The Role of Academic Process in Student Achievement: An Application of Structural Equations Modeling and Cluster Analysis to Community College Longitudinal Data

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Abstract
Using a combination of path analysis and cluster analysis, parallel models of the academic process at Prince George’s Community College (PGCC) were developed, supported by data tracking the Fall 1990 first-time entering credit student cohort during a period of six years. Path analysis revealed the centrality of student attitude factors (motivation, flexibility, academic gamesmanship) to study career success compared with the lesser impacts of social background, college preparedness, and various other process model components. It also highlighted the importance of the formative early semesters in setting student trajectories. Cluster analysis identified several varieties of success-prone students, as well as five different student subbodies, each highly problematic for distinctive reasons. The predictive power of the academic process Structural Equations Modeling (SEM) was found to be at least equal to levels typically reported for models informed mainly by the predominant social psychological paradigm of student achievement associated with names Tinto, Astin and Bean. The argument is made that a fuller theoretical formulation needs to be developed which takes into account institutional system effects and levels of student “academic capital.” From a more practical perspective, the value of academic process modeling for identifying specific blockage points to student progress and for developing institutional strategies tailored to differing at-risk student populations is discussed.

Introduction
Since the Fall of 1990, the Office of Institutional Research and Analysis at PGCC has been tracking the academic careers of a cohort of first-time entrants (N=2,386). The Cohort data set was drawn from PGCC student records, augmented with socio-economic statistics on student home Census tracts and with data on movement to four-year schools supplied by the Maryland Higher Education Commission. Attendance patterns, remediation needs, course performance and study progress, program completion, transfer behavior, financial aid and student support services usage, and other related data were all organized on a term-by-term basis. This enabled us to assess student academic status and level of achievement at any term point, to connect study career indicators with final academic outcomes in a systematic fashion, and to summarize any part of the process in terms of time to outcome.

The support of college assessment benchmarking and program planning was the original purpose of establishing this database. But when the cohort effectively completed its life span in the spring of 1997 (six years was sufficient to reduce the continuing student component to near zero), it was decided that the cohort file’s unique breadth of information on student career justified its use as the basis of an attempt at a full-scale causal modeling on the forces bearing on student academic outcomes at PGCC. This article is a report on the major results of that modeling effort.
In many ways, our study is typical of scores of predecessors in the long-standing area of student outcomes research. As so many before us, we also were careful to distinguish among input, environmental and output indicators in developing our explanatory model, and methodologically tied all variables together by means of a causal path analysis which allowed the systematic distinguishing of direct and indirect effects. Examples of this type of research date back to the 1970s (Spady 1971 and Bean 1979a, 1979b, for example), so there is nothing new, broadly speaking, in this approach.

But our study did diverge from the mainstream in particular ways. Among the less important, two stand out: First, we developed and employed a new combinatorial student outcomes indicator (program graduation, four-year transfer, sophomore status attainment), one we felt was better suited to measuring academic achievement at multiple mission postsecondary education providers like community colleges. Second, we supplemented our structural equations analysis with a cluster re-analysis to produce a student academic career typology paralleling and informing the student outcomes causal model.

But what really set our research apart from all previous outcomes studies was our focus on the academic process itself — the articulated complex of academic requirements and testing procedures, phased remedial and instructional programs, financial aid, advisement and academic support systems, and student academic goals, study approaches (course load, session selection, attendance pattern), curriculum choices, and course performance. The true novelty of our approach was the placement of academic process squarely at the center of our model, as indeed it is at the center of student collegiate experience. Until now, all published comprehensive outcomes models to our knowledge have revolved around one or another social psychological theory of the collegiate environment.

The Shape of Past Outcomes Research

For the last several decades, the main trajectory in the study of postsecondary student outcomes has been set by three prominent researchers — Vincent Tinto, Alexander Austin and John Bean.

Strongly influenced by Durkheim’s sociology of group cohesion, in an early seminal paper Tinto (1975) proposed that postsecondary retention could best be understood as a function of the level of student integration into two complementary and interacting environments — the social (student peer group inclusion, college social event participation, etc.) and the academic (informal faculty contacts, intellectual event participation, etc.). Although restricting his research method to linear regression, Tinto thoroughly tested his environmental integration theory, particularly in the research presented in his famous Leaving College (1987, 1993), and his approach encouraged the development of a host of generally confirmatory path analytic models testing his theory across the full range of postsecondary institutional types — most notably, by Terenzini and Associates (1981), and Pascarella and Terenzini (1983) for large research universities; by Terenzini and Wright (1986, 1987) and Thomas (1998) for liberal arts and other four-year residential colleges; by Pascarella and Associates (1983) and Fox (1984) for four-year commuter colleges and universities; and by Pascarella and Associates (1986), Nora and Associates (1990), and Halpin (1990) for community colleges. Comparative institutional studies, while mostly validating Tinto, have found significant variations in the effect of social integration on student retention by school type. In particular, there has been observed that postsecondary school size tends to be inversely related to the exploratory power of the Tinto model, and also that commuter colleges and universities, especially community colleges, are educational loci where the Tinto effect seems to be least present (for example, Pascarella & Chapman 1983). This is usually taken as a kind of negative confirmation of Tinto’s approach, because larger schools generally, and schools without residential student bodies or high proportions of older, part-time students, are less likely to induce strong institutional identification and to foster an active school-centered social life.

Astin also took the sociological tack, but emphasized the fit of individual student social and psychological traits with institutional and student body characteristics rather than the internal dynamics of social integration within postsecondary institutions. In proposing his famous Input-Environment-Output paradigm of retention analysis (1970, 1971), he argued that good student-institutional fits tended to lead in a chain to high levels of student satisfaction, academic involvement, institutional and academic goal commitment, and ultimately to academic success. The key variable academic involvement was conceptualized as a behavioral pattern combining academic social interaction (e.g., informal student-faculty contact, intellectual event participation) with various aspects of academic effort (e.g., good study habits) and progress (e.g., grade point average). The popularity of Astin’s approach inspired the creation of the Cooperative Intercollegiate Research Project (CIRP) involving scores of postsecondary institutions in conducting the standardized student survey data collection necessary systematically to operationalize and apply I-E-O models components within and across participating schools. The main product of CIRP’s first wave of data was Astin’s own magisterial Four Critical Years (1977), a regression-based cross-school grand summary of generally confirmatory findings. Path analysts following Astin have also claimed mostly validating results (e.g., Whitaker 1987; Long & Amey 1993; Knight 1993, 1994; Kelly 1996). Sensing a considerable conceptual overlap between Tinto’s and Astin’s approaches to explaining student
outcomes, one team of researchers (Milem & Berger 1997) recently attempted a path analytic, comparative testing of the two models, finding that a high level of model consolidation was possible.

Although Bean also adopted an essentially sociological explanation of student outcomes, he replaced Tinto’s and Astin’s focus on the group dynamics of college social environment with a concentration on the social psychological dynamics of college organizational environment. Bean built on the organizational turnover studies of Price, March and Simon, who argued that successful organizations encouraged worker productivity and retention of personnel by providing an effective “economy of incentives” to participate in the group and to strive on the job. Bean (1979b) analogized college student experience with that of employees in work organizations, theorizing that colleges and universities which well met student academic needs and expectations were rewarded with high levels of student motivation, positive institutional perception and affect, institutional and aspirational commitment, and finally with decisions to persist in study. Always a strong proponent of causal modeling (1979a), Bean undertook several path analytic studies to confirm his approach to explaining postsecondary student retention generally (e.g. 1981, 1982, 1985), and in his collaborations with Metzger (1985, 1987) he gave special attention to the dropout tendencies of non-traditional students. Because his model de-emphasized campus social environment and centered on organizational incentives to participate, Bean was freer to include model components representing student external environmental factors like personal finances, family responsibilities and job pressures, which often acted as disincentives to persist in college. This made his model more directly applicable to analyzing the dropout behavior of adult learners and part-time students, two growing postsecondary student groups minimally interacting with campus life and maximally involved in worldly concerns. This helps explain the Bean model’s particular appeal for researchers studying attrition and retention at community colleges (for example, Broughton 1986; Bers & Smith 1991).

The final step in the development of the social psychological model of student outcomes analysis was taken by Cabrera and his associates (1993). Believing the social environment approach of Tinto and Astin and the organizational environment approach of Bean to be complementary, they constructed both Tinto- and Bean-style structural equation models for the same data set, finding different, non-conflicting virtues in each, and recommending an integrated model for future research.

**Academic Process: A Missing Component**

For us, what clearly shone through our fairly comprehensive survey of academic outcomes research since the 1970s, only the highlights of which we have reported here, was the absence of any serious consideration given to the possibly independent role of academic process in conditioning student success. For Tinto, Astin and their followers, only student social background and campus social dynamics were considered essential explanatory dimensions. And even the research tradition begun by Bean, with its organization theory underpinnings, paid little attention to the actual features and functionings of postsecondary organizations, but instead stressed how the sociology of the college “workplace” affected student psychological dispositions. While academic process-type variables occasionally did find their ways into outcomes research, these tended to be included as isolated, secondary conditioners of student success (e.g., academic goal, financial aid receipt) or as ill-fitting members of social process scales (e.g., grade point average as part of academic integration).

The last few years, however, the work of several researchers in the field has exhibited a growing, if still partial, awareness of this major oversight and therefore of the insufficiency of past approaches. On the technical statistical side, Pike (1991, 1992, with Simpson 1997), for example, began a series of careful methodological studies challenging the cohesiveness of the scales typically used to measure Tinto’s concepts of social and academic integration. Particularly pertinent here was the finding that confirmatory factor analysis consistently chaffed at placing objective measures of student academic performance like GPA on the same academic integration scale with social interaction variables like informal faculty contacts, and that when scale items were allowed to function individually in attrition models, objective performance measures proved far more powerful predictors than social interaction variables.

Perhaps more importantly, conceptual misgivings have arisen, even among the main proponents of the social psychological tack. Reviewing outcomes studies based on the first decade’s worth of CIRP data led Pascarella and Terenzini (1991, chs. 9, 10) to lament the amount of student attainment which remains unexplained in psychological tack. Reviewing outcomes studies based on the first decade’s worth of CIRP data led Pascarella and Terenzini (1991, chs. 9, 10) to lament the amount of student attainment which remains unexplained in sociologically-oriented studies (typically over half), and to call for a broadening revision of retention theory to include, among other things, academic process variables. As if in response, Astin (1993) shortly thereafter published a re-analysis of the accumulated CIRP data, this time, however, augmenting it with copious new data derived from special cross-campus surveys, including the following academic process-type variables: institutional classification (four-year, two-year, public, private non-denominational, denominational, etc.), institutional size, instructional expenditures, student-faculty ratio, graduate student proportion, faculty compensation levels, structure and content style of core curricula, faculty instructional styles, morale, professionalism, and attitudes toward students, and student academic characteristics based...
on self-ratings (academic ability, drive to achieve educationally, intellectual self-confidence, etc.). Unfortunately, from our perspective, Astin did not treat these measures as elements of an integrated academic process, but as the partial constituents of a series of social psychological sub-environments (institutional, curricular, faculty, peer) within a larger, only loosely articulated, general academic environment. Still, by our lights this represents a significant move in the right direction.

**Defining the Academic Process**

In the meantime, a vast literature of practical research consisting of ad hoc tests of the impact of various aspects of the academic process on student success has been accumulating, more than enough to justify our assertion of the need to include this explanatory domain in outcomes modeling and to help us identify its specific elements. Most of this literature, often not to be located in professional journals, is the product of institutional researchers charged by their administrations to help them find solutions to pressing problems of student enrollment maintenance and institutional performance assessment actually affecting their institutions. Below, we briefly characterize and discuss the particular aspects of the academic process such researchers found making significant positive and negative contributions to student retention and achievement, citing representative studies as appropriate. This material is organized according to natural break-out of the academic process into constituent sub-systems as suggested by the patterns emerging in literature overview.

(1) **Instructional Core Sub-System.** At the core of the academic process is the instructional system itself—the actual mechanism of teaching and learning consisting of carefully articulated and staged sequences of general education courses and degree programs formally leading to initial degree attainment and transfer to higher level degree programs. Various retention effects, especially relating to the specific nature of the general education program, have been noted, among them the impact of curriculum content and instructional style (Pascarella & Terenzini, 1974; Astin 1993; Knight, 1993; Belcheir et al. 1998), and the effect of course section size (Borden 1995; Keil & Partell 1998). Other researchers have found special enhancements to entry-level courses and the core curriculum designed for at-risk students salutary for retention (Holohan 1980; Blanc et al. 1983; MacDonald 1987). Finally, several studies have identified aspects of the classroom experience as important to academic progress (Santa Rita 1993, and Volkwein and Cabrera 1998).

(2) **Process Stage Effects.** The progressive nature of the instructional core of the academic process leads to differential retention effects depending on student location within the process. The most outstanding example of this, of course, is the disproportionate enrollment attrition typically occurring on most American campuses between the first two and subsequent terms. The Freshman year has been conceived as a sort of shake-down period for students new to college, and consequently as posing a unique set of adjustment challenges, such as undergoing separation from familial and childhood culture (Tinto, 1993; Elkins et al. 1998), and coping with adult independence and responsibilities, stress of class work, academic unpreparedness, poor adolescent self-image, goal uncertainty and unrealistic expectations of college (Bragg 1994; Riehl 1994; Napoli & Wortman 1998; Zhang & RiCharde 1998). Other researchers have also discovered different special sets of retention conditioners associated with later process stages (Wilder 1993; Hefferman et al. 1995; Gentemann et al. 1998).

(3) **Process In-Take Sub-System.** Fronting the instructional system are several in-take operations such as course scheduling and class registration which may impact on retention rates. Poor institutional course scheduling and registration advisement may result in the immediate alienation and loss of many students with tough personal schedules and campus access problems and long-term attrition effects among others whose program progress is retarded by unnecessarily low course loads and inappropriate course choices.

Several researchers have found that planned enhancements of the registration process (more flexible course scheduling, improved course and section choice, better access to course advisers during registration) often lead to significant retention gains (Baratta 1978; Gresty 1981; Gardner 1985). Also, many colleges and universities have reportedly seen gains in retention by establishing orientation courses and advisement programs occurring prior to or during first semester classes so that new students might be more attuned to the academic process they are entering (Keyser 1980; Gass 1990; McIntire et al. 1992; Glass & Garrett 1995).

(4) **Remediating Sub-System.** Of course, the single most important pre-credit instruction sub-system for most postsecondary institutions is remedial education for those who come to college unprepared in one or more basic skill areas (reading, English usage, mathematics). In 1995, more than a fifth of all entering students attending four-year schools and two-fifths of those at community colleges participated in at least one “developmental” program, either voluntarily or as a requirement before proceeding to credit course enrollment (Phillippe, 1997). Numerous studies have documented important developmental program retention effects. The two most commonly reported were that placement into pre-credit remediation greatly decreases the odds of academic...
success because of typically low completion rates, but that the odds tend to improve very significantly for those who do manage to complete their remediation requirements, often rising above non-developmental student odds (for example, Stark 1994; Weissman et al. 1995; Olaggett 1997; Schoenecker et al. 1998; Easterling et al. 1998). There also have been many reports of retention boosts resulting from special enhancements of remedial programs, such as the inclusion of an intensive advisement and tutoring component, utilization of programs to encourage participant peer group formation and block scheduling, and the application of new learning strategies and technologies (e.g. Blane 1983; Seltzer 1998).

(5) Student Support Sub-System. As students attempt to work through the instructional core of the academic process, there are usually many support services and agencies, established by federal, state and local governments or by the postsecondary institution itself, to help them on their way. Students usually avail themselves of these on a voluntary basis, and correlations of program participation with various measures of academic progress have been demonstrated for financial aid receipt (Moline 1986; Nora 1990; St. John et al. 1991; Cabrera et al. 1992; Murdock et al. 1995), and involvement with traditional student support services, like the federal TRIO programs, which offer ongoing, intensive, academic and personal counseling (Read 1982; Boughan 1996; Chaney et al. 1997; Muraskin 1997), minority student programs emphasizing morale-building and peer-support (Mueller 1993; Alexander 1997), standard and innovative general advisement programs (Jefferson 1982; Nelson 1993; Vanderpool & Brown 1994), and drop-in tutoring centers and writing workshops (Blane 1983; Seltzer 1998).

(6) Special Retention Management Efforts. Some college administrations have inaugurated comprehensive plans for managing institutional retention efforts across the academic process. Typical features include at-risk student early identification and progress tracking programs, high levels of faculty participation in special continuing advisement activities, serious study skill training efforts, tutoring and supplemental instruction customized to student academic programs. Successful community college plans of this kind have been described by Patrick (1978), Akridge (1987), Schreiner (1988), Ruddmann (1992), Grevatt (1992) and Fink (1994).

(7) Process Global Characteristics. As we have already noted, several comparative studies have found student retention and academic attainment rates varying according to certain global institutional characteristics, namely enrollment size, school classification (two-year, four-year), and system control (state, local government, private denominational, private non-denominational, etc.). Another institution-wide dimension recently identified as having academic outcomes effects is administrative culture, the pattern of work-related behaviors and attitudes of institutional staff and faculty. The National Center for Higher Education Management Systems has defined four basic types among the postsecondary schools surveyed — the clan culture (emphasizing office autonomy, "chieftain" leadership and a shared traditional education belief system), the adhocracy (entrepreneurship, growth and adaptability), the hierarchical culture (order, uniformity, fixed norms, bureaucratic process), and the market culture (competitiveness, environmental interaction, customer orientation). Using this typology, Cameron and Ettington (1988) discovered that clan-style process environments were disproportionately productive of student educational satisfaction among four-year post-secondary institutions, and Smart and Hamm (1993) found that adhocracy best promoted student personal and career development but market culture correlated most noticeably with student academic development at community colleges.

(8) Student Academic Process Options. Certain critical choices are made by students, both upon entering college and during their academic careers, which determine how they approach and interact with the academic process and to what academic and non-academic ends. These include study load (full-time, part-time), class session (day, evening, weekend, distance learning), class locus (main campus, extension centers, etc.), study major (English, biology, business management, etc.), program classification (transfer or terminal, arts and sciences or occupational program), academic goal (type of degree or award sought, including no award/unmatriculated), and attendance motivation (transfer preparation, career preparation, current job advancement, personal enrichment, etc.). The academic outcomes effects of study load, goal and motivation variations are so well known in the retention literature that we will forego research citations here. As to the less studied effects of study major and program classification, some representative research confirmations of their impact are Lueck and Gilbert (1978), Dressel and Simpson (1980), Steele and associates (1993), Kroc and associates (1997), and Andrade (1999).

(9) Student Academic Process Behavior. In-process measures of student behavioral responses to, and indicators of student progress within, the academic process include patterns of attendance (major semester enrollment, occasional stopping-out, any summer term enrollment, etc.), number of attempted and earned credit hours and their ratio, process phase completions (general education entry-level courses and program, degree program entry-level courses), and credit course performance (cumulative and program grade point average, proportion of course failures and repeat
enrollments, honors program participation, occurrences of academic probation, restriction or dismissal, official at-risk designation, etc.). So central are these variables to the very notion of student achievement that research citations establishing their outcomes impact credentials are unnecessary.

Educational researchers will probably find the most of the above analytic description of the academic process uncontroversial, but some may object to our inclusion of the student option and behavior components as integral constituents. This approach diverges greatly from their treatment in the social psychological literature where student option explanatory elements like student goal are usually assigned to the input phase preceding the environmental phase of retention/achievement causal models, and student performance indicators like GPA most frequently have either been conflated with campus activity and intellectual self-image variables into academic environment factors or treated as outcomes indicators separate from retention and graduation. Our contention is that student process options and behavior are properly conceived as part-and-parcel of the academic process, the functioning of which to produce differing achievement results cannot be understood except in terms of a tight systemic bonding with the initial and progressive academic circumstances of the “processed.” For example, a pattern of poor grades and deficient credit accumulation may lead to formal academic restriction status and the consequent closing off of instructional parts of the academic process to the student (or to official “at-risk” designation and the opening up of many academic support programs).

Finally, it needs to be emphasized that our focus on the academic processes role in conditioning student outcomes is not meant to imply that we consider social and organizational factors unimportant or even secondary in the causal matrix. Our intention here is merely to address what we consider to be an unfortunate theoretical and empirical oversight. We are definitely not recommending replacement of the current paradigm with a rival one. We are only suggesting that, along side social input and environmental variables, inclusion of academic process variables, especially when positioned proximately to output measures, would yield more complete and realistic models and produce superior predictive results.

An Illustrative Process Model of Student Outcomes

In the remainder of this article we present a heavily process-weighted structural equations model of student outcomes at one postsecondary institution — Prince George’s Community College. The goal of our modeling effort here was to produce and test a representation of outcomes causality, however limited, which might demonstrate or at least point to the explanatory potential of the academic process approach. The components of the PGCC model were mostly restricted to those process-type variables we could extract from readily available college transcript and program tracking data, and there was never any pretense that we were attempting anything like the construction and testing of a completely delineated process model, let alone a general outcomes model balancing process with internal social and external environmental effects.

As a first step in the modeling process (described in Boughan & Clagett 1996), in 1997 the college’s Office of Institutional Research and Analysis created a database for the fall 1990 first-time entering student cohort embodying an exhaustive set of 92 mostly process-type variables. We then used successive regression analyses to explore the pattern joint six-year academic achievement impact of this candidate set of predictors. The dependent variable employed was the dichotomous form of a complex outcomes indicator developed by OIRA specifically to measure academic outcomes for community college students (Boughan & Clagett 1995). This outcomes indicator classifies as achievers any students who accomplish at least one of the following by the date of assessment: graduation (associate degrees or certificate), transfer to a four-year school, or sophomore status (30 or more earned credit hours) with a 2.0+ GPA; all others are classified as non-achievers. After six years, 28 percent of the students of Cohort 1990 sorted into the achiever category.

The purpose of regression series was data refinement preparatory to structure equation modeling. Exploratory regression enabled us to discern collinearity problems, to weed out egregiously weak predictors, and to get a sense of the interaction pattern among robust predictors which would help guide us in structuring our causal path model. Before we could proceed to the modeling stage, regression results pointed to the need for a preliminary program of radical predictor reduction. This was accomplished by means of factor analysis, which consolidated the 43 variables surviving regression analysis into just 11 factor scales. These are summarized in Table 1, which provides the name used to identify each factor scale in all data displays, a capsule review of each factor’s defining (most highly loading) variables, and the academic process sub-system or other model component type to which each factor belongs.

As Table 1 indicates, our factor analysis of generated 11 factor scales, seven of which readily and obligingly fit within our nine-fold process component scheme — Early Term Performance (process phase effects), Remediation Progress (remedial sub-system) Financial/Academic Support (academic support sub-system), Academic Objectives (process options), Course Load (process options), General Course Performance (process behavior) and Enrollment Persistence (process behavior). In
addition, an eighth process-related factor scale (Academic Problem Syndrome) turned up which seemed to signal poor student progress because of a special negative interaction between the remedial and credit instructional sub-systems (inability to complete multiple remedial courses in a timely manner, leading in sequence to lack of prerequisites for entering key credit courses, subsequent poor credit hour accumulation and probationary academic status, plus a discouraging delay in start of general education course-taking). Process components not represented by the scalar products of the factor analysis were global process characteristics (irrelevant in single school studies), the process in-take sub-system and, most regrettably, the credit instructional sub-system. Unfortunately, in the latter two cases we lacked the data needed to measure these process dimensions.

We were taken by surprise, however, by the ninth factor analysis product — a scale, founded upon process-type variables, which nevertheless clearly pointed beyond process to a psychological dimension conditioning the behavior of Cohort members. This factor featured the following high loading pattern: non-normative course scheduling (taking both day and evening classes, taking both main campus and extension center classes, and attending both major and summer terms), midstream change in program curriculum, and strict sequential semester enrollment (no "stopping-out"). We dubbed its

Table 1. Model Component Factor Scale Names, Descriptions and Process Placement

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<thead>
<tr>
<th>Scale Name</th>
<th>Description</th>
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<tbody>
<tr>
<td>SOCIO-EDUCATIONALLY ADVANTAGED</td>
<td>White Racial Background/ High Income, High Job Status, College-Educated Home Neighborhood* Prestige County High School Graduate* [Social Background/Input]</td>
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<tr>
<td>TRADITIONAL STUDENT</td>
<td>Under 20 Years Old/Unmarried/ Entry Immediate from High School [Social Background/Input]</td>
</tr>
<tr>
<td>EARLY TERM PROGRESS</td>
<td>Enrolled in All 3 Earliest Major Terms/ Year-1 Good Academic Standing/ 10+ Credits Earned in Year-1/ Post-Fall-1 Enrollment/ Any Year-1 Credits / Year-1 GPA [Process Phase Effects]</td>
</tr>
<tr>
<td>COLLEGE PREPAREDNESS AND REMEDIATION PROGRESS</td>
<td>High Basic Skills Placement Test Scores/ Number of Required Remedial Programs (-)/ Completed Remedial Programs/ No Remedial Math Requirement [Remedial Sub-System]</td>
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<tr>
<td>SYNDROME OF ACADEMIC PROBLEMS</td>
<td>Number of Remedial Programs Required/ Any Year-1 Remedial Course-Taking/ Any Remedial Course Repeating/ Any Academic Restriction or Probation Terms/ No Credit Course-Taking/ No Credit Course Passing/ Remedial Math Incomplete [Remedial Sub-System/Process Behavior]</td>
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<tr>
<td>REGULAR ACADEMIC OBJECTIVES</td>
<td>Transfer Program/ Arts &amp; Sciences Program/ Stated 4-Year Transfer Motive/ Stated PGCC Degree Goal/ No Stated Enrichment or Occupational Motive [Process Options]</td>
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<tr>
<td>COURSE LOAD</td>
<td>Mean Year-1 Course Hour Attempts/ Mean Major Term Course Hour Load/Fall-1 Course Hour Load 15+ [Process Options]</td>
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<td>INSTITUTIONAL FINANCIAL &amp; ACADEMIC SUPPORT</td>
<td>Pell Grants Received/ Any Minority Retention Program Participation/ Any Student Services Participation/ Any Job Planning or Study Technique Courses [Academic Support Sub-System]</td>
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<td>GENERAL COURSE PERFORMANCE AND ACADEMIC STATUS</td>
<td>Year-1 GPA/ Final GPA/ Earned-to-Attempted Hours Ratio/ Always in Good Standing/ Good Standing Terms-to-All Enrolled Terms Ratio [Process Behavior]</td>
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<td>ENROLLMENT PERSISTENCE AND CONTINUITY</td>
<td>Attendance Term Span/ Number of Major Terms Attended/ Any Post-Year-1 Enrollment/ Any Post-Fall1 Enrollment/ 10+ Credits Earned/ No &quot;Stopping Out&quot; [Process Behavior]</td>
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<td>IMPLIED GOOD STUDY ATTITUDES</td>
<td>Combined Day-Evening or Campus-Extension Center Attendance/ Any Summer Term Attendance/ Any Study Major Shift/ No Stopping Out/ Enrolled in All 3 Earliest Major Terms [Implied Dispositional]</td>
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a. Derived from an analysis of student home Census Tracts (1990 Census Data)
b. Based on a prestige ranking of area high schools by a panel of PGCC staff
Figure 1. The Academic Process at PGCC (Fall 1990 First-Time Students after Six Years)

Path Coefficients

Squared Multiple Correlation Coefficients

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<td>.10 and above</td>
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Goodness of Fit Statistics

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scale *Study Attitude*, interpreting it as a gauge of student commitment to academic success, because each of the defining variables, in its own way, seemed to imply extra effort, determination or attention to study goals. As we shall see, this turned out to be a key component of the overall causal matrix.

Finally, two input scales appear in the table. These were the results of a factor analysis of selected social and educational student background variables. Race (white/minority), home Census tract median household income, professional/executive occupation rate and college education rate, plus prestige rank of last county secondary school attended, coalesced under factor analysis in a measure of Socio-Educational Advantage; while factor combination age under 20 years, unmarried status, and immediate college entrance after secondary school seem to capture the traditional/non-traditional student dimension fairly well.

### Path Analysis and Findings

At this point, we were ready to proceed to our path analysis, using the 11 factor scales plus the dichotomous academic achievement variables as nodes in the model. We selected the structural equations modeling method in small part to ease comparison of our work with the bulk of past student outcomes research, but mostly because it truly is the only statistical technique capable of explicitly depicting the myriad interactions expected to be found among variables representing as complex a phenomenon as the academic process while doing analytic justice to the impact weights involved (Bean 1979a).

The reason is that structural equations modeling treats the relationships among the components of a complex system as series of multiple regressions overlapping in their independent and dependent variables, the interactions among which are set by the analyst. This allows the analyst to structure and empirically validate variable linkages according to theory and causal logic, leading to a more realistic mapping of the network of forces at work. Furthermore, because each variable takes the independent position with respect to some other variables and the dependent position with respect to still others, the analyst is free to assess the importance of each component in the overall model according to its local effects. For example, although demographic factors like race and social class may not directly impact on a single criterion variable like academic achievement (as expected in regression, path analysis may find it a key influence on neighboring academic process components which do directly impact on academic achievement (e.g., level of college preparedness), and therefore to be an important indirect achievement level conditioner.

Figure 1 graphically depicts our final path analytic model, evolving out of a series of progressively more refined SEM constructs. What is presented is a schematic map of the causal network making up PGCC’s academic process, showing the 11 predictor variables distributed in rough terms of temporal, logical, and structural distance from the achievement classifier and from one another. Diagrammatically, the causal flow works downwards, with many lateral links in between. The existence and direction of causal paths linking variable pairs are indicated by means of arrows. Each is shown with its associated path coefficient ($\rho$), a probability weight measuring the impact of the first on the second variable, controlling for all causally preceding variables. The thick arrows indicate moderate to strong links ($\rho \geq .10$) while the dash-pattern arrows show marginal relationships (.05 - .09). Because path coefficients are *discrete* probability weights, absolute p-values for a sequence of paths can be summed, and their total ($P$) can be used as a very rough and ready gauge of the causal importance of the entire “trail.”

Our path model results in a wealth of insights concerning local areas of academic process function, but space permits only observations concerning the model’s major features:

- The total path model explained almost half of the achievement variance ($R^2 = .47$). This suggests that the model’s ability to portray just how process vectors impact on this final key component was reasonably good. Technically, however, this coefficient of determination statistic only estimates the model’s predictiveness at a single, albeit very important, node; it does not measure overall model performance or *goodness-of-fit*. For path analysis, this involves tests of numerous aspects of model operation, not all of which our model passed; in general, however, our model performed acceptably within key diagnostic parameters.

- A central feature of the path diagram turned out to be the existence of two semi-independent “trails” (sequences of paths), of almost equal probability weight, leading to Achiever Classification. The first was the “Effort Trail,” which linked the following in rough causal sequence: “traditional student” attributes (young, single, immediate from high school), transfer program orientation, level of institutional support, typical term study load, and attendance persistence ($P = 1.56$). The second was a broad “Performance Trail” of student socio-educational attributes (race, social class, quality of high school experience), college preparation level and remedial need, early term survival and progress, course performance, and academic problem syndromes ($P = 1.58$). These may be compared with the whole model path sum (7.06).

- Another prominent feature of the path model was a busy junction of paths with *Study Attitude* at its center. Moderate-to-strong paths ran from it to Achiever Classification and to virtually all nodes along the Effort
<table>
<thead>
<tr>
<th>Factors</th>
<th>(RAW)</th>
<th>Student Career Clusters (Index Values)</th>
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<tbody>
<tr>
<td>Cluster %</td>
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<td>Traditional Student</td>
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**NOTE:** In the Student Career columns, all figures are indexed group means (\(\text{Index} = 100 \times (\text{raw group mean/\text{raw whole population mean}}))\). In the Whole Cohort column, unitaicalized figures are percentages of all cohort students in the variable criterion category; figures in italics (e.g. 50.0) are transformed factor scale score means. In their original format, factor score whole population means are always 0, with scores below the mean indicated by negative numbers. This format does not permit indexing because indexing requires division by the population mean and mathematics forbids zero division. The transformation formula (\(\text{Index} = 50 + (20 \times \text{cluster score mean})\)) resets the population factor mean to 50, with a constant multiplier (20) which has the effect of creating a factor score case range of between 0 and 100.
and Performance trails. The centrality of study motivation in student achievement, as represented by its strategic positioning in the model and its very high total probability weight \((P=1.83)\), was the most unanticipated finding of this study.

The path diagram shows student background variables as exerting little direct influence over student achievement (Socio-Educational Advantage\(^{®}\) Achievement \(p=.06; P_{\text{of Traditional Student®}}\) Achievement beneath modeling threshold). This is a relatively common finding in outcome research. But an examination of the interior path of our model further suggests that the impact of social input may be significant after all in the form of indirect effects. Situated at the “head” of the Performance Trail, the factor scale summarizing various forms of Socio-Educational Advantage showed strongly local predictive power \((P=1.13)\) with all impacted variables, especially affecting Remediation need and progress; and the Traditional Student attributes scale, beginning the Effort Trail, proved to have a good deal to do with Academic Objectives, level of Institutional Support, and Study Load \((P=.99)\).

As we have already seen, the bulk of the energy of the model flows down causal trails anchored by Enrollment Persistence and Course Performance, the two components representing student process behavior; in fact, after Study Attitude these components were the strongest direct contributors to academic achievement \((p=.14\) and \(.16, \text{respectively})\). In contrast, the main academic effects of the model’s more structural process components (Remedial Progress, Institutional Support, Academic Objectives, Course Load, Early Term Progress) tended to express their force in a more complex and indirect fashion. Academic Objectives and Institutional Support turned out to be prime conditioners of Course Load \((P=.21\) and \(.25, \text{respectively})\). Remedial Progress had a discernable positive affect on both Study Attitudes \((p=.14)\) and on our sole process phase indicator Early Term Progress \((p=.09)\). Early Progress also significantly depended on Institutional Support \((p=.12)\), Course Load and Early Progress, in their turn, showed robust, direct effects upon achievement \((p=.14\) and \(.17, \text{respectively})\). The latter also proved to be a major conditioner of General Course Performance \((p=.40)\).

Cluster Analysis and Findings

As mentioned in the introduction, our research plan called for a follow-up cluster analysis of the SEM data to capture the actual study career patterns resulting from the academic process at PGCC. Cluster analysis is a powerful technique for typology development, but for some unfathomable reason it has been rarely employed by institutional researchers.\(^7\) Cluster analysis works by sorting cases into “clusters,” which are maximally within-group homogeneous and without-group heterogeneous, according to the patterns found in an all-case distance matrix based on multiple dimension scores. When applied to our Cohort 1990 tracking data, its product is a typology of stable student career patterns defined by the main variety of treks actually made through the academic process. While path analysis models the academic working out of the academic process itself at PGCC, cluster analysis, in effect, models the student body with respect to the workings of that academic process. The student typology provides a useful complement to the academic process path model, especially when types are assessed by collective achievement levels. By revealing the specific diversity of process behavior patterns linked to academic success or failure, cluster analysis can generate insights of immediate practical utility for college policy formulation.

To assure that only process-related data would define student career types, the two background scales Socio-Educational Advantage and Traditional Student were dropped and only the nine process scales were used in the clusterization. The cluster analysis itself took the \(k\)-means form, which calculates the mathematically optimum case sort for a specified number of group breaks. Reviewing cluster solutions 5 through 15, we determined that the 10-fold solution was best in satisfying our two key evaluation criteria—high realism of emergent student career types, and high articulation of types with achievement level. The student career types proved easy to interpret. The “personality” of each cluster was proved unambiguous implicit in its defining mean factor scores pattern, and found ready characterization in a nickname. Furthermore, the \(\text{Eta}^2\) correlation\(^8\) between student career type and achiever classification with the former as the predictor came in at a robust .381.

Table 2, (page 10), embodies the model. The table displays the ten cluster-derived student career groups, labeled by nickname, in percent Achiever order, plus non-degree-seeking cohort members who, though outside the cluster analysis, nevertheless constituted a meaningful, extra student career category. The data columns display cluster means for the original nine process variables used in the sort, indexed to the overall cohort averages to make cross-scale and cluster comparisons easier. Also shown are indexed cluster achievement tendencies by main classifier and achievement sub-types, plus indexed scores for the Traditional Student and Socio-Educationally Advantage factors to identify the socio-educational backgrounds predominating within each career type. The cluster model is rich in detail, but again, space limitation permits only a general review:

- **High Achievement Clusters (60% or more).** Three
student clusters registered high achievement levels. All had in common elevated group preparedness, academic goal, launch period success, course performance and study load scores, and low cumulative problem scores, but each distinguished itself in some salient fashion. The Collegian cluster was special for its below-average Persistence and Attitude scores; it contained the highest concentration of full-time “traditional students” (the youngest and most straight-from-high-school group), most strongly favored transfer programs, especially in the Arts & Sciences, and had the highest transfer rate (especially early and without a degree). In contrast, Extra Effort students registered extreme Persistence and Attitude scores and exhibited strong degree-seeking behavior. While also inclined to be “traditional students,” nevertheless many were a bit older, entered PGCC on a somewhat delayed basis, often took evening and extension center classes, and tended more to favor technical programs like computer programming and allied health. The Persistence and Attitude scores of the Supported Scholars fell somewhere between those of the first two. These were mostly strongly motivated African American “traditional students” from the middle socio-educational ranks, while Collegians and Extra Effort students were mostly white and upper-middle class. Most notably, students with this academic career pattern were the likeliest of any to bolster their success chances by participating in institutional support programs.

High Medium Achievement Clusters (40-59%). At this level of achievement we found only one study career pattern—True Grit. Many in this essentially African American middle class cluster of older students, often part-timers taking evening classes, experienced significant problems with remedial programs and credit courses, but over two-fifths eventually became achievers through drive (second highest Attitude score) and pluck (second highest Persistence score).

Average Achievement Clusters (20-39%). Two unlike clusters occupied this niche. The somewhat more successful Pragmatists, like True Grit students, tended to be middle class adult learners, but were predominantly white, much older, more part-time (fourth lowest Load score), and more oriented to occupational courses and job-related goals (second lowest Academic Objectives score). Most arrived at PGCC poorly prepared, but nevertheless did well academically as a group (tied for highest General Performance score). Their only moderate group Persistence score and 30% achievement rate may be related to a prevalence of short-term occupational objectives for attendance. In contrast, Full-Time Strugglers were mostly young working class African American full-time students straight from lower prestige high schools. They entered PGCC somewhat unprepared, exhibited only moderate drive and persistence, and then typically bogged down in the remediation process (highest group Problem Syndrome score). Despite a strong tendency to avail themselves of support programs (second highest Support score), approximately a quarter became Achievers by their last term.

Low Achievement Clusters (Under 20%). Five disparate study career types were found in this category. Part-Time Strugglers, mostly African American, were fully-employed, delayed-entry, part-time students (lowest Traditional Student score) with clear job-related attendance objectives (lowest Academic Objectives score). Below average college preparation, low study loads and high “stop-out” tendencies prevented any more than one in five becoming Achievers, despite high Persistence scores (third best mean). Vanishers, on the other hand, were predominantly white, degree- and transfer-oriented full-time students with excellent initial course performance records. Nevertheless, most of them dropped out within a few terms (second lowest Persistence score)—as if study had been cut short by some personal emergency like ill-health or financial collapse. Hardly more than one in ten made it into the Achiever category. Much less mysterious were the Unprepareds, who arrived at PGCC with the greatest remediation needs of any cluster; most of the students in this working class African American group did not survive the first year of study (57% never earned a single credit hour), and less than 1% became Achievers. Finally there were the Casuals who were mostly well-prepared, part-time students from middle and upper-middle class neighborhoods, many explicitly giving job and personal enrichment reasons for attending, who took a single course now and then, exerting little effort to get good grades. These were educational dabblers who, as their academic career pattern makes plain, never had degrees. Like the Unprepareds, fewer than 1% became Achievers.

Discussion and Conclusion

Prince George’s Community College is a large two-year postsecondary educational provider (around 12,000 average fall credit student enrollment) situated in the Maryland suburbs of Washington, D.C. Compared with its institutional peers in the state (and probably the nation), it can be characterized, by and large, as unexceptional in its physical plant, operational set-up and open enrollment policy, credit program inventory, course roster and instructional approach, nature of remediation program and support services, number and quality of faculty and staff, and other standard institutional traits. The college’s main distinction is the high concentration of African Americans in its credit student body (48% in Fall 1990). Most of its minority students are from middle class homes, and the institution’s academic performance scores at
assessment time have always fallen well within the normal range for state community colleges. Thus, our academic process model of student achievement is rooted in a postsecondary institution sufficiently normative to encourage us in making some cautious summary remarks and generalizations.

The explanatory performance of the PGCC path model, the components of which were primarily measures of aspects of the college’s academic process, equaled or exceeded that of past, social psychologically conceived SEM analyses of student achievement. At a minimum, this strongly suggests that outcomes researchers need to take academic process effects more seriously then they have tended in the past and to make appropriate room for process variables in future modeling efforts.

Progress through the academic process is fostered by many factors, but certainly salient to this movement are certain student attributes like native intelligence, pre-college academic preparedness, possession of a prior store of general knowledge, a facility for critical and abstract thinking, which collectively can be labeled academic resources. If the academic process plays an integral role conditioning student outcomes, as we believe our results indicate, then the distribution of academic resources ought to be a principle determinant of academic achievement probabilities. Unfortunately, we lacked sufficient data to measure and test the importance of student academic resource levels in our model but Adelman (1998, 1999) recently developed some cogent evidence along this line.

Our model implied that student academic achievement might also hinge in part on the prior possession or subsequent development of certain psychological resources going beyond simple study motivation and goal commitment. A surprise product of our factor analysis of process behavior variables was the identification of patterned set of extraordinary study exertions and goal shifts highly predictive of achievement classification. We interpreted students placing high on this attitude factor as manifesting a personal disposition to accept responsibility for study outcomes and to do whatever it took to succeed in light of a realistic self-assessment of one’s capabilities and circumstances. This might relate to concepts like study outcome locus of control attribution and student personality resilience recently explored for outcomes effects by Burns (1994), Westfall and Pisapia (1994), Pascarella and Associates (1996), and Zhang and RiCharde (1998).

Our cluster analysis of the model’s process data produced a complex but viable typology representing 10 different varieties of student academic career. Four achiever clusters were found (academically talented, transfer-bound traditional students; job-advancement-driven, high energy, full-time evening students; first-career-oriented, less well-prepared minority students highly participant in academic support programs; poorly prepared but extremely determined full-time persisters). In addition to these were three moderately at-risk clusters (job-oriented, part-time adult learners; poorly prepared, full-time minority students participating in support programs; unsupported, poorly prepared part-time minority students), a profoundly at-risk cluster (completely unprepared, part-time minority students from the poorest neighborhoods) and two “outrider” clusters (recreational course-samplers; progressing students forced to withdraw because of personal circumstances). Other community college researchers attempting this sort of analysis might turn up a somewhat different list of student career types, but we believe all would find a similar range of types, each requiring a different retention strategy. More generally, the typology’s richness of detail implies that retention researchers who ignore the workings of the academic process run the risk of oversimplifying their representation of outcomes phenomena, perhaps crucially compromising the realism of their models.

Finally, it needs to be said that we consider the modeling of PGCC’s academic process to be a work in progress. The product just presented is a tentative first step toward a future model which, among other things, will feature from a fuller representation of process components (e.g. the development of new institutional data measuring instructional and advisement/tutoring system effects), and will benefit from survey data allowing us to test for the input effects of student academic and psychological resource levels, and the classic environmental effects of campus social and external personal circumstances. In the mean time, we hope that the success we have obtained in our early, limited modeling effort convinces many that at the very least the academic process domain deserves more deliberate and sustained attention than it has thus far received in student outcomes research.
References

Bracketed citation codes are ERIC reproduction service reference numbers


Phillippe, K. (1997). National Profile of Community...


This article is a much revised version of “New Approaches to the Analysis of Academic Outcomes: Modeling Student Performance at a Community College,” a paper presented at the Annual Forum of the Association for Institutional Research, Minneapolis, May 1998.

Excluded from the cohort were 257 “non-degree-seeking” students (those enrolling in fewer than three major terms who gave only job-related or personal enrichment reasons for attendance in response to a state-require admission question).

Variables were sorted into a number of related predictor groups, based on earlier regression patterns and face content. A separate factor analysis was performed for each group, and in each case the oblique rather than orthogonal rotation option was selected. These two methodological moves were made to preserve as much of the original cross-type predictor co-varying as possible in the derived factor scales, a condition required for the emergence of appropriate paths in the SEM when components are factorial.

Relative County secondary school prestige ranks were established through interviews with knowledgeable PGCC staff. Out-county Cohort members and those never attending a secondary school were assigned to the middle rank.

The specific version of structural equations modeling employed was the maximum likelihood-based technique developed by James Arbuckle and embodied in the Amos 3.6 statistical analysis computer module (see Arbuckle 1997).

According to the most common measure, the Joreskog and Sorbom Goodness-of-Fit coefficient (GFI), our model performed at a very high level (.988 unadjusted, .956 adjusted for non-parsimony effects). Using another popular measure, the Tucker-Lewis Index which controls for sample size effects, also indicated an acceptable level of model fit (.934). The Chi-square test, however, showed a significant difference between the actual model and the saturation model (p<.0001), although even here the normed fit index, which compares actual and independence model chi-squares, suggested that our model greatly does move us quite far towards the saturation ideal (.976).

A thorough search of the ERIC data file turned up just nine instances of cluster analysis usage, only two of which involved developing a student academic performance typologies (Margrain 1978; McGuire 1986). The most notable researchers venturing in this direction was Pascarella & Terenzini (1977) in an early exploration of student psychological types.

Eta$^2$ is the appropriate statistic for gauging how much of the variance of a two-category variable can be explained by a typology; it is highly analogous to the $R^2$ statistic used in linear models like regression and causal path analysis.

Using recently acquire National Student Loan Clearinghouse data, we tested for the possibility that the sudden disappearance of many Vanishers might actually trace to transfers not tracked by the state enrollment flow system data we employed in our achievement assessment, but found not “hidden transfer” effect.

A weak, single indicator would have been average developmental placement score but factor analysis assigned this along with remediable performance variables to a single College Preparedness/Remedial Progress measure.

Endnotes

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