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The Use of Background and Ability Profiles to Predict College Student Outcomes

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To determine whether profiles of predictor variables provide incremental prediction of college student outcomes, the authors 1st applied an empirical clustering method to profiles based on the scores of 2,771 entering college students on a battery of biographical data and situational judgment measures, along with SAT and American College Test scores and high school grade point average, which resulted in 5 student groups. Performance of the students in these clusters was meaningfully different on a set of external variables, including college grade point average, self-rated performance, class absenteeism, organizational citizenship behavior, intent to quit their university, and satisfaction with college. The 14 variables in the profile were all significantly correlated with 1 or more of the outcome measures; however, nonlinear prediction of these outcomes on the basis of cluster membership did not add incrementally to a linear-regression-based combination of these 14 variables as predictors.

Keywords: student profiles and outcomes, biodata and student outcomes, situational judgment and student outcomes, clustering students using biodata, predicting student grades

College admissions tests predict college performance well, particularly 1st-year grade point average (GPA; Kuncel, Hezlett, & Ones, 2001, 2004). Noncognitive measures such as those measuring interests, background experiences, and motivational characteristics may add incremental validity to traditional cognitive college admissions tests and high school GPA (HSGPA), in that they assess a broader range of dimensions reflecting the potential of college students—such as those measuring leadership, interpersonal skills, and ethics. Another potential advantage of noncognitive measures is the reduction of racial subgroup differences in test performance (Oswald, Schmitt, Kim, Ramsay, & Gillespie, 2004; Sternberg et al., 2000). Some work on the prediction of college student success and subsequent life outcomes has considered background data that represent social, motivational, and developmental constructs (Mumford & Stokes, 1992; Owens & Schoenfeldt, 1979; Stokes, Mumford, & Owens, 1989).

Most efforts to predict academic and employment success examine linear relationships between individual-differences variables (both cognitive and noncognitive) and relevant outcomes. In fact, linear models for prediction may be adequate in most, if not all, instances (Coward & Sackett, 1990). However, the notion remains intuitively appealing that people can be classified into subgroups or types that each have a different profile of background characteristics and abilities, the idea being that members of each subgroup will behave and perform differently under a similar set of circumstances. Empirical support for this notion was provided by Owens and his colleagues (e.g., Mumford & Owens, 1982), who reported impressive long-term predictive relationships using their subgrouping methods. However, these studies did not compare the predictive ability of subgrouping with simple linear models of the predictor–outcome relationship.

In the current article, we seek to improve on earlier attempts to profile student potential in several ways. First, we develop profiles on the basis of a combination of biographical data scales reflecting students' past experiences, a situational judgment measure of students' responses to hypothetical academic and nonacademic situations, and traditional indicators of cognitive ability. Earlier attempts to profile students used only factors derived from biographical data or from a single domain of individual-differences characteristics, such as interests or cognitive abilities. Obviously, limiting measurement to a single domain will lower the potential level of explanation. Second, we use multi-item biographical scales (as opposed to single items or factor scores) to assess dimensions of behavior relevant to student success (Oswald et al., 2004). These two major characteristics of the current study are important because any effort to identify groups with different profiles must use measures that are relatively uncorrelated and reliable (Nunnally & Bernstein, 1994). To the extent that there are high correlations among variables used for profiling purposes, the main difference in profiles will be the level of the correlated scores, indicating the dominance of linear relationships between predictors and outcome. Including measures of constructs from both cognitive and noncognitive domains should reduce the intercorrelations of the profile measures on the basis of both conceptual grounds and established research findings on individual differences (Guion, 1998; Ployhart, Schneider, & Schmitt, 2006). Using multi-item scales that are developed to maximize reliability and

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minimize intercorrelations will also serve to make profiling efforts more likely to produce meaningful and interpretable results. When highly correlated predictor variables are used to form profile groups, profiling does not contribute much prediction beyond that offered by a linear regression model. Third, we examine differences among the subgroups, as characterized by these profiles, on relevant performance and motivational outcomes external to the profile. Fourth, we examine the differences in various demographics of these subgroups as one means of interpreting the nature of the profiles. Finally, we evaluate the degree to which subgroup profiles of students' background, situational judgment, and ability variables provide incremental predictive value beyond a simple linear combination of the variables that define the profiles across all subgroups.

Predictions of Academic Success

Academic success in the college student population has been of interest to researchers, practitioners, educators, and policy makers for over 75 years (Willingham, 1985). For both high school and college institutions, knowledge of factors underlying academic success can inform the development of curricular and extracurricular programs, career counseling and training materials, and college admissions criteria. Very often, concerns about career development and career choice are also informed by the pattern of characteristics an individual is thought to possess, a pattern reflected either in a profile of measures or in a profile arrived at intuitively by an expert's interview and judgment about an individual's strengths and weaknesses. The profile-oriented approach is consistent with the biographical data and vocational interests literature (e.g., Holland, 1985; Owens & Schoenfeldt, 1979).

Research indicates that scores on standardized tests of ability, such as the SAT and the American College Test (ACT), as well as past academic performance (generally measured by HSGPA and class rank) are the most valid predictors of success in college, as measured by college GPA. When corrections for measurement unreliability and range restriction are taken into account, scores on standardized tests have demonstrated strong criterion-related validities with cumulative college GPA ($r \approx .45$) and correlations with HSGPA and rank (rs $\approx$ .44 to .62; Hezlett et al., 2001); correlations with 1st-year college GPA are often higher (Willingham, 1985). Currently, the SAT, ACT, and HSGPA are the measures used most frequently to determine college applicant selection decisions (Harackiewicz, Barron, Tauer, & Elliot, 2002).

Although scores on standardized tests and past academic performance have been found to be the most valid predictors of college achievement, they do have limitations. Much variance in college achievement remains unexplained (Hezlett et al., 2001; Mouw & Khanna, 1993). These traditional indexes of student potential represent a relatively narrow view of a successful college student, and they are predictive of a similarly narrowly defined conceptualization of college student performance (i.e., often 1st-year college GPA). Consideration of a broader range of relevant predictor and outcome variables and the investigation of alternative forms of predictive models may enhance prediction of college student outcomes. Moreover, for some minority subgroups, such as African Americans and Hispanics, performance on traditional, cognitively based predictors has tended to be substantially lower than that of Caucasians, leading to lower selection rates for these groups in college and employment settings (Sackett, Schmitt, Ellingson, & Kabin, 2001).

Student Outcomes

A vast number of studies have defined college student success primarily in terms of college GPA, and, of those studies, the majority have focused on 1st-year college GPA (Hughes & Douzenis, 1986; Kanoy, Wester, & Latta, 1989; Mouw & Khanna, 1993; Pettijohn, 1995; Ting & Robinson, 1998; Young & Sowa, 1992). However, a few notable studies have investigated longer term success. For instance, Boyer and Sedlacek (1988) examined how the Non-Cognitive Questionnaire predicted the GPA of international students over the course of 2 years and found that self-confidence and availability of a strong support system predicted GPA. Harackiewicz et al. (2002) found that achievement goals and ability functioned as predictors of early success in college and over the long term. Although they broadened the set of predictor variables considered, these two studies still focused on the usual 1st-year college GPA outcome. Oswald et al. (2004) claimed that, in terms of predicting college GPA, it was unlikely that motivational or background characteristics would improve prediction beyond that afforded by standardized tests and HSGPA. However, they then suggested that motivational and background characteristics were stronger predictors of nontraditional college outcomes. They proceeded to develop and investigate a predictive model of various dimensions of student performance that universities valued and claimed to be developing in their students. The predictor and criterion measures they developed and administered were based on a performance model that included the following 12 dimensions (see Table 1): (a) knowledge and mastery of general principles, (b) continuous learning and intellectual interest and curiosity, (c) artistic and cultural appreciation, (d) appreciation for diversity, (e) leadership, (f) interpersonal skills, (g) social responsibility and citizenship, (h) physical and psychological health, (i) career orientation, (j) adaptability and life skills, (k) perseverance, and (l) ethics and integrity. Furthermore, noncognitive measures, in particular biographical data and situational judgment tests, were then constructed as potential predictors of each of these dimensions. This performance model and corresponding predictor measures were used in the research described in the current article.

In this article, we expand further the set of student outcomes considered. Previous educational research (Aitken, 1982; Astin, 1964; Eaton & Bean, 1995; Marshburn, 2000) and practical concerns on the part of universities, students, and parents have long focused on the importance of student retention. In all of these discussions as well as the turnover models that have been the subject of research in employment contexts (e.g., Hulin, Roznowski, & Hachiya, 1985; Lee, Mitchell, Wise, & Fireman, 1996; Mobley, 1977), noncognitive and motivational factors have played prominent explanatory roles in determining student or employee persistence and/or turnover and dropout. The biodata measures that are used to describe students in this article include several dimensions (e.g., adaptability and persistence) that are conceptually related to student retention concerns. Hence, students' intent to drop out of the school they were attending was an additional outcome considered.

Several other student behaviors—class attendance, organizational citizenship behavior (OCB), and satisfaction—were also treated as potential correlates of the biodata, situational judg-

Table 1
Conceptual Definitions of Student Performance Dimensions Represented in the Biodata Scales, the SJI, and the Self-Rating BARS Instrument

Knowledge and mastery of general principles (knowledge) Gaining knowledge and mastering facts, ideas and theories and how they interrelate, and the relevant contexts in which knowledge is developed and applied. Grades or GPA can indicate, but not guarantee, success on this dimension.	Interpersonal skills (interpersonal)* Communicating and dealing well with others, whether in informal social situations or more formal school-related situations. Being aware of the social dynamics of a situation and responding appropriately.
Continuous learning, and intellectual interest and curiosity (learning) Being intellectually curious and interested in continuous learning. Actively seeking new ideas and new skills, both in core areas of study as well as in peripheral or novel areas.	Social responsibility and citizenship (citizenship) Being responsible to society and the community, and demonstrating good citizenship. Being actively involved in the events in one's surrounding community, which can be at the neighborhood, town/city, state, national, or college/university level. Activities may include volunteer work for the community, attending city council meetings, and voting.
Artistic and cultural appreciation (artistic) Appreciating art and culture, either at an expert level or simply at the level of one who is interested.	Physical and psychological health (health) Possessing the physical and psychological health required to engage actively in a scholastic environment. This would include participating in healthy behaviors, such as eating properly, exercising regularly, and maintaining healthy personal and academic relations with others, as well as avoiding unhealthy behaviors, such as alcohol/drug abuse, unprotected sex, and ineffective or counterproductive coping behaviors.
Appreciation for diversity (diversity) Showing openness, tolerance, and interest in a diversity of individuals and groups (e.g., by culture, ethnicity, religion, or gender). Actively participating in, contributing to, and influencing a heterogeneous environment.	Perseverance (persevere) Committing oneself to goals and priorities set, regardless of the difficulties that stand in the way. Goals range from long-term goals (e.g., graduating from college) to short-term goals (e.g., showing up for class every day even when the class isn't interesting).
Leadership (leadership) Demonstrating skills in a group, such as motivating others, coordinating groups and tasks, serving as a representative for the group, or otherwise performing a managing role in a group.	Ethics and integrity (ethics) Having a well developed set of values, and behaving in ways consistent with those values. In everyday life, this probably means being honest, not cheating (on exams or in committed relationships), and having respect for others.
Career orientation (career) Having a clear sense of career one aspires to enter into, which may happen before entry into college, or at any time while in college. Establishing, prioritizing, and following a set of general and specific career-related goals.	
Adaptability and life skills (adapt) Adapting to a changing environment (at school or home), dealing well with gradual or sudden and expected or unexpected changes. Being effective in planning one's everyday activities and dealing with novel problems and challenges in life.	

Note. SJI = situational judgment inventory; BARS = behaviorally anchored rating scales. Abbreviations for each dimension appear in parentheses; these abbreviations are used in subsequent tables.
* The Interpersonal Skills scale was not incorporated into our profiling or regression analyses due to a lack of internal consistency and high intercorrelations with the other biodata scales.

ment, and ability measures. These outcomes are often considered precursors to dropout status and/or academic performance (Bean & Bradley, 1986; Chen, Hui, & Sego, 1998; Dowaliby, Garrison, & Dagel, 1993; Mobley, 1977; Organ, 1988) as well as important organizational objectives in their own right. Class attendance is obviously a necessary element of learning (Van Blerkom, 1992). Student satisfaction is often related to student performance (Aitken, 1982; Rode et al., 2005; Rotenberg & Morrison, 1993) directly or indirectly. OCBs have been investigated primarily in employment situations, but we believe they have relevance for the academic setting as well. Helping fellow students academically and socially, contributing to local community service efforts, and helping to recruit new students are all OCBs that most academic institutions depend on and encourage. All these outcomes are logically related to the noncognitive constructs that were targeted with our biodata instrument.

Predicting Performance Using Profiles

Owens and his colleagues (e.g., Owens, 1976; Owens & Schoenfeldt, 1979; see also Mumford & Stokes, 1992; Mumford &

Owens, 1987) have reported extensive efforts to use background data, in the form of biodata items, to separate samples of individuals into subgroups. Their background data items were designed to capture important behaviors and experiences related to student development. Item responses were summarized with principal-components analysis. Weights from the orthogonal components were then applied to the items to score the respondents, and their profiles of component scores were used to cluster individuals whose background profiles were similar according to a procedure first described by Ward and Hook (1963). Using this paradigm and a sample of approximately 2,000 freshmen, Owens and Schoenfeldt (1979) found 23 male and 15 female subgroups. Results indicated that 73% of these students could be fitted to one of these groups, whereas 20% could be assigned to two or more groups equally well and 7% were isolates who did not seem to fit any of the groups.

The utility of this subgrouping approach was assessed by comparing the subgroups on external variables not used in the profiling attempt and by relating subgroup membership to external performance criteria (Owens and Schoenfeldt, 1979). Subgroup status using the Owens methods has been found to be substantively related to a variety of educational outcomes, including over- and underachievement, college GPA, academic probations and dismissals, and number of course withdrawals in a series of master's theses and dissertations. Brush and Owens (1979) classified petrochemical employees into 18 subgroups on the basis of 263 background items and nine factors. Owens and Schoenfeldt (1979) found that members of these subgroups differed in terms of the jobs they held as well as in terms of turnover rates and productivity. Mumford, Connelly, and Clifton (1990) reported that subgroups identified in this manner also predicted motivational criteria such as person–job fit and situational choice. Davis (1984) found modest evidence for the stability of subgroup membership over a 7-year period, but there were only minor differences in work-related experiences. Female subgroups differed on the level of independence they displayed in transitioning to work as well as on life satisfaction and social contacts.

Many previous attempts to develop profiles and clusters of individuals on the basis of these profiles have focused on a single domain, such as biodata measures or interest measures (Holland, 1997). Recently, Ackerman and Beier (2003; Ackerman & Heggestad, 1997) considered measures derived from cognitive, motivational, and affective domains to form trait complexes that reflected differences in choice of four broad university major fields of study (i.e., physical sciences, social sciences, arts and humanities, and business). The trait complexes were also correlated with domain knowledge in these four areas. Ackerman and Beier (2003) were interested in developing a more unified perspective on the manner in which cognitive, affective, and motivational characteristics contribute to career choice and, more broadly, adult intellectual development. Oswald and Ferstl (1999) also presented work integrating individuals' ability and interest profiles within an occupational classification framework, noting that the occupational framework relied on groups that paralleled Ackerman and Beier's (2003; Ackerman & Heggestad, 1997) four trait complexes.

With a few exceptions, such as these, researchers seem to have abandoned the effort to profile and subgroup research respondents in favor of linear prediction models, presumably because the linear model seems to provide predictive results that are rarely, if ever, exceeded by nonlinear models based on statistical methods or expert knowledge or judgment (e.g., Coward & Sackett, 1990; Dawes & Corrigan, 1974). We believe that these attempts to profile individuals—whether in the work context, the academic context, or elsewhere—do have merit in their own right in terms of understanding patterns of individual differences and how they relate to human behavior. We also believe that the previous work on profiling can be improved, and we offer the following modifications to the Owens methods. First, we used rationally constructed biodata scales as our background measures, as opposed to factor scores, the former being more theory driven and the latter being established on a post hoc basis. In constructing these scales, we paid special attention to the measurement of specific content domains and the development of internally consistent measures that are empirically distinct. From a content validity standpoint, scales that are internally consistent allow for more convincing interpretations of the resultant profiles as well as any profile differences among groups. From an empirical standpoint, scales that are empirically distinct, with relatively low intercorrelations with one another, allow for profiles to differ in their shape. When the converse is true and scales are highly correlated, the resulting profile solutions tend to be different only in level, not shape, and profiles that are only different in level will not provide more predictive power than what is found in the linear relationships between profile variables and outcomes.

Second, we used measures of cognitive ability along with our biographical data measures and situational judgment inventory (SJI) as profile variables. Ability measures are appropriate, as they are typically used to predict student outcomes and, as noted previously, are highly related to student performance outcomes that are cognitively based. In addition, ability measures are usually unrelated empirically to biographical measures (e.g., Mumford & Stokes, 1992; Pulakos & Schmitt, 1996), which makes them a statistically attractive complement to the profile measures. This is especially true when the constructs the biodata measures are designed to address are noncognitive in nature, as is the case for most of the biodata dimensions targeted in this study. Conceptually, student performance likely relates to both motivational and ability components; hence, both should be meaningful elements of a college student profile.

Third, it is reasonable to expect that there will be differences in the opportunities and experiences available to members of different ethnic groups because of both cultural and socioeconomic differences that are well documented (Neisser et al., 1996). Some of these differences are inherent in our biographical measures, as is obvious from the description of the measure that follows. Men and women do also tend to have a different set of life experiences, which has been well documented in the profile literature we mentioned previously. Thus, several early studies using biographical data proceeded to develop separate clusters or subgroups for gender groups a priori (e.g., Owens & Schoenfeldt, 1979).

Fourth and finally, we are assessing the degree to which knowledge of an individual's profile-based subgroup adds to prediction of important student outcomes beyond a simple linear combination of the variables used to construct the profile. In more formal terms, we propose the following specific research objectives and hypotheses:

1. The use of biographical and situational judgment measures, in combination with measures of ability, can provide meaningful profiles that define subgroups of students.

2. Subgroups formed by these profiles will exhibit different levels of performance (i.e., 1st-year college GPA, self-rated performance, class absenteeism, intent to quit college) and attitudinal or motivational outcomes (i.e., satisfaction, OCB).

3. There will be race and gender differences in the composition of the subgroups formed by these profiles.

4. Subgroup membership, as defined by the profile into which each individual fits most closely, will add incrementally to a regression equation predicting student outcome beyond the linear prediction afforded by the variables that make up the student profiles.

Method

Sample

A total of 2,771 freshman students at 10 colleges and universities across the United States participated in the data collection. We deliberately sampled from participating universities that were diverse in terms of region of the country; one was in the Southwest, two were historically Black colleges in the Southeast, five were Big Ten midwestern universities, one was in the Southeast, and one was a highly selective private midwestern school. The numbers of participants in the original set of schools ranged from 139 to 464.

The average age of our participants was just over 18 years; in fact, over 97% of our sample was either 18 or 19 years of age. Sixty-four percent of the sample was female, 96% were U.S. citizens, and 94% indicated that English was their native language. Regarding the ethnicity breakdown, this sample was 55% Caucasian, 25% African American, 6% Hispanic, 7% Asian, and 7% other ethnicities. All students provided responses to our paper-and-pencil measures in the first few days or weeks of their college career by participating in group sessions supervised by admissions officers or other staff members at the university. Detailed instructions were provided to students and staff. Responses were recorded on machine-scorable answer sheets and were mailed to us. These staff members were paid for their help, and students were paid ($40 per student) for their participation. The complete data collection effort at each college or university took approximately 2 hr.

To assess possible behavioral implications of cluster membership, we collected a variety of external measures at the end of the students' 1st academic year via a Web-based survey of all student participants in the original assessment. Students who returned the survey were awarded a $20 gift certificate from www.Amazon.com. Students were recruited via e-mail. Each student was sent the original request and up to two reminders. The 220-item survey took most students between 15 and 20 min to complete. Usable returns were received from 901 students (or 33% of the original sample). Characteristics of those who returned the survey at the end of the 1st year are described below.

Measures

Profile Measures

Biodata, a situational judgment measure, standardized admissions test scores, and HSGPA were used as the bases to form student profiles and clusters.

Biodata. Biographical data (biodata), reflecting information about an individual's background and life history, were collected in the initial data collection phase. Some of the information collected in the biodata instrument is contained within college applications, but it is often provided by students in an open-ended way and tends to be used by admissions officers in an intuitive or implicit manner (e.g., in interpreting the extracurricular activity lists and résumés that applicants provide). By contrast, we undertook the development of a biodata inventory, which is a more systematic and standardized way to obtain similar information and which would therefore allow for more explicit and consistent methods for admissions officers to incorporate this information in making college admissions decisions or in providing guidance with respect to major or course choices. The biodata inventory contained standard multiple-choice questions about one's previous experiences, similar to tests used in job selection processes. Participants completed 126 biodata items reflecting 11 of the 12 dimensions of college student success proposed by Oswald et al. (2004). Because of a lack of internal consistency along with high intercorrelations with other biodata scales, the interpersonal skills dimension was not used. Descriptions of these dimensions are contained in Table 1.

SJI. During the initial data collection phase, we also administered an SJI containing 36 hypothetical situations representing the kinds of situations typically faced by college students. Respondents were required to indicate the action they were most and least likely to take from a set of four to six alternative actions. Details regarding the development of this instrument are contained in Oswald et al. (2004). SJI items were each scored from -2 to 2, with higher scores indicating situational judgment that is in line with average responses across a set of students deemed to be experts (i.e., junior and senior college students who have successfully persevered through at least 2 years of college). Item content reflected the 12 dimensions listed in Table 1 (i.e., 3 items per dimension, including interpersonal skills, which was not included among the biodata scales). Because situational judgment scales were not empirically distinct given the complex content and small number of items per scale, they were combined into a single composite SJI score, or measure of the student's general situational judgment capability.

Ability measures. Information about participants' SAT scores, ACT scores, and HSGPA were collected from the relevant admissions or registrar's offices at the participants' home institution. All available scores for each SAT and ACT test were standardized via nationally reported norms; then they were averaged together to create a single ability variable.

These 14 variables—those reflecting background and experience (11 biodata scales), practical judgment (SJI), ability (SAT/ACT), and past academic performance (HSGPA)—were the variables used to profile and cluster the respondents. Demographic information was also collected in the survey, including items on gender, major, and ethnicity.

External Correlates of Cluster Membership

As indicated above, a Web-based survey sent to the entire initial group of respondents was returned by 33% of the students. Those who returned the end-of-year questionnaire differed from those who did not on a number of variables, with the former tending to be higher than the latter on the biodata measures ($ds < 0.30$), with the exception of the career orientation scale, on which the nonrespondents' mean score was slightly higher. Mean HSGPA was higher among respondents than among nonrespondents ($d = 0.50$), as was the SAT/ACT composite ($d = 0.70$). These are rather high d values, which means that students who responded to our second survey were relatively higher in ability than those who did not respond. Of the respondents to the first survey, 31%, 53%, 13%, and 44% of the Hispanic American, Asian, African American, and Caucasian groups, respectively, responded to the second survey. Respondents to the second survey were slightly more likely to be female (2%) than were respondents to the first survey. Two thirds of the African American participants came from the two historically Black colleges, and one third of the Hispanic American participants came from the southwestern school. Because of this confounding of ethnic status with university, statements about differences in ethnic status may also be a function of the particular circumstances at that school.

First-year college GPA. First-year college GPA was collected from all participants' respective institutions in the summer of 2005 for those students who completed the 1st year of college. Because admissions policies at our different schools meant that students with widely different SAT/ACT scores were admitted, we corrected 1st-year college GPA using a procedure that the College Board uses in assessing the validity of the SAT in similar instances. That is, we first standardized the GPA variable within university. We then regressed the standardized grades across universities on the ability measure (i.e., the summed composite of SAT and ACT scores) along with a set of nine dummy variables representing the 10 colleges and universities. The coefficients for the dummy variables indicated the differences in grades that would be expected for students with comparable SAT scores at the various universities. Grades for students at each school were then adjusted by that school's regression coefficient, such that students at universities with higher average SAT scores received a relatively higher adjusted college GPA and, conversely, students at universities with lower average SAT scores received a relatively lower adjusted college GPA.

Behaviorally anchored rating scales (BARS). Students' self-reported performance on 12 dimensions of college student success (see Table 1) was measured via BARS. The BARS provided descriptions of each dimension of success as well as example behaviors that reflected different levels of performance on that dimension. Respondents rated their performance on a 5-point scale ranging from 1 *(very low)* to 5 *(very high).* These 12 BARS items were summed to create a composite measure of self-rated performance. The alpha coefficient associated with this self rating was .74.

Class absenteeism. Skipping classes and being late to classes may be proximal evidence of physical and psychological withdrawal from the university community and may be correlated with eventual transfer to another college or with dropping out of college entirely. In the Web-based follow-up, students answered two items referring to the number of times they had missed classes in the past 6 months for "avoidable" reasons (or inexcusable absences) and "unavoidable" reasons (or excusable absences). Because inexcusable absences should more strongly reflect psychological withdrawal than excusable absences, the number of inexcusable absences on the part of respondents in the different clusters was the absence outcome variable of more interest. It was assessed with a single item with five response options, ranging from *missed less than five times* to *missed more than 30 times.* No internal consistency reliability coefficient can be calculated from this one item, but, given the fairly objective nature of the measure along with evidence from previous work that self reports of college GPA correlated above .90 with actual GPA and the fact that students had no motivation to distort their reported absenteeism, we felt confident in the psychometric quality of this outcome measure.

Intent to quit. Students' intentions to drop out or transfer were assessed with three self-report items on a 5-point Likert-type scale ranging from 1 *(strongly disagree)* to 5 *(strongly agree).* Items were adapted from the intent to turnover scales described by Eaton and Bean (1995) and Griffeth and Hom (1988). The alpha coefficient of this three-item measure was .79. A sample intent to turnover item reads as follows: "I intend to be enrolled in this school 6 months from today." Items in this measure were coded such that higher scores reflected greater intention to leave.

OCBs. OCBs refer to nonrequired behaviors that promote the welfare of the university (Organ, 1988). This measure consisted of a series of 15 five-point Likert-type scales with responses varying from 1 (*strongly disagree*) to 5 (*strongly agree*). Example items included "Gone out of your way to make new students feel welcome at school," "Defended your school when other students tried to criticize it," and "Participated in student government or other clubs that try to make your school a better place." Alpha for this scale was .85.

Satisfaction. Student satisfaction was measured with three items with a five-option response scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). Representative items included "Overall I am satisfied with this school" and "This school was the right choice for me." The alpha coefficient for this scale was .93.

In addition to examining differences in these variables across clusters of students in our sample, we examined the demographic composition of each cluster (i.e., race/ethnicity, gender, major declared by the student on entry into college).

Data Analyses

We first examined the descriptive statistics, reliability, and intercorrelations of the variables used to profile students. As mentioned in the introduction to this article, low intercorrelations among the variables used to profile and cluster students are necessary if the procedure is to add anything to our understanding of student performance beyond that provided by simple linear prediction of student performance (i.e., beyond knowing that more ability and greater levels of motivation tend to result in superior performance).

Although our approach to the identification of different clusters of student profiles across the 14 ability, biographical, and situational judgment variables was exploratory in nature, two a priori goals guide these analyses. Our first goal was to specify a useful but not unwieldy number of student profile clusters, somewhere between three and eight profiles inclusive. In other words, we did not want to specify too many profiles, because then some profiles would be unreliable, capitalize on chance, or reflect distinctions that were not meaningfully different. Conversely, too few profiles would likely not adequately represent many college students in the data set. Second, the goal was to cluster individuals into subgroups that were as internally consistent yet externally distinct from one anther as possible and as conceptually interpretable as possible.

A large number of clustering procedures have been examined in previous research (e.g., Milligan, 1980, examined 15 of them), but with no consensus that one procedure is superior to the others. We used the *K*-means clustering procedure because it is in keeping with the goal of creating clusters that are as internally consistent as possible. Students can be reassigned from one cluster to another as the clusters are formed in the cluster-formation process, in contrast to hierarchical agglomerative methods, according to which students must remain in clusters that, at the end of the clustering procedure, may turn out to be suboptimal as smaller clusters are successively built up into larger clusters. A legitimate concern with *K*-means cluster analysis, however, is the fact that any single solution is sensitive to the specific order of the cases in the data set, which should be irrelevant. Therefore, we used a program (Clustan's Focal Point software; Wishart, 2000) that allowed for exploring three- to eight-cluster solutions, where there were 1,000 runs, each run based on a random permutation of the data set (i.e., 1,000 random permutations and runs of a three-cluster solution, 1,000 random permutations and runs of a four-cluster solution, and so on up through an eight-cluster solution). The greatest improvement in the within-group expected sum-of-squares criterion was from the five-cluster solution, and a five-cluster solution was also suggested by the Ward and Hook (1963) clustering procedure (the latter procedure was recommended by Colihan & Burger, 1995, as a way to specify the number of clusters prior to *K*-means analysis). Going beyond the number of clusters to the specific results, we note that our clustering results were remarkably similar to the five-cluster results we obtained from the SPSS two-step procedure, a procedure that differs from *K*-means in that it creates "pre-clusters" in the first step that are themselves clustered through a hierarchical agglomerative procedure applied in the second step (SPSS, Inc, 2005). Thus, the *K*-means solution converged with an alternative approach to clustering the same data.

Note that we selected the five-cluster *K*-means solution that showed the highest replicability across 1,000 random permutations of the data set; we did not simply select the one solution that had the very best expected sum-of-squares criterion. Exact replication was around 40%, but closeness of replication from a practical standpoint was above 70%. Note again that most *K*-means analysis software programs (e.g., in SPSS) conduct a single *K*-means analysis of the data, and thus no information on replicability of the results is available unless one were to randomize the data and rerun the analyses oneself, a practice that is rarely done, if ever. Because we ran the present *K*-means analysis for five clusters 1,000 times, on the basis of 1,000 random permutations of the data set, the five-cluster *K*-means solution we ultimately selected was based on information about replicability that is typically unavailable.

Following the cluster analyses and the identification of each student's cluster membership, we did a series of analyses of variance in which we examined the various possible behavioral correlates of cluster membership (i.e., 1st-year college GPA, self-rated performance, class absenteeism, intention to quit college, satisfaction, OCB, gender, and race). In each of these analyses, cluster membership served as the independent variable. Because the student outcomes were based on data collected at the end of the 1st academic year and the return rate to our Web-based survey was approximately 32%, the sample sizes for some outcomes were much lower (approximately 900) than the original sample size.

To examine the degree to which knowledge of cluster membership afforded incremental prediction of student outcomes, we used hierarchical regression in which each outcome variable was regressed on the set of profile variables in Step 1, followed in Step 2 by a set of four dummy-coded variables reflecting status on the cluster membership variable. Significance of the dummy-coded status variables was taken as evidence that they improved prediction of the outcome variable beyond the use of a simple linear combination of the profile variables (i.e., HSGPA, SAT/ACT, biodata, and SJI scales).

Results

Means, standard deviations, reliabilities, and intercorrelations of HSGPA, SAT/ACT, the biodata scales, and the SJI scale are presented in Table 2. Similar statistics for the six outcome measures are reported in Table 3. Correlations between these two sets of variables are available in Table 4. As can be seen in Table 2, the biodata scales and the SJI reliabilities ranged from .65 to .86, with most in the .70s and .80s. HSGPA and SAT/ACT reliabilities are unavailable for the sample, although SAT/ACT reliability is known to be quite high (around .90), and HSGPA reliability should also be high, given that it is an average for each student across a large number of course grades. Equally as important as the reliabilities, the intercorrelations between the biodata and SJI variables, on the one hand, and HSGPA and SAT/ACT, on the other, were relatively low, indicating the discriminant validity that is a prerequisite for any of the profiles generated with the clustering procedures to differ in shape as well as level. Relatively high correlations were observed between the biodata knowledge and learning dimensions ($r = .47$); between the leadership and citizenship dimensions ($r = .53$); between perseverance and the dimensions of knowledge, career orientation, and adaptability (rs $= .49$, .41, and .47 respectively); between appreciation for diversity and the continuous learning and artistic appreciation dimensions (rs $= .51$ and .60); and between both learning and ethics and the SJI (rs $= .33$ and .46, respectively). However, the magnitude of these correlations does not preclude shape differences in profiles, and the other correlations were lower. The average correlation between all biodata scales and the SJI scale was low ($r = .27$).

Table 3 indicates that the outcome measures were relatively uncorrelated. The moderate negative correlations between OCB, on the one hand, and satisfaction and intent to quit, on the other, were expected and may reflect a general dissatisfaction or withdrawal factor. Self-rated performance was negatively related to class absences, intent to quit, and OCB, as expected. The very low correlation between self-rated performance and college GPA was expected given that the students rated their performance on several nonacademic dimensions.

Cluster Results

Again, to decide how many clusters represented the student profiles reasonably well, we used the expected sums-of-squares criterion, replicability across the three- to eight-profile cluster *K*-means solutions, and supplementary information from the Ward and Hook (1963) and SPSS two-step clustering methods, as indicated previously. Taking all these criteria into account, we decided that a five-cluster solution was the best empirical representation of students' background and ability and the most clearly interpretable one. The profiles for each of these five clusters are displayed in Figure 1. As can be seen in the figure, the profiles of these five groups differed in terms of level but also in terms of shape. Two profiles, that of the third and fifth groups described subsequently, differed primarily in terms of the level of scores across all 14 variables used to cluster the sample of students. Profiles of the three other groups, however, were more varied across the 14 measures. There were relatively large mean differences across the five profiles for most of the 14 variables. These differences ranged from 1.03 standard deviation units on the health variable to 1.90 standard deviation units on the knowledge measure. Standard scores on the 14 predictors for the five groups are presented in Table 5.

The first cluster, labeled *low academic, career oriented,* was characterized by the lowest average scores on the SAT/ACT dimension and the lowest HSGPA scores. On most other biodata dimensions and the SJI, these participants scored about average. The one exception was the career orientation measure, on which they received the highest average score (closely followed by the fifth cluster, to be described). This group comprised 348 students (14% of the sample).

The second cluster, labeled *high ability, culturally limited,* was average in ability although relatively high in terms of HSGPA. These individuals' SAT/ACT scores were just above the mean, but their scores on most biodata dimensions were relatively low, especially on the artistic and diversity dimensions, although their health, adaptability, and ethics biodata scores were above average, as was their SJI score. This group was composed of 581 students (23%).

The third cluster, of 521 students (21%), was *marginal* on most dimensions. These individuals' SAT/ACT and HSGPA scores averaged about 0.5 standard deviations below the mean, and on most biodata dimensions and the SJI their scores were between 0.5 and 1.0 standard deviation units below the average of the total group. Their average scores on the knowledge and perseverance dimensions were particularly low.

The fourth cluster, of 473 students (19%), was labeled the *able artistic* group and was characterized by the highest average SAT/ACT scores, the highest artistic biodata scores, and the second highest diversity biodata scores. Scores on most other dimensions were average to below average, with the lowest scores being on the

Table 2
Correlations Among HSGPA, SAT/ACT, Biodata Scales, and Situational Judgment Inventory

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Ability																
1. HSGPA	3.50	0.43	—													
2. SAT/ACT	0.61	0.92	.58	—												
Biodata scale																
3. Knowledge	3.15	0.47	.32	.26	**.67**											
4. Learning	3.09	0.61	.06	.17	.47	**.78**										
5. Artistic	2.91	0.82	.14	.26	.27	.44	**.86**									
6. Diversity	2.98	0.66	.05	.12	.27	.51	.60	**.80**								
7. Leadership	3.07	0.81	.16	.14	.27	.35	.34	.38	**.86**							
8. Citizenship	3.32	0.76	.21	.18	.25	.31	.38	.41	.53	**.79**						
9. Health	3.25	0.51	.14	.13	.28	.14	.01	.04	.20	.11	**.68**					
10. Career	3.32	0.65	−.08	−.21	.23	.31	.04	.16	.27	.24	.09	**.77**				
11. Adaptability	3.38	0.45	.10	.07	.33	.22	.08	.15	.30	.17	.46	.20	**.65**			
12. Perseverance	3.73	0.49	.12	−.03	.49	.38	.17	.26	.42	.31	.31	.41	.47	**.75**		
13. Ethics	3.86	0.54	.20	.13	.43	.24	.20	.16	.17	.26	.19	.16	.18	.31	**.67**	
SJI																
14. SJI	0.66	0.33	.25	.20	.33	.21	.21	.22	.21	.31	.12	.13	.16	.27	.44	**.76**

Note. HSGPA is on a 4-point scale. SAT/ACT is on a standardized (*z*-score) metric. All biodata scales are on a 1–5 Likert scale. Alpha coefficient reliability estimates for the predictor variables at Time 1 are on the diagonal in boldface. Alphas were computed with all participants at Time 1. HSGPA = high school grade point average; ACT = American College Test; SJI = situational judgment inventory.

biodata dimensions of career orientation, adaptability, and perseverance.

The fifth group, of 566 students (23%), was referred to as the *academically able, well-rounded* group. Although these participants' average standing on the SAT/ACT composite and HSGPA measure was nearly 0.5 standard deviation units above the average, they were not the very brightest group as represented by these two indexes. Of the five groups, however, their scores were the highest on the knowledge, continuous learning, diversity, leadership, social responsibility, adaptability, perseverance, and ethics biodata dimensions as well as on the SJI.

Cluster Differences on External Variables

These five clusters of students, as just described, suggest important differences in patterns of ability and motivation and the manner in which these students approach academic and other life goals or situations. However, clustering students into groups is a practically useful exercise only if there are group differences on important behaviors and performance outcomes that are external to (and not redundant with) the variables used to compose the clusters. In this case, we compared our five empirically derived clusters on a range of student attitude, behavior, and performance variables collected at the end of their 1st year in college. These outcome measures were described in the *Method* section of the article and are listed in Table 6. Table 6 also includes the means and standard deviations of each outcome for each cluster as well as standardized mean differences among cluster groups relative to the highest scoring cluster. In addition, we describe the gender, race, and major area of study of individuals who were assigned to each of the five clusters in Table 7. As we mentioned previously, ethnic status was partly confounded with school, and there were differences in return rates across schools. These differences are relevant when we consider the outcome variables in Table 4 other than GPA.

One-way analyses of variance indicated that mean differences across clusters were statistically significant ($p < .05$) for each of

Table 3
Means, Standard Deviations, and Intercorrelations Among the Outcome Variables

Variable	*M*	*SD*	1	2	3	4	5	6
1. First-year college GPA	3.00	0.92	—					
2. BARS	3.61	0.50	.15	—				
3. Class absenteeism	1.78	1.04	−.09	−.27	—			
4. Intent to quit	1.41	0.68	−.20	−.21	.00	—		
5. OCBs	2.88	0.61	−.06	.39	−.06	−.25	—	
6. Satisfaction	3.76	0.54	.19	.30	−.03	−.48	.28	—

Note. Correlations are based on listwise deletion of cases resulting in $n = 961$. The means and standard deviations for all but the GPA measure are also based on $n = 961$. The mean and standard deviation of the college GPA variable are based on those of the original sample, for whom the universities had a 1st-year GPA ($n = 2{,}666$). The OCB variable was reflected, so that high scores on the variable indicate that students engage in more of this behavior. GPA = grade point average; BARS = behaviorally anchored rating scales; OCBs = organizational citizenship behaviors.

Table 4
Correlations of Outcome Variables With Predictor Variables and Cluster Membership

Variable	First-year college GPA	BARS self-rated performance	Class absenteeism	Intent to quit	OCBs	Satisfaction
Ability						
SAT/ACT	.65*	.03	.17*	−.13*	.15*	.14*
HSGPA	.61*	.10*	−.04	−.08*	.08*	.10*
Biodata scale						
Knowledge	.29*	.26*	−.15*	−.04	−.03	.06
Learning	.13*	.26*	−.07*	−.02	−.07*	.05
Artistic	.21*	.24*	−.03	−.09*	−.07*	.04
Diversity	.12*	.29*	−.04	−.07*	−.19*	.06
Leadership	.14*	.32*	−.06	−.03	−.29*	.04
Citizenship	.19*	.31*	−.08*	−.10*	−.28*	.09*
Health	.17*	.23*	−.17*	−.10*	.04	.22*
Career	−.17*	.23*	−.05	.00	−.22*	.05
Adaptability	.10*	.26*	−.10*	−.09*	−.10	.20*
Perseverance	.09*	.33*	−.18*	−.04	−.22*	.09*
Ethics	.16*	.26*	−.17*	−.06	−.09*	.03
SJI						
SJI	.26*	.28*	−.16*	−.11*	−.14*	.10*
Profile						
Cluster 1	−.36*	.02	−.08*	.07*	−.11*	−.11*
Cluster 2	.14*	−.13*	−.05	−.02	.15*	.02
Cluster 3	−.29*	−.27*	.15*	.10	.09*	−.05
Cluster 4	.23*	−.06	.09*	−.04	.08*	−.05
Cluster 5	.22*	.37*	−.10*	−.06	−.22*	.13*

Note. GPA = grade point average; BARS = behaviorally anchored rating scales; OCBs = organizational citizenship behaviors; ACT = American College Test; HSGPA = high school GPA; SJI = situational judgment inventory; Cluster 1 = low academic, career oriented; Cluster 2 = high ability, culturally limited; Cluster 3 = marginal; Cluster 4 = able artistic; Cluster 5 = academically able, well rounded.
* $p < .05$.

the six outcomes described in Table 6. Standardized mean differences (d) were calculated as differences from the group with the highest average on a given variable. Thus, all d values are reported as positive values reflecting the difference between the highest scoring group and a particular focal group. As can be seen in the table, low SAT/ACT and HSGPA scores are reflected in the low 1st-year college GPA of the low academic, career-oriented group and the marginal group. The other three groups were not very different in terms of the grades they received in their 1st year of college. On self-rated performance (BARS), the academically able,

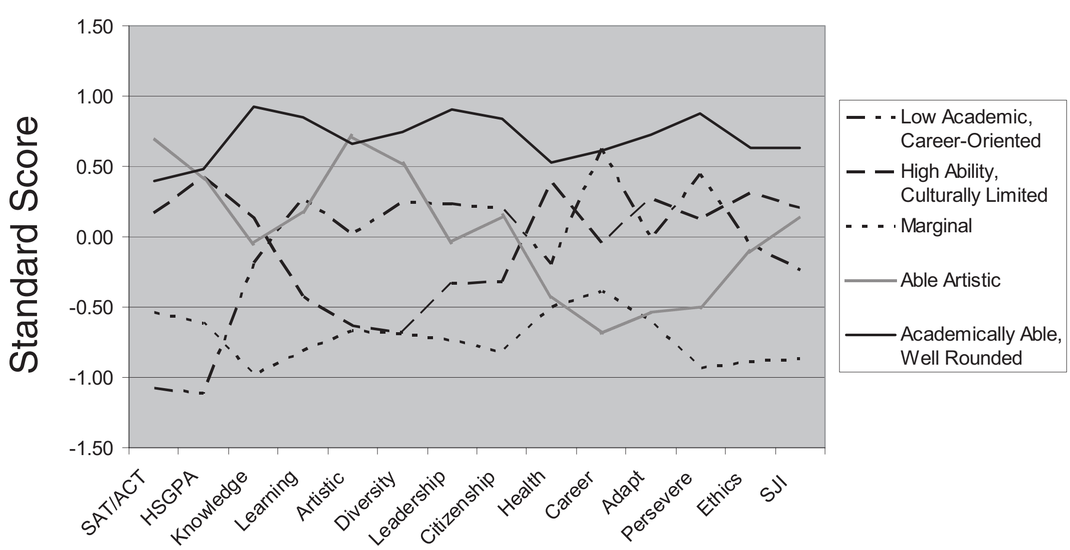

Figure 1. Profiles of biodata, ability, high school grade point average (HSGPA), and situational judgment inventory (SJI) scores of members of the five clusters. ACT = American College Test; Adapt = Adaptability; Persevere = Perseverance.

Table 5
Standardized Cluster Means on the 14 Variables Used to Form the Clusters

Variable	Low academic, career oriented	High ability, culturally limited	Marginal	Able artistic	Academically able, well rounded
Ability					
SAT/ACT	−1.08	0.17	−0.54	0.70	0.40
HSGPA	−1.11	0.42	−0.61	0.41	0.46
Biodata scale					
Knowledge	−0.19	0.13	−0.98	−0.05	0.92
Learning	0.27	−0.42	−0.81	0.18	0.85
Artistic	0.02	−0.63	−0.67	0.71	0.66
Diversity	0.25	−0.68	−0.69	0.51	0.75
Leadership	0.24	−0.33	−0.74	−0.04	0.91
Citizenship	0.20	−0.32	−0.82	0.14	0.84
Health	−0.20	0.39	−0.50	−0.42	0.53
Career	0.62	−0.05	−0.39	−0.69	0.61
Adaptability	−0.02	0.27	−0.60	−0.54	0.73
Perseverance	0.44	0.12	−0.93	−0.50	0.88
Ethics	−0.06	0.31	−0.89	−0.11	0.63
SJI					
SJI	−0.24	0.21	−0.87	0.14	0.63
n	348	581	521	473	566

Note. All variable means are on a standardized (*z*-score) metric. ACT = American College Test; HSGPA = high school grade point average; SJI = situational judgment inventory.

well-rounded students clearly rated themselves much higher than the other groups. Conversely, individuals in the high ability, culturally limited group rated their performance on the BARS as relatively low even though their 1st-year college GPA was among the highest of the five clusters. Self-reports of class absenteeism were highest among the marginal group and lowest among the low academic, career-oriented individuals. We interpret this to imply that the latter are likely motivated to do well, despite not being as well qualified academically. It is interesting that the able and artistic participants also reported that they missed a relatively large number of classes, but they were getting the highest grades. Two of the groups (the low academic, career-oriented group and the marginal group) were most likely to indicate that they had intentions to quit school. In general, these intentions were relatively low across groups, however, as the means are reflective of responses about midway between *strongly disagree* and *disagree* on our 5-point response scale.

Two groups (low academic, career oriented and academically able, well rounded) had lower means on the OCB measure than the other three groups. However, scores on this measure were reverse coded so that these means actually reflect a higher level of OCB activity for these two groups, consistent with their higher scores on the leadership and social responsibility biodata dimensions. Mean responses to the measure of overall satisfaction with college were highest for the academically able, well rounded group and lowest for the low academic, career-oriented group.

The data presented in Table 7 indicate that the major composition, gender, and, particularly, race of the five clusters were quite different. Chi-square tests of the association between cluster membership and all three demographic variables were statistically significant ($p < .01$). It is perhaps surprising that women were nearly twice as likely to fit the profile of the low academic, career-oriented category as were men. Men were slightly more likely to be members of the marginal group and the high ability, culturally limited group than were women.

Hispanic and African American students were four to five times as likely to be members of the low academic, career-oriented cluster as were Asian and Caucasian students. They were also somewhat more likely to be members of the marginal group and less likely to be identified as members of the able and artistic cluster than were Caucasians and, in particular, Asian American students. If we examine the profile of the low academic, career-oriented cluster in Figure 1 and Table 5, we see that the students in this cluster, whose members were often of Hispanic and African American background, were low in ability as measured by traditional academic indexes (SAT/ACT and HSGPA) but that they appeared highly motivated (i.e., their standing on career orientation and perseverance). Their relatively low scores on the SJI suggest that they also lacked knowledge of how to make good decisions regarding everyday events in college students' academic and social life. These low judgment scores are also indicative of the marginal group, in which a relatively large proportion of the African and Hispanic American students were clustered. In terms of numbers rather than percentages, however, both of these clusters also included more Caucasians than either African Americans or Hispanic Americans.

The proportions of students majoring in various areas in each cluster reinforce some stereotypes. Engineering majors were disproportionately represented in the high ability, culturally limited cluster. Those in the fine arts and humanities were heavily represented in the able and artistic group, and students in the natural sciences were most likely to be in the high ability, culturally limited group and the academically able, well-rounded group. Students who had not declared a major or whose major was in the *other* category were more likely to be in the marginal cluster. Students with an undeclared major were also unlikely to be in the low academic, career-oriented cluster and likely to be in the able and artistic cluster, which suggests that many students in this category are quite unsure of what they want to do and perhaps why they are in college, despite their potential to do well.

Table 6
Means and Standard Deviations of the Clusters on Attitudinal, Behavioral, and Performance Outcomes

Cluster	First-year college GPA			BARS self-rated performance			Class absenteeism			Intent to quit			OCBs			Satisfaction		
	M	*SD*	*d*	*M*	*SD*	*d*	*M*	*SD*	*d*	*M*	*SD*	*d*	*M*	*SD*	*d*	*M*	*SD*	*d*
Low academic, career oriented	2.22	0.83	1.62	3.67	0.57	0.55	1.48	0.75	0.67	1.58	0.85	0.01	2.64	0.53	0.69	3.89	1.08	0.40
High ability, culturally limited	3.24	0.70	0.28	3.51	0.40	0.91	1.69	1.03	0.46	1.39	0.66	0.30	3.04	0.60		4.09	0.73	0.15
Marginal	2.50	0.91	1.25	3.29	0.45	1.40	2.16	1.13		1.59	0.82		3.02	0.65	0.03	4.06	0.79	0.19
Able and artistic	3.45	0.72		3.58	0.41	0.76	1.92	1.07	0.24	1.36	0.58	0.34	2.96	0.58	0.14	4.05	0.75	0.20
Academically able, well rounded	3.39	0.70	0.08	3.92	0.49		1.60	0.95	0.55	1.35	0.66	0.36	2.67	0.56	0.64	4.21	0.84	

Note. *d* represents the standardized mean difference between the group with the highest average on an outcome and the average of the group with which it is compared. All overall mean differences were statistically significant at $p < .05$. *Satisfaction* refers to the overall student satisfaction with their university. *Class absenteeism* refers to the number of classes students reported they did not attend for excusable reasons (e.g., health). GPA = grade point average; BARS = behaviorally anchored rating scales; OCBs = organizational citizenship behaviors.

Using Cluster Membership to Predict Student Outcomes

To address our fourth hypothesis, concerning the incremental validity of cluster membership, we used hierarchical regression analysis. Each of the six outcomes was regressed on the 14 variables used to profile students in the first step of this analysis and then on a set of dichotomous variables that represented membership in the five clusters at the second step (see Table 5). The statistical significance and practical magnitude of the increment in multiple correlation were taken as indexes of the nonlinear prediction of student outcomes afforded by profiling and clustering students.

Linear prediction of all six outcomes was quite good. Adjusted multiple correlations for these outcomes were .72 for 1st-year college GPA, .49 for self-rated performance, .34 for class absenteeism, .18 for intent to quit college, .41 for OCB, and .29 for overall satisfaction. Correlations among the 14 predictors, cluster membership, and the six outcomes are presented in Table 4. As can be seen, SAT/ACT and HSGPA predicted 1st-year college GPA very well, but the biodata scales and SJI were shown to be predictively useful as well. For outcomes other than 1st-year college GPA, the biodata and SJI were more valid predictors than were SAT/ACT scores or HSGPA, consistent with our effort to use noncognitive measures that are valid predictors of student outcomes that go beyond 1st-year college GPA and have a less cognitive emphasis. Correlations of the outcomes with cluster membership are consistent with the mean differences displayed in Table 5.

The results of the hierarchical regressions, however, reveal no evidence that knowledge of cluster membership increased the prediction of the six outcomes beyond that afforded by simple linear regression based on the 14 predictors used to profile students. The change in squared multiple correlation associated with cluster membership for the six regressions was negligible, ranging from .001 for 1st-year college GPA to .005 for self-rated performance. In fact, none of the squared multiple correlation change values was statistically significant ($p > .05$). Given the sample size and the magnitude of the squared multiple correlation change statistics, we conclude that nonlinear prediction as represented by cluster membership does not enhance prediction of these six outcome variables beyond that of simple linear regression.

Discussion

Cluster analysis revealed five clusters of students who had empirically distinct profiles of ability, biodata, and SJI scores. These clusters reflected conceptually interpretable motivational and ability differences across the five groups of students. Certainly, we and others might be able to provide different labels for these groups, but we believe that our labels reasonably describe the defining characteristics of each of the groups. On all outcome dimensions, there were statistically significant and interpretable differences among the students in the five clusters. The demographic differences described above and presented in Table 6 were also significantly different across student clusters.

Implications of Profile Membership

We believe this information suggests different interventions with members of the various profiles that are most likely to aid

Table 7
Percentage of Gender, Race, and Majors in Each of the Five Clusters

Variable	Low academic, career oriented	High ability, culturally limited	Marginal	Able and artistic	Academically able, well rounded	*n*
			Gender			
Male	8.7	27.4	23.4	19.4	21.1	892
Female	16.9	21.1	19.5	18.8	23.7	1,596
			Race			
Hispanic	25.4	11.2	23.9	14.9	24.6	134
Asian	6.0	15.6	16.2	36.5	25.7	167
African American	33.8	16.1	28.4	7.4	14.4	585
Caucasian	5.4	29.4	18.5	21.4	25.3	1,441
			Major			
Undeclared	5.4	21.5	25.6	36.9	10.6	312
Business	18.1	24.9	23.6	10.2	23.3	382
Engineering	5.0	33.6	19.5	18.1	23.8	298
Fine Arts/Humanities	17.2	13.0	14.3	29.4	26.1	238
Social Sciences	17.0	16.3	20.2	21.4	25.1	406
Natural Sciences	10.5	28.9	13.1	16.8	30.8	429
Other	21.8	23.2	28.4	8.3	18.2	422

these students to adapt to college life and optimize their college experience. What follows are some general suggestions regarding interventions with members of the different groups; obviously, any one individual in these groups may benefit or require other help as well. Students who fall into the low academic, career-oriented group are highly motivated but lack essential academic skills. Interventions that provide additional academic skills are most likely to be successful with this group. Many of these individuals come from minority groups that may have less than ideal educational opportunities; remedial efforts directed to members of this group should increase retention of those individuals. Given these students' career orientation, systematic efforts to link their college work to career possibilities are likely to be motivating. Alternatively, if their dissatisfaction with university life continues, they might be best advised to attend technical programs or schools of interest to them in which they receive preparation that is more directly linked to a specific job or occupation.

Members of the high ability, culturally limited group scored above average on the SAT/ACT and HSGPA indexes but were low on the continuous learning, artistic appreciation, and appreciation for diversity dimensions. They appeared to be doing reasonably well academically, were engaged in university activities of a nonacademic nature (OCBs), and were relatively satisfied with their college experience. This group might achieve a more well-rounded experience, however, by seeking out a wider range of academic and cultural experiences. If universities are committed to developing the cultural and artistic awareness of students, as many university mission statements indicate they are, it may be necessary to motivate these students to seek greater exposure to arts and culture.

The marginal group averaged one half standard deviation below the mean on SAT/ACT and HSGPA scores and was uniformly low on the biodata scales and SJI measure. These students' low standing on all the profile variables as well as the outcome variables suggests that they were at the highest immediate risk for failure in college. Clearly, students who fall into this group are at high risk of failing as college students and could be flagged by college admissions and counseling staff as students most in need of immediate and wide-ranging interventions. In addition to the need for remedial work in basic academic areas, these students should receive vocational counseling. Many of these students have not declared a major; this fact, along with their low standing on most of the noncognitive indexes, suggests that they lack direction. Until they find a niche, they are not likely to do well academically.

The able and artistic cluster was characterized by the highest average SAT/ACT scores and relatively high HSGPA. On the biodata scales, they scored highest of all five groups on the artistic appreciation dimension and also relatively high on the diversity dimension. Members of this group rated their own performance relatively low, but they were doing well and expressed the greatest satisfaction with their college experience in general. Students who fit this subgroup appear to be highly likely to be successful in college with little or no special attention. If these individuals have any problems in college, they are likely to be the result of the students' own high standards for performance.

The academically able, well rounded group was the nearly exact opposite of the group we labeled marginal; the group was defined by relatively high SAT/ACT and HSGPA scores and was superior to the other four groups on most of the biodata and SJI measures. In terms of demographics, these students had clear educational goals and were performing very well on all the outcome variables we examined. Students of this group are least likely to require developmental interventions, although their continued progress could be monitored for any performance declines. Because of their high ability, leadership, and helpfulness, members of this group might make ideal peer mentors and may be identified early in their college years to support students in other clusters.

Our cluster and profile results confirm the utility of considering a broad range of student characteristics across motivational, affective, and cognitive domains to understand student behavior and performance, as do the results of Ackerman and Beier (2003), which complement ours. If constructs from one or more of these domains are neglected, colleges and universities are not likely to have as complete an understanding of students' behavior or to be as effective in providing career guidance. In our clusters, we identified some student groups that were academically qualified but not well motivated, or vice versa. Interventions to improve the performance of these different groups should be adapted accordingly. Cluster information could also lead to better high school or precollege counseling for some individuals.

Prediction on the Basis of Cluster Membership

Although there were meaningful differences across the complement of 14 variables that defined the clusters, our hierarchical regression analyses indicated that knowledge of the student cluster membership did not add to the prediction of any of the six outcomes beyond the simple linear combination of the profile variables. However, knowledge of students' levels on the various measures that were used to profile students and define their cluster membership did yield a better understanding of the configurations of ability, motivation, and interests that relate to various outcomes. The cluster profiles also provide potentially useful information on which to introduce interventions (e.g., particularly with the low academic, career-oriented group and the marginal group), but if one is only interested in the best prediction of student outcomes, optimally weighted linear combinations seem to be adequate, consistent with previous literature in this area (e.g., Dawes & Corrigan, 1974).

The fact that cluster membership did not add to the multiple regressions raises the question of the value of the profiles and clustering of students that is the major focus of the article. It is clear that such clustering does not have predictive value above a linear regression. However, regression is compensatory, and students can have the same predicted value for some outcome in multiple ways, especially when the predictor set includes a relatively large number of variables, as was the case in the current research. Different score profiles can provide the same predicted outcome and the same multiple correlation across the students within different clusters. What clustering provides, then, is an understanding of the different sets of motivational, experience, and ability characteristics that result in predicted student outcomes—even when the predicted student outcome is the same. Although the regression results certainly suggest that some variables are more highly associated with maximum levels of performance than others, the profile data suggest that there are different combinations of predictors that can and do produce desired (or undesired) outcomes. These data provide greater insight into student potential and offer the possibility for a wider array of interventions that can be targeted to students' specific deficiencies.

Some previous studies have reported curvilinear relationships between noncognitive variables and various performance measures (e.g., LaHuis, Martin, & Avis, 2005; Robie & Ryan, 1999) as well as interactive effects of personality constructs on performance (e.g., Witt, Burke, Barrick, & Mount, 2002). These are certainly different forms of nonlinear effects than those represented by the profiles tested above. It is possible that other tests of nonlinearity of the relationships between predictors and outcomes in our study would have yielded more support of such relationships.

In our introduction, we noted the earlier large gender differences found in the biodata work of Owens and Schoenfeldt (1979). We did find some gender differences in our clusters, but these differences were relatively minor compared with those of Owens and Schoenfeldt. In one instance, that of the greater proportion of women in the low academic, career-oriented group, the gender differences are not consistent with what one might have expected 30 years ago, when Owens and Schoenfeldt's data were collected. A larger group of women in this cluster means that they are more career oriented than are men.

Limitations

Perhaps the most significant limitation of the study is the fact that responses to our end-of-year follow-up were only about 33% of the original group. This did not affect the profile and cluster analyses nor the analyses involving 1st-year college GPA, as the profile data come from the original data collection and we obtained GPA data on all students who completed the 1st year. However, it might have had some impact on the analyses involving the other five outcomes because of an overall range restriction effect and differential range restriction effects across the five clusters. As mentioned previously, those who did respond to the end-of-year survey clearly were more able students, with large effect sizes on the HSGPA and SAT/ACT measures.

Also, our original sample was not a random sample of college students as a whole or even of the campuses on which data were collected. With respect to demographics, women were overrepresented, as were African Americans. This might have had an influence on the nature of the subgroup composition of our clusters. For example, a good portion of our Hispanic group came from one institution. If that institution recruits a relatively homogeneous student body with certain ability and background characteristics, students from that university likely ended up in a single cluster. A more broadly representative Hispanic group might be distributed across several clusters. However, in terms of the applicants admitted at the 10 universities, the students in our sample were typical in terms of ability and age. They were slightly over 18 years of age, on average; their SAT Verbal and Math scores averaged 565 and 581, respectively (respective standard deviations were 112 and 121); and their various ACT scores averaged between 24.50 and 25.65, with standard deviations ranging from 4.74 to 5.71. Cooperating universities ranged from highly selective institutions to large state institutions that serve a student body with more diverse abilities. However, as we have stated several times, the fact that ethnic status was confounded with university and return rates requires caution with respect to interpretation of the correlates of these variables, particularly the ability measures that also correlated with ethnic status.

Summary

Our analyses indicate that students can be clustered meaningfully via a combination of biodata, ability, and judgment measures. All three of these types of measures related to predicted important behavioral and affective outcomes. Moreover, analyses of student subgroup performance levels indicated that students earned different grades in college; contributed differentially in nonacademic ways; and differed in satisfaction levels, class attendance, and stated intention to leave college. However, there is little evidence of nonlinear prediction of student performance, at least as reflected in cluster membership. Results have implications for practice in high school counseling settings, in college admissions, and in identification of college students who are at high risk or might otherwise profit from specific interventions aimed at improving success in college.

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