in her literature review was to shift attention from programs per se toward the processes and conditions under which they enact academic and social support. What Beatty-Guenter's types and Karp's mechanisms do not do, nor purport to, is specify the particular programmatic and curricular elements (or combinations) or their relative emphasis that together uniquely define programs.

Typologies of postsecondary program interventions derived through empirical analysis are relatively scarce. Two notable examples that utilize statistical techniques include Hurtado et al.'s (1991) investigation of types of general education programs, a study which utilized factor analysis of information from college catalogs and student survey data, and Inkelas et al.'s (2008) study on the differences in student outcomes by types of living-learning programs in which the authors used *k*-means clustering techniques to analyze institutional-level survey data. Empirical typology studies have an advantage of providing a way to reveal previously unobserved taxonomies based on otherwise latent patterns of phenomena. The present study uses an empirical approach to derive order out of otherwise disparately conceptualized programs by investigating shared patterns of design features.

## Prior Program Conceptualizations in the Literature

Astin and Antonio (2012) in their elaboration of the influential input-environment-outcome (I-E-O) framework, note that the conceptualization of the college environment is by far the most difficult and complex of the three, and that it is also the most neglected. Since Astin introduced the notion of I-E-O, environmental factors have arguably received a great deal more attention—indeed, leading to the recent focus on so-called high-impact and promising practices (cf. Kuh 2008). Yet, studies of college environmental factors for the most part have

investigated only dichotomous program participation in their research design. Conceptual frameworks for further unpacking those environments remain elusive.

A review of the literature of student success programs shows the degree to which student success program labels both reveal and hide numerous shared features. We utilized the inventory of programs proposed by CCCSE (2012) to organize our review and make sense of ambiguous program descriptions. CCCSE's list of practices has advantages over previous inventories (Bailey and Alfonso 2005; Crisp and Taggart 2013; Kulik et al. 1983; Mills 2010; Swaner and Brownell 2009) in that it is more expansive and the practices are divided conceptually depending on whether they are for planning, initiating, or sustaining student success. In previous inventories, authors have typically grouped together practices based mostly on the preponderance of published research, but without conceptual inclusion or exclusion criteria. CCCSE's inventory includes formal and informal interventions and some policy-related actions. From this list, we selected practices inclusive of those covered by previous authors, that are formally organized programs, and—as seen in our review below—whose names are often used interchangeably: first-year experience, orientation, student success course, learning community, and accelerated developmental education.

We include research from the 4-year college sector due to the relatively small numbers of studies specific to community colleges. By considering how researchers tend to delimit and define student success programs they study, we observed, as have previous authors, that the degree of detail regarding specific program features varies widely and tends to be sparse overall. In most cases, we found that authors discussed program characteristics in the course of delimiting their own particular study but without detailing program design and implementation features specifically.

### Orientation Programs/Student Success Courses

Orientation programs and student success courses go under the same heading for the simple reason that the two terms are frequently used interchangeably, both across studies and within single articles, to such an extent that it is impossible to separate them across the literature. These programs take many forms. National surveys (Hatch and Bohlig 2015; Whyte 2007) show that the most popular time frame is the traditional beginning-of-semester orientation, such as the one studied by Pascarella et al. (1986). But often colleges extend their orientation activities into the summer before an academic year—in the form of bridge programs—and into the academic year through week-long, half-semester long, semester-long or even year-long orientation courses (Perrine and Spain 2008; Robinson et al. 1996; Zimmerman 2000). Illustrative of the terminology overlap is Duggan and Williams' (2010) study which uses *community college student success courses* in the title and then go on to use this and the terms *orientation* and *success course* synonymously throughout the paper.

For some authors, the label of an orientation program or student success course appears to operate as a catch-all or umbrella term for a wider variety of program types. For instance, O'Gara et al. (2009) carried out a study on student success courses in two urban community colleges and in the opening paragraph defined the term *success course* in part by listing the synonymous terms *college 101*, *introduction to college*, *student orientation*, or *freshman experience*. In Robinson et al.'s (1996) article on orientation programs, the authors talk about broader *orientating activities* that colleges implement in the form of *freshman seminars*, *learning communities*, *summer bridge programs*, and *mentoring*. Indeed, in these authors' view, orientation programs incorporate a wide variety of activities that “facilitate student learning in three general dimensions: transition processes, academic integration, and



personal and social integration” (p. 55). Strumpf and Hunt (1993) likewise contextualized their study on an *orientation program* by framing the discussion in terms of *freshman seminars* and *first-year experiences* and went on to describe a semester-long *orientation course*—an indication of the conceptual challenge of defining and delimiting related programs.

### First-Year Experience/Seminars

Research on first-year experience programs or first-year seminars is one of the most well-established among student success programs in large part due to the work of the University of South Carolina’s National Resource Center for the First-Year Experience and Students in Transition (NRC; Fidler 1991; Gardner 1986; Keup and Barefoot 2005; Schnell and Doetkott 2003; Schnell et al. 2003). In this tradition, first-year seminars are conceptualized as both a curricular innovation and a programmatic tool designed to enhance the academic and/or social integration of first-year students by introducing them to a variety of topics, essential skills for college success, or creation of a peer support group (Keup and Barefoot 2005). The common goal of first-year seminars to “increase academic performance and persistence through academic and social integration” (Goodman and Pascarella 2006, p. 26; cf. Pascarella and Terenzini 2005).

Barefoot’s (1992) widely cited taxonomy of first-year seminars is based on the historical evolution of their purposes and differentiates among four types: *academic seminars* (with either uniform or variable content), *basic study skills seminars*, *extended orientation seminars*, and *pre-professional or discipline-linked seminars*. The latter two overlap with traditional orientation programs, as noted above (cf., Rice 1992; Strayhorn 2009) and with learning communities, as described below. Porter and Swing (2006) in their study regarding the differential impacts of first-year seminar design features used a taxonomy adapted from Barefoot’s that differentiates according to the seminar’s theme: (1) transition to college, (2) interdisciplinary academic topics, (3) introduction to a major or discipline, (4) remedial education, or (5) a mixed-theme format. Thus, this taxonomy extends the first-year seminar concept into program areas related to developmental education. And developmental education programs in turn, as noted below, often incorporate support services and co-curricular aspects typical of first-year seminars.

Tobolowsky et al. (2005) noted that “one of the unique developments [in the history of first-year seminars] is the inclusion of the seminar in learning communities” (p. 5). The interface between the two kinds of programs has received special attention in recent studies (e.g. Friedman and Alexander 2007). Henscheid (2004) described at least nine areas where first-year seminars and learning communities increasingly share programmatic approaches that include skills-training, mechanisms to keep students “on-track,” career exploration, and service learning, among others. This kind of hybridization further blurs the conceptual lines between student success courses, first-year seminars, and learning communities.

### Learning Communities

Many studies of learning communities, while spanning a variety of programs, define them “simply as a formal program where groups of students take two or more classes together, and may or may not have a residential component” (Zhao and Kuh 2004, p. 119; cf. Malnarich 2005; Tinto and Russo 1994). Several authors have proposed typologies that account for a variety of configurations in terms of, for example, the degree or kind of coordination among faculty and students, the types of students, or integration of material across content areas,

and the program's residential nature (Gabelnick et al. 1990; Inkelas et al. 2008; Love and Tokuno 1999; Shapiro and Levine 1999; Smith 2010; Zhao and Kuh 2004).

Despite a common conceptualization based on the prominent and idiosyncratic feature of linked courses, these programs are sometimes defined using broader terms. Smith and Hunter's (1988) review of community college learning communities provided a definition—also adopted by Minkler (2002) in his updated review 14 years later—using broad language to define them as “a deliberate restructuring of the curriculum to build a community of learners among students and faculty ... so that [they] are actively engaged in a sustained academic relationship ... over a longer period of time than in traditional courses” (p. 46). Likewise, Shapiro and Levine (1999) define them broadly as programs designed around small-group interaction to provide support, academic and social integration, and to cultivate key learning outcomes (cf. Inkelas et al. 2008).

### **Accelerated Developmental Education**

Strategies to reform developmental education include, among other things, contextualized learning through vocational programs, providing supports such as tutoring and supplemental instruction, advising, student success courses; and other methods for accelerating progress through developmental education (Zachry-Rutschow and Schneider 2011). In this sense, the term *accelerated developmental education* is one way to summarize these strategies collectively since their purpose is to move students out of remedial coursework as soon as possible and on to college-level courses. One of the most commonly proposed strategies, going back to at least the 1990s (Koski and Levin 1998), is to connect developmental courses in some way to other courses, akin to the strategy of learning communities, to form a support network and reinforce the transition to successful college-going. In such scenarios, some of the innovative alternatives to traditional remedial instruction extend to supplemental instruction, peer tutoring, counseling, or other academic support services, in addition to experiential learning, bridge programs (a version of orientation noted above), career exploration, and other features (Edgecombe 2011; Edgecombe et al. 2013; Fong and Visser 2013; Hodara and Jaggars 2014; Jenkins et al. 2010), further illustrating linkages among these and other programs despite their labels.

## **Method**

### **Data Source**

Data came from the 2012 administration of the Community College Institutional Survey (CCIS) administered online by CCCSE (2012) March to July 2012 as part of an initiative focused on identifying and promoting high-impact educational practices. We use this data source because of its scope and purpose. Beyond surveys of first-year seminars (Porter and Swing 2006; Young and Hopp 2014), no other data source provides detailed program-level information about these and related programs on a broad scale. The CCIS survey was specific to the community college sector and developed by CCCSE in consultation with community college practitioners and in light of engagement research that points to effective undergraduate practices (CCCSE 2012).

College presidents at 1084 public 2-year colleges in the United States and selected CCCSE-affiliated international colleges were sent an invitation letter requesting that the



**Table 1.** Characteristics of colleges in sample versus public U.S. 2-year colleges

College characteristics	In sample (N = 314) <sup>a</sup>		Population (N = 1028)	
	N	%	N	%
<b>Size</b>				
Small (fewer than 5000 students)	133	42.4	564	54.9
Medium (5000–9999 students)	95	30.3	240	23.4
Large (10,000–19,999 students)	59	18.8	159	15.5
Very large (20,000 or more students)	27	8.6	65	6.3
<b>Degree of urbanization</b>				
Rural	103	32.8	360	35.0
Town	55	17.5	199	19.4
Suburban	51	16.2	171	16.6
City	105	33.4	298	29.0
<b>Geographic region</b>				
New England CT ME MA NH RI VT	23	7.3	45	4.4
Mid East DE DC MD NJ NY PA	27	8.6	92	9.0
Great Lakes IL IN MI OH WI	41	13.1	131	12.7
Plains IA KS MN MO NE ND SD	35	11.2	107	10.4
Southeast AL AR FL GA KY LA MS NC SC TN VA WV	91	29.0	318	30.9
Southwest AZ NM OK TX	53	16.9	126	12.3
Rocky Mountains CO ID MT UT WY	11	3.5	41	4.0
Far West AK CA HI NV OR WA	33	10.5	168	16.3

Source: 2012 IPEDS data

a. Missing = 22 due to different forms of campus organizations in IPEDS versus CCCSE records.

survey be delegated to the person or persons most knowledgeable about the programs and practices included. Respondents included 431 colleges, representing a 40% response rate. The current analysis utilizes data from 336 U.S.-based colleges that provided complete responses and includes a total of 1047 program records. Table 1 shows that the colleges in the sample are fairly representative of public U.S. 2-year colleges nationally in terms of their size and setting, with medium colleges being slightly overrepresented, small colleges underrepresented, and colleges located in a city setting slightly overrepresented.

The first and second parts of the survey asked questions about the presence of and implementation details of the five promising practices noted in the literature review above. The data for this study came from the second part of the CCIS in which a set of 24 common curricular and programmatic elements were presented in list form, with each of the five programs indicated across the top, creating a matrix of programs and elements. Responding colleges may have indicated having none, one, or up to five of the named programs, thus contributing up to five records each. The 24 elements are listed in Tables 2 and 3. Respondents were requested to identify which of the elements are incorporated in each program.

Table 2 shows in descriptive terms the extent to which the 24 elements are implemented across the 1047 nominal student success programs. Although there are notable trends according to this nominal classification, all program elements are nonetheless present to some degree across categories, underscoring the programmatic overlap beyond labels that this study addresses.

**Table 2.** Percent of element implementation, by nominal student success programs and overall

Programmatic and curricular elements	Percent implementation					
	Orientation ( <i>n</i> = 286)	Student success course ( <i>n</i> = 266)	First year experience ( <i>n</i> = 178)	Learning community ( <i>n</i> = 151)	Accelerated dev. ed. ( <i>n</i> = 166)	Overall: across all programs ( <i>n</i> = 1047)
TIME—Time management skills	53	96	93	57	40	69
STDY—Study skills	39	95	89	65	55	68
NOTE—Note-taking skills	24	92	81	58	36	58
TEST—Test-taking skills	23	91	80	57	46	59
INFO—Use of info. resources (e.g., library, finding and evaluating sources)	63	88	89	68	37	70
TECH—Basic technology skills (e.g., using Internet, word processing)	46	70	72	48	51	58
WEB—Online learning skills (e.g., course management system, “netiquette,” constructive discourse)	33	62	70	37	32	47
STYL—Learning style assessment	12	83	79	38	13	45
STWK—Identification of personal strengths and challenges	17	82	77	40	19	47
STDGRP—Assigned study groups	5	23	18	37	20	19
GRPPRJ—Assigned group projects/ assignments	6	55	49	62	30	38
CMNRD—Common reading(s)	6	55	50	68	36	40
CMNASG—Study/ assignments focused on a common theme	5	53	48	75	40	40
CONTEXT—Contextualized curriculum or discipline-related activities	6	37	33	64	45	33
PLAN—Development of a written individual academic plan	29	62	65	29	8	40

**Table 2.** continued

Programmatic and curricular elements	Percent implementation					Overall: across all programs (n = 1047)
	Orientation (n = 286)	Student success course (n = 266)	First year experience (n = 178)	Learning community (n = 151)	Accelerated dev. ed. (n = 166)	
SOCSPT—Info. about and/or use of personal/social support services	88	77	87	55	24	70
ACSPT—Info. about and/or use of academic support network	86	83	88	65	46	76
GRPADV—Group advising	50	37	48	28	16	38
SRVC—Campus or community service project(s)	10	20	26	34	5	18
EXCRCL—Participation in campus activities/ events outside classroom	37	49	63	45	14	42
SRVLRN—Service learning	9	14	21	30	4	14
MNTR—Mentoring	17	29	37	30	14	25
TUTR—Tutoring	51	56	56	62	73	58
SUPP—Supplemental instruction	7	20	21	30	41	21

dev. ed. = developmental education

### Analytical Approach

It is apparent from the literature and the descriptive data in Table 2 that various kinds of student success programs share programmatic features though to different degrees and in different combinations. That is, there appear to be simultaneously different kinds of program features that “hang together”—for instance, different kinds of academic skills training or various kinds of group work—and different combinations of those building blocks. A given program in curricular terms might be characterized by the extent of its focus in different areas and its combination of foci. To account for both kinds of latent patterns, we take advantage of factor mixture modeling (FMM; Lubke and Muthén 2005) which is a hybrid of continuous and categorical latent variable analysis. Because FMM is rare in higher education research, and there are few examples of how it is applied in practice, we provide a relatively in-depth treatment of our procedure and results. For technical statistical details and other applied examples, we refer readers to Clark et al. (2013) and Ma-syn et al. (2010).

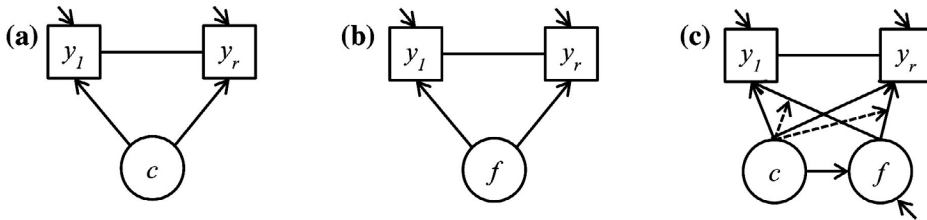
**Table 3.** Promax-rotated principal components loadings of program elements

	Principal component				
	I	II	III	IV	V
	College success skills	Collaborative/contextualized learning	Academic and student services	Co-curricular/community activities	Ancillary instruction
Programmatic and curricular elements					
TIME—Time management skills	0.90				
STDY—Study skills	0.94				
NOTE—Note-taking skills	0.93				
TEST—Test-taking skills	0.93				
INFO—Use of information resources (e.g., library, finding and evaluating sources)	0.66				
TECH—Basic technology skills (e.g., using Internet, word processing)	0.58				
STYL—Learning style assessment	0.73				
STWK—Identification of personal strengths and challenges	0.71				
STDGRP—Assigned study groups		0.65			
GRPPRJ—Assigned group projects/assignments		0.78			
CMNRD—Common reading(s)		0.85			
CMNASG—Study/assignments focused on a common theme		0.90			
CONTEXT—Contextualized curriculum or discipline-related content and activities		0.84			
WEB—Online learning skills (e.g., course management system, “netiquette,” constructive discourse)			0.50		
PLAN—Development of a written individual academic plan			0.62		
SOCSPPT—Information about and/or use of the college’s personal/social support services			0.85		
ACSPT—Information about and/or use of the college’s academic support network			0.83		
GRPADV—Group advising			0.74		

Table 3. continued

	Principal component				
	I	II	III	IV	V
	College success skills	Collaborative/ contextualized learning	Academic and student services	Co-curricular/ community activities	Ancillary instruction
Programmatic and curricular elements					
SRVC—Campus or community service project(s)				0.86	
EXCRCL—Participation in campus activities/events outside the classroom				0.61	
SRVLRN—Service learning				0.89	0.58
MNTR—Mentoring					0.86
TUTR—Tutoring					0.63
SUPP—Supplemental instruction					2.11
Variance explained	6.15	4.17	3.54	2.40	

N = 1047. Loadings  $\geq 0.50$  were considered to be salient



**Figure 1.** Generalized model diagrams of (a) latent class analysis, (b) factor analysis, and (c) factor mixture model. Adapted from Clark et al. (2013) and Masyn et al. (2010).

FMM is closely related to latent class analysis (LCA) used to distinguish categorical dimensions of data, but it can simultaneously account for the dimensional nature of data as revealed through factor analysis (FA) or principal components analysis (PCA). FA techniques the complementary inverse of LCA, while FMM lies between them on a dimensional-categorical spectrum of latent variable modeling techniques (Masyn et al. 2010). In conceptual terms, Figure 1 depicts generalized models of LCA, FA, and FMM. In Figure 1a, a series of variables  $y_l$  through  $y_r$  indicate an unordered latent class variable  $c$  which reflects differences *in kind* among individuals (or programs in this case). In Figure 1b the variables are indicators of a continuous latent variable,  $f$  which reflects differences *in degree* without class distinctions. Figure 1c shows how individuals can be assigned to latent classes while simultaneously measuring heterogeneity of factors across individuals.

FMM techniques are model-based with rigorous methods for comparing alternative models (Lubke and Muthén 2005) and allows for various types and scales of data, including multivariate binary data (Cagnone and Viroli 2010) of which the present dataset was composed. FMM presents important advantages over other commonly used classification methods for typological analysis. For instance, FA is not ideal for classification studies, even though researchers commonly utilize it for this purpose (e.g. Hurtado et al. 1991; Zhao and Kuh 2004). FA is a method for reducing the dimensionality of a data set to a smaller number of variables necessary to accurately reflect the correlation matrix, but does not provide an empirical classification of individuals per se. It can facilitate the task of identifying relatively homogeneous groups of individuals, but as a schema for subjective classification. LCA has shown to be very useful for categorical analysis of individuals and has begun to appear in higher education journals (e.g., Denson and Ing 2014; Marti 2008; Weerts et al. 2014), but LCA ignores any heterogeneous dimensional aspects of data that may be present. Cluster analyses, which has some parallels with LCA, is a useful and popular method for typological studies (e.g. Bahr 2010; Inkelas et al. 2008), but has important limitations such as sensitivity to measurement scales, no criteria beyond theory and judgement for determining the number of clusters, and rigid assumptions of conditional independence which often do not match real-life data or theoretical assumptions (Morin et al. 2011).

Our analysis to uncover empirical latent patterns of program design was pursued in two stages: a PCA to reduce the dimensionality of the relationships among the original 24 program elements, followed by a series of FMMs which integrate the relationships found in the PCA. Finally, we compared the patterns of elements in latent program groupings with patterns of elements in nominal program groupings via descriptive statistics in order to explore and understand how the typology might contribute to the research agenda of success programs.



### *Principal Components Analysis*

The type of correlation statistic conventionally utilized in PCA is the Pearson product–moment correlation of continuous measures. But for dichotomous variables, Pearson correlations can generate artificial factors due to the unspecified margins between nonendorsement and endorsement that violate the assumption of bivariate normality (Kubinger 2003). For dichotomous data, statisticians recommend factoring tetrachoric correlations (Bonett and Price 2005). We used the SAS POLYCHOR macro (SAS Institute, Inc. 2012) to derive a tetrachoric correlation matrix of all 24 dichotomous program element variables and used this in turn for factor extraction. We used the promax oblique rotation method (Costello and Osborne 2005; B. O. Muthén 1989) after factor extraction and examined the scree plots and loadings to determine how many factors to retain.

### *Factor Mixture Models*

With the principal components (PCs) in hand, several nested factor mixture models were then tested using Mplus software (B. O. Muthén and Muthén 2010) to determine the best fit to the data. The procedure we followed was adapted from Clark et al. (2013) which involves formulating a series of models, increasing, in turn, the number of specified latent classes in combination with different numbers of retained latent factors. Since we previously established the principal component structure of the data, we used FMM to explore the latent class structure of the student success programs while holding the dimensional relations constant. Statistical and substantive evidence and theoretical guidance, if available, is used to determine the best fit from among several solutions.

Guidelines for the process of determining the appropriate number of classes, called enumeration, are contested in the literature (Nylund et al. 2007), but point to the need to use several criteria: statistical tests of model fit, such as the likelihood ratio test of neighboring models; various information criteria indices; and substantive interpretability criteria (Clark et al. 2013). We relied on the Vuong-Lo-Mendell-Rubin test (VLMR LRT), its adjusted counterpart (aVLMR LRT), and the parametric bootstrapped LRT (BLRT), all of which approximate a likelihood ratio test and provide a  $p$  value to provide evidence as to whether a  $k$ -class model is a better fit than a  $(k - 1)$ -class model (Henson et al. 2007; Lo et al. 2001). We also kept track of the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), and its adjusted counterpart (aBIC) for each model. Lower values of these criteria lend evidence of a better fit. Along with these fit indices, we also kept track of the condition number calculated for each model, which may indicate nonidentification of the model. Regardless of fit indices, class enumeration must have substantive meaning and utility.

Following Clark et al.'s (2013) recommendations, we started with a model whose only parameters that vary across classes are the factor means. The thresholds and factor loadings are held invariant across classes, and the factor covariance matrix is fixed at zero. In essence, this restrictive model specifies that the difference between individual programs arises from the number of elements and, due to the dimensional specification of the model, which PC the item belongs to. Due to the exploratory nature of this study investigating curricular structures, and the fact that the variables are not conceptualized in the first place as manifest variables of underlying constructs, further refinement of the models by relaxing other parameters is not prudent at this time, and may not be practically interpretable.

## Limitations

Data for this study, despite coming from a relatively large number of community colleges across the United States, should not be construed as representative. Many colleges that opted to participate in the CCIS have established relationships with CCCSE and may otherwise be a self-selective group of respondents. Given the focus of the CCIS and the nature of the questions, there appears to be no appreciable threat to the validity of these self-reported data. However, a survey format does pose certain challenges to gathering this type of data. First, the labels assigned to these programs are not standardized across colleges (precisely the challenge this study addresses). Second, a survey format does not allow for the collection of detailed information regarding the extent or quality of implementation of the programmatic elements. That something is present in a program does not mean it is adequately implemented or effective in all settings. A survey is a cost-effective way to gather data on a large scale, the tradeoff being a loss of detail and nuance.

This study accounts for the curricular elements of student success programs, but there are other structural features that research shows may influence student experiences and outcomes including faculty and staff roles, program duration, credit-bearing status, performance expectations, experiences with diversity and other features (Inkelas et al. 2008; Kuh and O'Donnell 2013). Descriptive survey results related to these broad programmatic features, using the same CCIS data, are reported by Hatch and Bohlig (2015). Such features should be considered in conjunction with the kind of curricular typology developed here to understand the relative variations among programs. Lastly, with up to five records from each college, there is a nested structure to the data not accounted for in the analysis. Hierarchical factor mixture modeling is technically feasible, but in this case overly complex for the research question and simply problematic with few first-level observations per second-level unit.

## Results

There are two steps to interpreting results of FMM analyses. First, determining the number and kind of latent factors and classes using multiple indicators of best model fit. Second, interpreting the meaning of the latent classifications by way of profile plots of variables and their probabilities of being manifest in latent classes (Clark et al. 2013).

**Table 4.** Average sum factor scores (average number of elements) across all programs and percent of maximum

Principal component	Mean	SD	Min	Max	Mean/max (%)
College success skills	4.74	2.86	0	8	59
Collaborative/contextualized learning	1.69	1.77	0	5	34
Academic and student services	2.71	1.57	0	5	54
Co-curricular/community activities	0.74	0.97	0	3	25
Ancillary instruction	1.05	0.95	0	3	35

## Results of Principal Components Analysis

PCA was the first step toward a typology. Table 3 provides the promax-rotated PCs for the 24 elements across all 1047 programs. Two criteria were used to determine if an element loaded on a component: a minimum loading of 0.50 and the interpretability of components. Five components emerged, and their compositions suggested the working labels of (1) college success skills, (2) collaborative and contextualized learning, (3) academic and student services, (4) co-curricular and community activities, and (5) ancillary instruction. Half of the 24 elements loaded on their respective components with a value of 0.80 or higher and no elements cross-loaded.

With these PCs in hand, we calculated summed factor scores to capture the number of elements incorporated by factor by program. Table 4 shows the overall average factor scores and the corresponding percent of the maximum (mean/max). Here, one can see overall differences in the dimensional nature of program elements. On average, the most prominent programmatic features were college success skills elements (4.47 of 8 maximum, or 59%) and academic and student services (2.71 of 5 maximum, or 54%). The least often used elements were those constituting the co-curricular/community activities principal component. On average, of the three elements that make up this principal component, programs included only 0.74, or 25%.

## Results of Factor Mixture Models

Table 5 lists the fit statistics for the FMMs. We tested solutions from one to eight latent classes, all of which integrate the five derived PCs. The condition numbers and entropy indicated that all of the models displayed good model identification and classification quality. The fit indices and likelihood ratio tests showed that each increment in latent class size was statistically a better model fit. However, the VLMR ratio tests indicated that a five-class solution may not be an improvement over a four-class solution (VLMR LRT  $p$  value = 0.06; aVLMR LRT  $p$  value = 0.08). Clark et al. (2013) recommend the first time LRTs fail to show a significant improvement, this is an important indicator, regardless of tests for subsequent increases in class numbers. The combined evidence, including the fact that an eight-class solution produced one class with merely 22 members, suggested that the appropriate number of classes was between four and seven. In favor of parsimony, we determined that a four-class solution was suitable.

## Interpreting the Emergent Latent Typology of Success Programs

To interpret the emergent latent typology of the FMMs, we considered the profile plot of variables (Figure 2) and the relative prevalence of elements in the PCs by latent class (Figures 3, 4). These plots show the nature of the emergent typology of latent classes and the patterns of program elements among types.

### *Probability of Endorsed Elements by Latent Class*

The profile plot in Figure 2, typical of FMM analyses (Clark et al. 2013), represents the predicted probabilities of the inclusion of individual elements (horizontal axis) by latent class (vertical axis). This plot reveals the extent to which a derived classification scheme is viable and discernible given the variables selected and their factor structure. Variables that

**Table 5.** Fit statistics and log likelihood ratio tests for factor mixture models

Model	Free params.	LL	AIC	BIC	aBIC	VLMR LRT <i>p</i> value	Adj. LRT <i>p</i> value	Bootstrap LRT <i>p</i> value	Entropy	Cond. no.	<i>n</i> of smallest class (% of sample)
1-class	43	-15,601	31,288	31,501	31,364	N/A	N/A	N/A	N/A	3.83E-03	1047 (100)
2-class	49	-13,434	26,978	27,220	27,065	0.00	0.00	0.00	0.91	7.15E-03	517 (49)
3-class	55	-13,006	26,122	26,394	26,220	0.00	0.00	0.00	0.88	2.39E-03	292 (28)
4-class	61	-12,684	25,490	25,792	25,599	0.00	0.01	0.00	0.89	2.02E-03	139 (13)
5-class	67	-12,514	25,161	25,493	25,281	0.06	0.08	0.00	0.88	8.30E-04	99 (9)
6-class	73	-12,374	24,893	25,255	25,023	0.05	0.07	0.00	0.88	2.01E-04	95 (9)
7-class	79	-12,273	24,704	25,095	24,844	0.07	0.09	0.00	0.86	1.06E-04	86 (8)
8-class	85	-12,218	24,606	25,027	24,757	0.31	0.34	0.00	0.86	2.25E-04	22 (2)

In this model: class invariant thresholds ( $\tau$ ), class invariant factor loadings ( $\lambda$ ), factor covariance matrix is equal to zero ( $\psi = 0$ ), class varying factor means ( $\alpha_k$ )

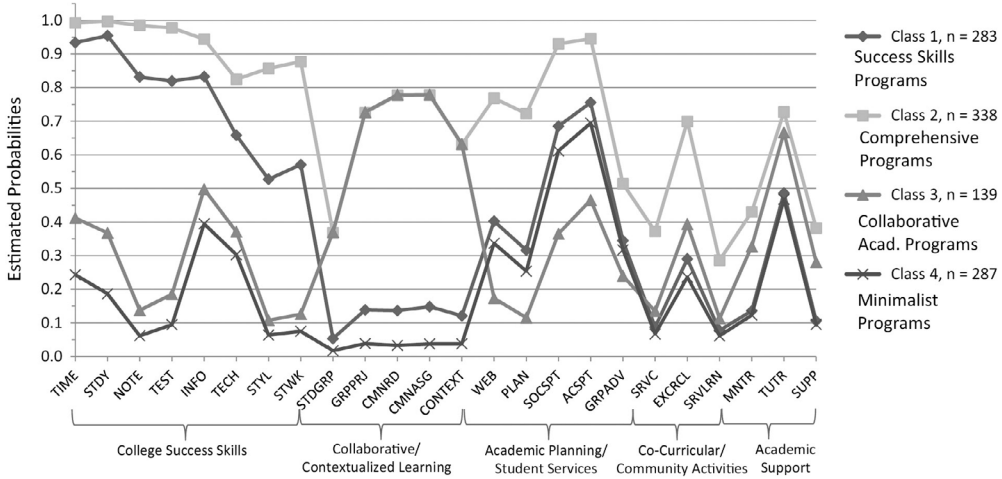


Figure 2. Profile plot of four-class solution showing estimated probabilities of the inclusion of program elements by latent class.

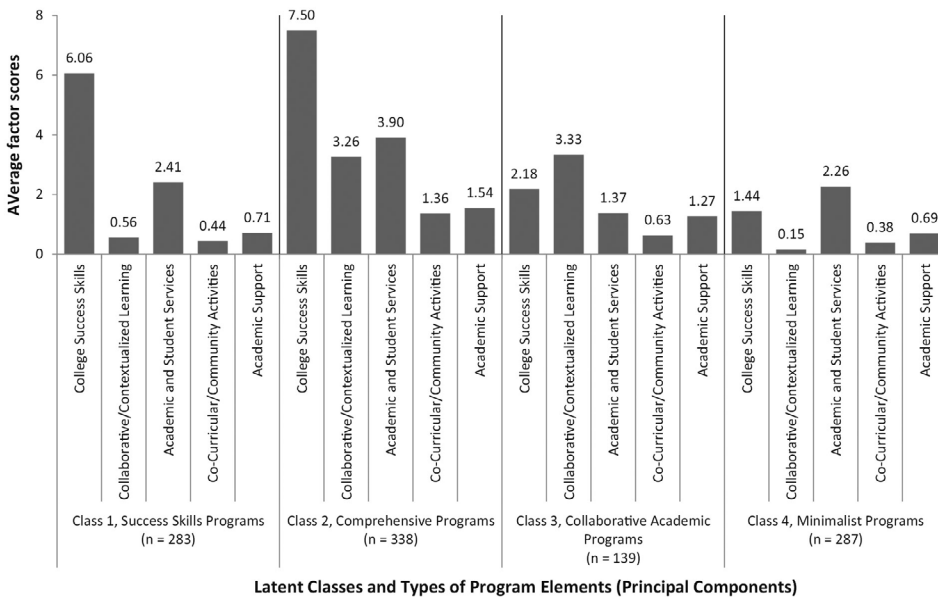
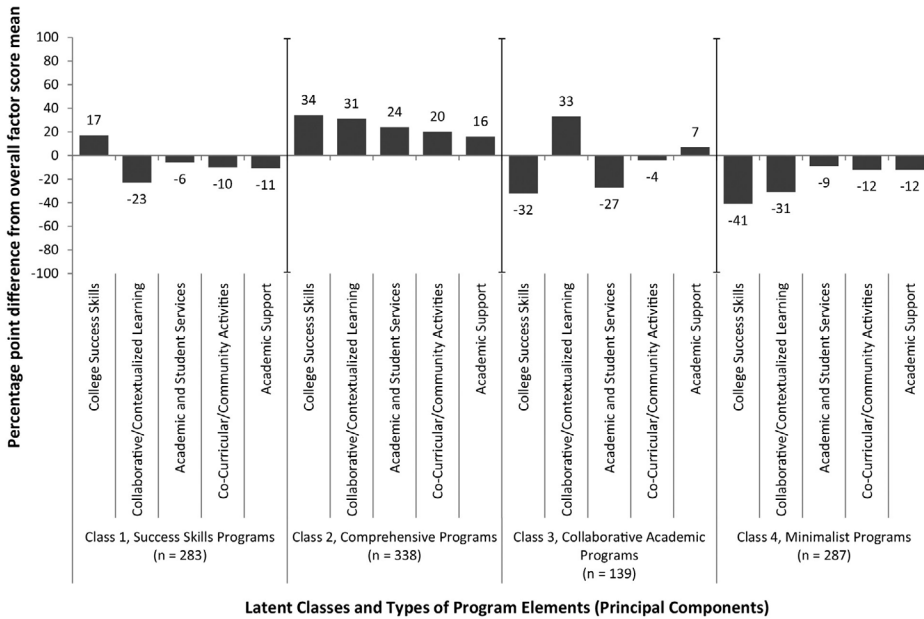


Figure 3. Mean of summed factor scores (average number of elements), per principal component, by latent class.

have values in the top and bottom ranges of this figure (above 0.7 and below 0.3) demonstrate a high degree of separation between classes. In other words, where the probability of the presence of a particular element is above 70 % for one class yet below 30 % for another class, that variable can be said to contribute to the distinguishability of classes.

Most variables in the four-class solution tended to demonstrate good distinguishing power, but two of the PCs, co-curricular/community activities and ancillary instruction,



**Figure 4.** Percentage point differences from the overall means of factor scores, per principal component, by latent class.

found toward the right-hand side of Figure 2, are composed of variables that have relatively poor distinguishing power. Many of these elements have either a small chance of being present in any particular class of programs or the probability is between 0.3 and 0.7 and so likely to be present more or less at random for any class. This is likely a function of their relatively infrequent implementation overall (cf. Tables 2, 4).

*Differences in Degree and Kind of Elements by Latent Class*

Figure 3 summarizes latent class profiles through a multi-panel display in a way that further illustrates how the FMM accounts for the PCA factors simultaneously. Figure 3 plots the average PC factor scores for each latent class. However, because each PC factor score has a different maximum value, it is necessary to recalibrate them to the same scale for comparisons (Table 3). To do this, we standardized and centered average mean factor scores by class around the overall average factor scores (cf. Table 4). Figure 3 shows that members of Class 1 implement on average 6.06 of the eight college success skills, or 76 % of the maximum. As seen in Figure 4, this is 17 percentage points higher than the overall mean. However, members of this same class implement on average only 0.56 elements of the maximum five for the collaborative/contextualized learning cluster, or 11 %. This is 23 percentage points less than the average. Figures 3 and 4 can be read together to understand differences across latent program categories. Based on such characteristics, we can make the following observations and give the latent program types working descriptive labels.

- 1) *Success Skills Programs* Programs in Class 1 incorporate 6.06 of 8 elements associated with the college success skills principal component, which is 17 % more frequently than the average of programs across all classes. These also incorporate 2.41 of 5 kinds



of academic and student services, just below the overall average. However, programs in this class implement on average less than one element for each of the remaining three kinds of programmatic elements, well below the overall average.

- 2) *Comprehensive Programs* Programs that are members of Class 2 are characterized by implementing elements in all five of the principal components more often than the average of the full sample of programs. For example, of the eight college success skills elements, these programs incorporate 7.5 of them on average, or 94 %, well above the overall mean of 59 %. The abundance of curricular elements is clear for all five principal components, making the programs of this class characterized by relatively extensive use of a wide variety of curricular and programmatic elements.
- 3) *Collaborative Academic Programs* Programs in Class 3 are characterized by much higher than average use (3.33 out of 5) of collaborative/contextualized learning elements and a corresponding de-emphasis on college success skills elements (average 2.18 of 8) and academic and student services (average 1.37 of 5). In other words, these 139 programs are characterized by a particular focus on assigned study groups, common readings, assignments focused on a common theme, and similar activities, in addition to a complementary above-average focus on ancillary instruction (on average 1.27 of 3). These features of tutoring, mentoring, and/or supplemental instruction add to the programs' collaborative academic focus.
- 4) *Minimalist Programs* Lastly, programs that are members of Class 4 are characterized by relative infrequent use of elements across all five principal components. The academic and student services principal component is the most prominent, though with an average of 2.26 elements of a maximum five for this category, these minimalist programs still incorporate fewer than the overall average. Minimalist need not mean ineffectual or deficient. Rather, very targeted or focused interventions may have important impacts on par with more complex designs. An important consideration in the study of program effectiveness is to not assume more is necessarily better.

Having established these four latent or empirical program types, the next question is to what degree these are distinct from nominal program types and how they could be used to define program types across contexts for comparative effectiveness assessment. The crosstabs of nominal program versus latent program classifications in Table 6 provide insight to address this question. A Chi square test of independence showed there was a relationship

**Table 6.** Crosstab analysis of nominal program types and empirical (FMM-derived) types

Nominal program types	Frequency of empirical student success program types (column percent)				
	Class 1: success skills	Class 2: comprehensive	Class 3: collaborative academic	Class 4: minimalist	Total
Orientation	71 (25.1)	12 (3.6)	4 (2.9)	199 (69.3)	286 (27.3)
Student success course	92 (32.5)	160 (47.3)	5 (3.6)	9 (3.1)	266 (25.4)
First-year experience	60 (21.2)	96 (28.4)	7 (5.0)	15 (5.2)	178 (17.0)
Learning community	22 (7.8)	56 (16.6)	60 (43.2)	13 (4.5)	151 (14.4)
Accelerated develop. education	38 (13.4)	14 (4.1)	63 (45.3)	51 (17.8)	166 (15.9)
Total	283	338	139	287	1047
Percent	27.0	32.3	13.3	27.4	100.0

between nominal program types and latent program types  $\chi^2(12, n = 1047) = 717.8, p < 0.001$ . In terms of college characteristics (cf. Table 1), simple Chi square tests initially showed dependence of latent types according to size classifications,  $\chi^2(9, n = 962) = 19.0, p = 0.03$ , and the degree of urbanization in the college setting,  $\chi^2(9, n = 962) = 19.5, p = 0.02$ ; however, comparisons of multiple sub-tables using Bonferroni corrections to identify the source of dependence turned up no significant relationships in either case. There was no relationship between latent program type and geographical region.

As seen in Table 6, the 283 success skills programs of latent class 1 cut across all five nominal types of programs quite evenly: 33% were identified by colleges as student success courses, 25% as orientation programs, 21% as first-year experiences, 13% as accelerated developmental programs, and 8% as learning communities—all but the last in double digits. The 338 comprehensive programs of latent class 2 were also spread out but to a lesser degree—with only a few instances classified nominally as orientation and accelerated developmental education. The broad reach of these two latent classes confirms the multiple and overlapping terms that researchers use to variously define success courses in the literature (e.g. Duggan and Williams 2010; O’Gara et al. 2009), even as a distinction between skills-focused and comprehensive programs shows through.

Table 6 also shows that 199 (69%) of the 287 latent minimalist programs were nominally orientation programs. It may not be surprising that many orientation programs do not implement numerous features, due to their common format of brief group meetings. From this observation alone, one might be tempted to say that minimalist is merely a synonym for orientation, especially if we have in mind one kind of brief orientation program (such as described by Pascarella et al. 1986). However, looking across the table, we see that 25% of nominal orientation programs ( $n = 71/286$ ) were assigned to the success skills programs of class 1 which, as seen above, go by many names and incorporate relatively many features. Additionally, 4% of nominal orientation programs ( $n = 12/286$ ) were found to be in the comprehensive group in their design, and four of the 286 (1%) nominal orientation programs were classified in the collaborative academic programs—more akin to a large portion of learning communities and accelerated developmental programs in this class.

Nominal learning communities for the most part grouped with collaborative academic programs of latent class 3 ( $n = 60/151$ ) and comprehensive programs of latent class 2 ( $n = 56/151$ ). However, looking across the table, nominal learning communities were also found to take the form of latent success skills programs ( $n = 22/151$ ) and latent minimalist programs ( $n = 13/151$ ). This classification of learning communities in terms of curricular content is qualitatively distinct from previous typologies of this kind of program (Gabelnick et al. 1990; Inkelas et al. 2008; Lenning and Ebbers, 1999; Love and Tokuno 1999; Shapiro and Levine, 1999) which were based principally on variations of course linking mechanisms, program goals, and who has oversight of them. The typology here shows that curricular elements also demarcate important differences among learning communities and that they may be similar to yet other student success programs in important ways.

These findings confirm broadly what can be observed in the descriptive data of Table 2: that student success programs often have much in common despite their nominal categorization. But with programs empirically sorted according to the underlying patterns of their curricular features, we gain important detail to identify specifically how disparate programs are alike or different. Below, we draw specific observations from these findings and in light of the literature reviewed above to illustrate the potential use and implications of this typology for researchers and practitioners.

## Discussion

The results of this study underscore the notion that features of a program are paramount to understanding them and that labels attached to programs can be as much a source of obfuscation as illumination. A descriptive look at 24 programmatic and curricular elements revealed that they are found extensively across five nominal programs though with some variation. The PCA revealed evidence for five kinds or types of elements. In turn, the FMM analysis revealed four latent types of programs that implement particular combinations of those element types. This two-part empirical program typology provides a map for identifying more precisely where and how programs differ, and it points to ways to bring more cohesion to student success program research.

The extent of overlap between latent and nominal program types illustrates one reason conceptual definitions for success courses, first-year seminars, and learning communities have traditionally been so challenging to pin down and why they so readily blend into orientation and developmental education programs (Bailey and Alfonso 2005; Barefoot 1992; Crisp and Taggart 2013; Smith 2010). Researchers have had to rely on ambiguous names and a narrow focus on the main organizing principles of programs to define and delimit their studies. The typology proposed here suggests that what distinguishes programs is not so much differences in their main purpose, but differences in the curricular and programmatic elements used to enact those purposes. This finding aligns with Karp's (2011) argument that a shift is needed, that "*efforts to improve persistence [and other student outcomes] should focus on processes, not programs*" (p. 24, emphasis in the original).

How the empirical typology here could be leveraged to improve the state of the art in program effectiveness research can be illustrated with a few examples from the studies reviewed above. For instance, taking the Duggan and Williams' (2010) study as just one example, the study used interviews at 10 different community colleges related to various orientation and success course programs. Though this study addresses the often cited limitation of single-site studies (cf. Bailey and Alfonso 2005; Crisp and Taggart 2013; Swaner and Brownell 2009), the authors are not able to fully capitalize on their research design to answer their questions about which features are more helpful and how to best design them. For example, the implication of their finding that "not all students had access to the same information" (p. 130) has limited utility since the study included varying program types without a way to specify their differences. With a conceptual framework such as the one proposed here, variations in program design could be efficiently operationalized and described in terms of the relative emphasis on different kinds of elements (mapping to the PCs we found) and as belonging to one of the four types (mapping to the full typology). O'Gara et al. (2009) likewise interviewed students in success courses at two colleges and noted that the program goals and foci varied. However, the authors only provided brief explanations of the most salient features to identify programs. At one college the program focused on connecting students with college support services and college skills training. The second program was similar with the addition of a focus on career preparation. Other program features, if present, were not discernible in this paper, just as they are not discernible in the majority of papers on this type of program and other interventions that may be programmatically related. A typology such as the one presented here would allow researchers to more precisely identify the programs within the typology, either to more closely delimit the programs selected and/or make more precise cross-program comparisons.

Whether studies are conducted in an experimental manner, such as the MDRC study mentioned in the introduction (Scrivener et al. 2015) that tested variance in outcomes due to random assignment, through quasi-experimental methods, or through program design impact research, such as Porter and Swing's (2006) study which tested variance in outcomes due to differences in first-year seminar course content, a design-based program typology is important for drawing comparative conclusions. In curricular terms, The CUNY ASAP program studied by MDRC emphasized advising, career services, tutoring, linked courses, and an extended seminar covering study skills and goal setting. The program appears to be comprehensive in its curricular approach, though the financial support and attendance requirements are perhaps the most remarkable structural features compared to most community college settings. Porter and Swing's study included first-year seminars that varied in terms of the emphasis on (1) study skills, (2) peer connections, (3) college knowledge, (4) campus engagement, and (5) health education—five factors that map very closely to the PCs we derived. Their analysis aimed to find the correlation of these kinds of elements with persistence intentions, but could have also considered the impact of certain combinations to test if the effects are cumulative or multiplicative. Perhaps comprehensive designs among those studied by Porter and Swing lead to outcomes comparable, even if not as extensive, to what was seen in the ASAP program. Perhaps there are more modest program designs which would lead to similar impacts. Perhaps different program designs matter for different outcomes, or for certain students. Or lastly, perhaps design does not matter nearly as much as issues of duration, financial supports, or factors outside the college environment (Kuh and O'Donnell 2013; Pike et al. 2011). The typology here suggests one way to more clearly conceptualize and operationalize program variation across studies and across sites to address these kinds of questions. It does not preclude the need for a more detailed accounting of program features, but the typology affords a common framework and language with which to conceptualize specific differences.

## Conclusion

The latent structure and classification system we describe invites higher education researchers and practitioners to reflect on how student success programs are being designed and implemented. On one hand, it reveals which elements many colleges happen to be implementing in certain combinations now. On the other, it begs the question of which combination(s) matter, if any, to making a difference in student success. The typology that this study puts forth does not answer this question, but it does provide an organizing framework that can be used by researchers and practitioners to identify programs based on what goes into them rather than by their name and additionally to make comparisons across contexts. This typology thereby addresses the shortcomings of research into program effectiveness at community colleges which have been pointed out in the literature (cf. Bailey and Alfonso 2005; Swaner and Brownell 2009) as to the lack of descriptive details of programmatic features that purportedly matter for student success. The typology may apply particularly to community colleges given the evidence that parallel programs in the 4-year sector may have distinct purposes (Young and Hopp 2014). The two-part latent classification built on types of program features and various combinations of those building blocks suggest at least two planes of potential shifts in curricular design. Indeed, certain features need not be bundled together in formal programs at all but rather inserted in other college environments inside and outside the classroom. Naturally, the typology needs to be put to empirical test to confirm or

disconfirm its usefulness, and to test the notion that it matters what colleges incorporate in the programs. In any case, it provides theoreticians and college leaders alike with a conceptualization of various program designs that helps distinguish programs by what they do, regardless of what names they go by. The typology presented here provides a heuristic tool to guide the definition, testing, and designing of student success courses.

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