Development of a Classification System for Engineering Student Characteristics Affecting College Enrollment and Retention

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BACKGROUND
In engineering education, a considerable amount of research effort has been dedicated to study the impacts of student characteristics on their college enrollment, major selection, and college retention. However, there is no standardized categorical classification system of engineering student characteristics in the current literature. Different researchers tend to focus on specific characteristics within the scope of their research interests. This study provides a comprehensive review and analysis of the existing research on the measurement of the characteristics of engineering students.

PURPOSE
The study addressed the three questions: (1) what engineering student characteristics have been measured; (2) how do engineering student characteristics impact their educational outcomes; and (3) what measurement and analysis methods have been applied in current studies? A standardized classification system for engineering student characteristics involving external, cognitive, affective, and demographic categories is also proposed.

SCOPE/METHOD
The study focused on engineering education. Representative research regarding common characteristics of students from majors of science, technology, engineering, and mathematics were also included. The review covers major academic journals, research books, conference proceedings, and government reports in the areas of science and engineering education for the past two decades.

CONCLUSIONS
The review analysis indicated that students with certain characteristics are more likely to choose engineering as a profession and that those characteristics are either correlated or causally related with one another. However, many research conclusions based on basic statistical analyses fail to model the interaction effects. More advanced measurement techniques are needed that can model the characteristics interactively and concurrently in a complete framework.

KEYWORDS
measurement, retention and enrollment, student characteristics

I. INTRODUCTION
Advancement in science and technology has been and will continue to be the engine for economic growth and national security in the United States. Maintaining this advancement relies on an adequate and well-educated workforce in science and engineering. However, analyses of the current situation indicate that the United States is facing critical challenges in the education of science and engineering. A recent ACT Policy Report, based upon the data obtained from high school students taking the ACT, shows that the number of students planning on majoring in engineering has been decreasing since 1991 (Noeth, Cruce, and Harmston, 2003). A National Science Foundation (NSF) report also indicates that the number of students enrolling in universities and colleges as engineering majors has been declining for the past two decades, whereas the U.S. market demand for engineering graduates has been on the rise during the same period (National Science Board (NSB), 2004). While attracting students to engineering schools is challenging, retaining these students raises another challenge. Many research results indicate that only about 60 percent or less than half of students who originally enter engineering majors actually graduate with an engineering degree (Astin and Astin, 1992; Besterfield-Sacre, Atman, and Shuman, 1997; French, Immekus, and Oakes, 2005; NSB, 2007). As the number of engineering graduates decline, recruiting employees with the necessary engineering skills has not only become one of the most pressing challenges to the U.S. industry (KPMG International, 2006), but also made the U.S. government and academia become more dependent on the foreign engineering workforce (NSB, 2003). Since “preparation of the science and engineering workforce is a vital arena for national competitiveness” (NSB, 2004), it is imperative that the U.S. government should lead an aggressive effort to better prepare the national engineering workforce (NSB, 2003).

Better preparation for the engineering workforce calls for a reform of engineering education. As a National Academy report emphasizes (Board on Engineering Education, National Research Council, 1995), this reform demands actions in engineering colleges including self-assessment and self-evaluation of educational outcomes, balancing faculty incentive systems, improving teaching methods and practices, reforming curriculum, and expanding beneficial interactions and outreach. The successful reform of engineering education at the college level also relies on a rigorous introductory engineering education at the K-12 level (Iversen, Kalyandurg, and Lapeyrouse, 2007). The goal of this introduction is to produce more K-12 students with adequate engineering characteristics. These students would be likely to choose engineering as their college major, be more persistent in completing their education in engineering,
and would likely remain in a professional engineering career after they graduate.

Among the various challenges in the reform of engineering education, the measurement of characteristics of engineering students remains a difficult issue. A reliable measurement is critical in identifying relevant student characteristics that are closely associated with successful educational outcomes. One task of this paper is to present a comprehensive review and analysis of the existing research on the measurement of characteristics of engineering students. The other task is to propose a generalizable classification system for engineering student characteristics based on the literature survey result. The scope of this study is centered around, but not limited to, the framework of engineering education, as students in other fields such as science, technology, and mathematics share many common characteristics with engineering students. Representative research regarding common characteristics of students from majors of science, technology, engineering, and mathematics (STEM) has been included in the discussion. This literature review covers major academic journals, research books, conference proceedings, and government reports in the areas of science and engineering education for the past two decades.

The rest of the paper is organized as follows: Section II reviews the current research effort on the measurement of characteristics of engineering students. The review topics addressed include identifying student characteristics that have been measured in the literature, analyzing research questions that reflect the impact of student characteristics on educational outcomes, and summarizing measurement and analysis methods that have been developed. Based on the analyses, a generalizable classification structure that categorizes engineering student characteristics is proposed. Section III points out the limitations in current studies and also provides suggestions for future research directions in this area. A structural model indicating correlation/causation among characteristics and educational outcomes is proposed. The final section concludes this literature review by emphasizing the significant implication of developing reliable measurement models in the reform of engineering education.

II. CURRENT ACHIEVEMENT IN THE MEASUREMENT OF CHARACTERISTICS OF ENGINEERING STUDENTS

The strong positive correlations between student characteristics and their educational performance have been studied by many researchers (Astin, 1993; Bean, 1983, 1986; Fleming and Malone, 1983; Tinto, 1993). Particularly in engineering education research, a considerable amount of effort has been placed on identifying student characteristics that have an impact on engineering educational outcomes (defined as recruitment and retention in engineering colleges). However, there exists no standardized categorical classification system of engineering student characteristics in the current literature. Different researchers have examined different characteristics of engineering students within their research interests or the limited availability of data resources. For example, in investigating how student characteristics affect college attrition, Tinto (1993) proposed a four-cluster model which included student characteristics such as adjustment, difficulty, incongruence, and isolation. Bean (1983, 1986) suggested a six-cluster model which included student characteristics like background, academic integration, social integration, environmental pull, attitudes, and GPA. Later Moller-Wong and Eide (1997) classified student characteristics into five categories including background, organization, academic and social integration, attitude and motivation, and institutional fit. After examining all engineering student characteristics measured in the existing literature, the authors believe that three broad characteristic categories, namely external, internal, and demographic, have emerged. Based on this observation, the authors have proposed in this paper a categorical classification structure for a systematic analysis of the characteristics of engineering students. This classification system, as shown in Figure 1, provides the organizational context for the literature review in the remainder of this paper.

A. Characteristics Measured

The first category in Figure 1 measures external characteristics of engineering students. Examples of external characteristics include institutional environment, curriculum requirement, peer or adult influences, and average income of engineers. These characteristics emphasize engineering-related properties of the external environment. An individual student is not able to change these environmental characteristics through personal endeavor. For example, a student might be able to improve his/her GPA through hard work; however, if he or she dislikes certain core courses in the curriculum, or feels the institution is too competitive, the student cannot alter the program. These characteristics may either encourage or discourage students to major in and remain in engineering.

The second category measures internal characteristics of engineering students. In this study, only internal characteristics that exert direct impact to the enrollment and retention results in engineering schools are considered. Since education is an aggregate of both intellectual (cognitive) and non-intellectual (affective) processes, it makes sense to further classify this category into two sub-categories: cognitive characteristics and affective characteristics. The cognitive characteristics, such as SAT scores, GPA, and learning style, represent the academic abilities of a student in an engineering program and directly affect that student’s academic standing. The affective characteristics, such as motivation to success, impression of engineering, and self-confidence in engineering knowledge, directly influence the attitude of a student toward the engineering education. Upon entering the engineering schools, students bring with them different academic abilities as well as various affective attributes regarding engineering study. Evolution of the characteristics in these two categories during their stay in engineering will eventually determine their success or failure in attaining an engineering degree.

The third category measures the demographic characteristics of engineering students. The commonly studied characteristics in this category are age, gender, race, family socioeconomic status, and school location. Some of these demographic characteristics can actually fit into either internal or external characteristic categories defined above. For example, if a student is from a region where engineers have above-average incomes, “location” thus becomes an external environmental characteristic that might attract the student to engineering career. Meanwhile, if a student is from an ethnic background where engineering is deemed a respectable profession, “ethnicity” is thus an external characteristic that might help the student to develop a positive attitude toward engineering. However, conventionally these characteristics are considered
under the demographic category. Accordingly, this convention is adopted in this paper.

B. Research Questions Answered

The current literature has addressed many substantial research questions regarding how engineering student characteristics affect their educational outcomes. To analyze these research questions systematically, the discussion in this section is presented in the order of external characteristics, cognitive characteristics, affective characteristics, and demographic characteristics.

1) External characteristics: External characteristics consist of two general categories, namely community characteristics and college characteristics. Community influence on students is evident through examples like peer influence (PI) and adult influence (AI). College environment determines characteristics such as course requirements (CR), cultural atmosphere of institution (CA), and faculty-student interaction. Figure 2 illustrates the classification structure for external characteristics (the meaning of the dashed line will be explained in Section III). The impact of these characteristics on engineering education outcomes are detailed below.

   a) Peer Influence: Peer influence is found to be the strongest and most consistent external characteristic during student development. Students are influenced by their peers in terms of major choice, college selection, as well as retention decision in the general areas of higher education (Bean, 1983, 1986). In the area of engineering education, it is found that the higher the ratio of a student's high school peers majoring in engineering, the more likely this student will end up choosing an engineering major (Astin and Astin, 1992; Shuman et al., 1999). High school peer influence is also a good predictor for successful graduation with a STEM degree (Leslie, McClure, and Oaxaca, 1998). At the university level, positive peer influence comes from opportunities like matching new students with peers acting as cultural mentors for engineering (Shuman et al., 1999), participating in honors programs, tutoring other students, and living on campus with other peers (Leslie,
McClure, and Oaxaca, 1998). Conversely, a lack of student community on campus has negative impact on student retention (Buyer and Connolly, 2006).

b) Adult Influence: Adult influence affects students significantly in their major selection and career choice (Astin and Astin, 1992; Shuman et al., 1999). Parental approval usually exerts a direct effect on a student’s institutional choice and dropout decision (Bean, 1983, 1986). In particular, having an engineer father often greatly increases a student’s chance of selecting an engineering major (Astin and Astin, 1992). On the other hand, research also shows that opinions of college educators have so far played a lesser role than they should. As Shuman et al. (1999) pointed out, “very few students who left engineering actually sought out career counseling services provided by universities.” Engineering schools should encourage students who consider dropping out of college or transferring to other majors to actively seek assistance from these services.

c) Curriculum Requirements: Research has indicated that most existing engineering curricula are overloaded, difficult, and lacking relevance to the current engineering practice (Besterfield-Sacre, Atman, and Shuman, 1998; Ohland et al., 2004a, 2004b; Froyd and Ohland, 2005; Heywood, 2005). This is arguably one of the most significant external characteristics responsible for the high attrition rate in engineering schools.

Heywood (2005) points out that the overwhelming content in engineering curriculum places too much stress on students. Under the stress of passing various difficult exams, many engineering students are forced to take a routine and mechanical approach to studying. Gradually, they may lose their interest in learning. Among all challenging courses, mathematics seems to be the most difficult and hence the largest stumbling block causing dropouts in the freshman year in engineering schools. Brannan and Wankat (2005) revealed in their survey of first year engineering programs that 73.4 percent of the entering engineering students are weak in mathematics preparation. If mathematics prerequisites can be relaxed, it can help to improve student grades in the subsequent semester, and therefore reduce the dropout rate (Ohland et al., 2004b). Providing pre-sessional mathematics and engineering course for students with weak mathematical background can also help to retain them in engineering (Bamforth et al., 2005).

A lack of relevance to the current engineering practice is another common problem in many engineering curricula. Most engineering curricula cover several pure math and science courses in the first year. Many freshman engineering students are thus led to the perception that engineering is sheer science. They fail to understand the relevance of these science courses to their initial needs and interests in engineering (Besterfield-Sacre, Atman, and Shuman, 1998).

Many engineering educators have proposed the idea of “integrated curricula” where math and science courses are instructed together with engineering or entrepreneurship components (Dabbagh and Menascé, 2006; Froyd and Ohland, 2005; Ohland et al., 2004a; Schneck, 2001). They have found that new curricula emphasizing fundamental relationships among subject areas can improve student learning satisfaction significantly. Curricula that emphasize problem solving, technical writing, teamwork, entrepreneurship, and business management skills can also help. That is, students will more likely overcome the barriers associated with relevance, obtain higher GPAs, and achieve higher retention rates. Specifically, it can improve the retention for white women and underrepresented minorities (Besterfield-Sacre, Atman, and Shuman, 1998; Dym et al., 2005; Dabbagh and Menascé, 2006; Froyd and Ohland, 2005; Ohland et al., 2004a).

d) Cultural Atmosphere of Institution: Many factors, such as campus social support, staff support, research involvement, and interaction with faculty determine the cultural atmosphere of a college environment. This cultural atmosphere plays an important role in student retention (Astin and Astin, 1992; Astin, 1993; Buyer and Connolly, 2006; Shuman et al., 1999).

Among all these factors, faculty is a critical juncture in student retention and performance in engineering programs (Vogt, 2008). Student-faculty interaction is found to have a significant correlation with college GPA, college retention, graduating with honors, and enrollment in graduate school (French, Immekus, and Oakes, 2003). In addition to retention and academic success, close student-faculty interaction can strongly improve students’ self-efficacy, effort, and critical thinking, and enhance student gains in engineering design and professional skills (Bjorklund, Parente, and Sathianathan, 2004). Interaction opportunities also enhance student satisfaction with engineering courses, faculty instruction, and the overall institutional experience. On the other hand, if faculty are less involved in teaching and advising students and students receive little support and encouragement from a faculty role model, it will lead to a significant negative effect on students’ satisfaction. In this regard, large institutions with less student-faculty interaction tend to have more negative effects on student persistence (Astin and Astin, 1992). Effective student-faculty interaction can take on many forms (Kuh and Hu, 2001). Classroom interaction includes discussions on course-related topics and offering academic advice. Non-classroom interaction includes conversations on non-academic related topics, faculty-supervised internships, and research opportunities. Bjorklund, Parente, and Sathianathan, (2004) recommended promoting student-faculty communication through integrating design projects and collaborative learning opportunities. Astin and Astin (1992) suggested interaction opportunities such as assisting faculty in teaching courses and getting involved in faculty research projects.

As Tinto (1993) has summarized, the academic and social characteristics of an institution can help to shape the student commitment to an educational goal as well as the commitment to remain with that institution. Engineering schools should promote a more interactive and supportive academic and social environment so that their students will develop a strong sense of belonging.

2) Cognitive Characteristics: Cognitive ability is generally considered as the most important factor in determining student educational performance. In engineering education, the impact of cognitive factors on college enrollment and academic success has been widely studied. The most well studied cognitive characteristic is academic ability (AA). Other frequently discussed characteristics include self-efficacy (SE) and learning attributes (LA). The left part of Figure 3 illustrates the classification structure for these cognitive characteristics. The impact of these characteristics is discussed below.

a) Academic Ability: Academic ability in mathematics and science is strongly correlated with admission and retention in engineering schools. At the high school level, quantitative and analytical preparations are strong indicators of the initial interest in engineering majors and careers (Astin and Astin, 1992). Academically well-prepared high school students are more likely
to be successfully recruited into engineering majors. After they join college, the entry level of quantitative and analytical competency of students is also the strongest and most consistent predictor of persistence in engineering programs (Astin and Astin, 1992; Moller-Wong and Eide, 1997; Zhang et al., 2004; Nicholls et al., 2007). By measuring two cohorts of engineering students in a large U.S. Midwestern university, French, Immekus, and Oakes, (2003, 2005) found that the SAT mathematics and verbal scores, as well as high school ranking, are significant in predicting college GPA. College GPA is subsequently a significant predictor of persistence in engineering. Consistent with French’s finding on the relation between GPA and persistence, Shuman et al., (1999) has shown that about one-fourth of the freshmen and one-third of the upper-class students have to drop out of engineering due to poor GPA. Mendez et al., (2008) have provided more information on academic performance other than GPA. Their findings indicate that cumulative GPA is most highly associated with STEM persistence. The SAT quantitative exam scores and the number of STEM courses taken in the freshmen year are positively associated with persistence, while the total hours enrolled in freshmen year and SAT verbal exam scores exhibit a negative association with persistence.

Not all researchers agree that academic ability is the most significant predictor for retention. Some argue that there is little difference in academic ability between students who persist and who do not. For example, Tinto (1993) shows that most students who drop out of college actually withdraw voluntarily rather than being forced due to failing to meet academic requirements. The measurement study on a high performing population conducted by Seymour and Hewitt (1997) also shows that the average GPA of women who leave STEM majors is actually higher than the average GPA of men who stay. Their finding suggests that, in high performing engineering schools, many of those who leave actually possess the necessary academic competence to complete STEM majors. Some research results suggest that superior academic ability sometimes becomes a negative predictor for retention. As Moller-Wong and Eide (1997) have found, very high composite scores and a greater than average number of semesters of high school English and arts are in fact significant predictors for attrition in engineering. Researchers in this group believe that some students leave engineering because of non-academic reasons such as a lack of motivation or lost of interests (Bernold, Spurlin, and Anson, 2007; Besterfield-Sacre, Atman, and Shuman, 1997, 1998; Levin and Wykoff, 1988). More discussion about the impact of non-academic characteristics on retention in engineering will be detailed in the succeeding section.

b) Self-Efficacy: Based on Bandura’s definition (1986, 1997), self-efficacy is the perception that individuals hold about their abilities in performing specific tasks necessary to achieve a desired outcome, while self-confidence is an attitude which allows individuals to have positive yet realistic views of themselves and their situations. Following this definition, self-efficacy is thus a cognitive associative attribute while self-confidence is an attitude-associated attribute. The discussion of self-efficacy is thus presented in this section, and the impact of self-confidence will be discussed later in the section about affective characteristics.

The impact of self-efficacy on recruitment and retention in engineering majors is substantial. At the high school level, self-ratings of mathematical ability, computer skills, and other academic ability are found to be good indicators for predicting STEM enrollment, on the other hand, self-assessment of needing remedial lessons in mathematics is an efficient prognosis for non-STEM orientation (Astin and Astin, 1992; Nicholls et al., 2007). Hutchison et al. (2006) found that motivation, understanding of the learning material, and computing abilities are the most influential factors in boosting engineering student self-efficacy. They have also indicated that factors such as teamwork skills, availability of help and ability to access the help, ability to complete assignments, problem-solving skills, interest and satisfaction in learning, and grades are strongly correlated with positive self-efficacy. Engineering educators need to spend more effort in these areas in order to boost student self-efficacy.

Research studies have recognized the statistically significant differences in self-efficacy in studying engineering exhibited among different gender and ethnic groups. More discussion will be detailed in the demographic section.

c) Learning Attributes: Student learning attributes are significantly correlated with academic performances and attitudes toward learning (Bernold et al., 2000, 2007; Felder, Felder, and Dietz, 2002; Felder and Brent, 2005). Among many learning attributes, learning style is a relatively stable indicator of “how learners perceive, interact with, and respond to the learning environment” (Keefe, 1979). Students with different learning styles tend to respond differently to different teaching approaches (Felder, Felder, and Dietz, 2002). According to Jung’s Theory of Psychological Types (Lawrence, 1993), these styles of learning exist within a system of dichotomies. For example, extraverts prefer settings that provide activity and teamwork, while introverts prefer settings involving internal processing. Sensors prefer concrete learning experience emphasizing memorization of facts, while intuitors prefer abstract instruction emphasizing conceptual understanding. Feelers prefer that instructors show appreciation of their efforts, while thinkers like logically organized instruction. Perceivers like to have flexibility in their assignments, while judges like clearly defined assignments. Given the unlimited variety of job descriptions in engineering, students with all these different learning styles have the potential to succeed as engineers. However, with the traditionally predominant mode of lecture-based instruction in engineering education where students attempt to absorb the lecture content and try to reproduce it in examinations, it is found that introverts, intuitors, thinkers, and judges generally outperform their extraverted, sensing, feeling, and perceiving counterparts (Bernold et al., 2000, 2007; Felder and Silverman, 1988; Felder, Felder, and Dietz, 2002). The
extraverts, sensors, feelers, and perceivers are usually disadvan-
taged in this one-size-fits-all teaching environment and appear
to have higher attrition rates than their counterparts (Felder
and Silverman, 1988; Zywno and Waalen, 2002; Felder and
Brent, 2005). Many engineering educators have suggested that
implementing an experimental instructional approach and
emphasizing active group exercises and cooperative learning
can help the historically disadvantaged learning types in engi-
neering (Wankat and Oreovicz, 1993; Felder, Felder, and
Dietz, 1998). Through their research, Felder and Silverman
(1988) have shown that the graduation rate in engineering of
the cohort taught by experimental instructional approach has
been significantly increased as compared to the traditionally-
taught comparison group.

Apart from having different learning styles, students also adopt
different learning approaches. Entwistle (2000) defined three dif-
ferent approaches to learning: deep approach, surface approach, and
strategic approach. Students using the deep approach try to under-
stand the course material rather than simply memorize it. Those
taking the surface approach tend to memorize facts but do not fit
the course material into a larger context. Students adopting the
strategic approach apply whatever necessary learning method to
achieve the highest possible grade. Engineering students using the
deep learning approach are likely to achieve academic success, while
students taking the surface approach are likely to exhibit academic
failure (Meyer, Parsons, and Dunne, 1990). The choice of
approaches a student might take in studying a particular subject
depends on many factors. Some factors are intrinsic to the student,
while others are determined by the instructional environment.
Problem-based instructional approach can create an inductive
instructional environment, making subject matter relevant to the
background knowledge, and emphasizing conceptual understand-
ing (Dochy et al., 2003). Implementing this instructional approach
can motivate students to take the deep learning approach and help
them to obtain better academic achievement.

Study skill is another important learning attribute strongly cor-
related with academic success. For example, time management
skills are found to be positively correlated with GPA (Bernold et al.,
2007). Students who can manage their time efficiently and use their
skills effectively are usually the ones who are more motivated to
learn. Motivation is classified as an affective characteristic in this
paper. Its effect on educational outcomes will be discussed in the
following section.

3) Affective Characteristics: Educational outcome is a result of the
combination of both cognitive and non-cognitive processes. Mea-
surement of cognitive characteristics like intellectual abilities and
knowledge skills have traditionally been involved in educational
practices. The impact of affective (non-cognitive) characteristics on
educational outcomes has received more recognition in engineering
education since the publication of the first book on emotional intel-
ligence by Goleman (1995). Measurement results obtained in the
affective characteristic category have indicated that characteristics
such as attitude (AT), self-confidence (SC), early commitment
(EC), and motivation (MT) are the significant factors determining
students’ affective opinion toward engineering education. The clas-
sification structure of the characteristics in this category is shown in
the central part of Figure 3.

a) Attitude: A student will encounter many different learning ex-
periences during the entire educational process. These experiences
will affect the student’s attitudes toward learning. Attitude is a
strong indicator in explaining the variations of GPA in engineering
students (Levin and Wyckoff, 1988) and predicting retention in en-
geineering schools (Woods and Crowe, 1984). Students come to en-
geineering schools with various expectations. Some may expect to
gain skills and knowledge in engineering, while others may prepare
for graduate study. If the real experiences in engineering schools do
not match their initial expectations, negative attitudes may emerge
and eventually attrition may occur (Astin and Astin, 1992; Shuman
et al., 1999). For example, if students have formed a negative im-
pression about engineering education after entering into college,
they may drop out of the engineering major (Besterfield-Sacre,
Atman, and Shuman, 1997, 1998; Seymour and Hewitt; 1997). If
students have less enjoyment in studying mathematics and science
or dislike the teaching methods in engineering, they also appear to
have a high attrition rates (Besterfield-Sacre, Atman, and Shuman,
1997, 1998; Bonous-Hammarch, 2000). On the other hand, if stu-
dents hold the strong belief that an engineering degree will enhance
career security, they may likely stay in engineering even though they
may have a negative view about certain aspects of engineering edu-
cation (Burtner, 2005).

As Besterfield-Sacre et al. (1998) have summarized, the set of
perceived attitudes about engineering that students bring with
them into the first year of college will potentially affect their per-
ceptions of engineering, motivation to learn, self-confidence,
competency, and performance. It will eventually affect their re-
tention decision. In the long run, the attitudes developed during
college years will affect their awareness of the contemporary
engineering issues, understanding of the impact of technology
on the advancement of society, and engagement in life long
learning. Therefore, helping students develop a positive attitude
toward engineering before and during their stay in college is an
imperative task for engineering educators.

b) Self-confidence: Self-confidence primarily refers to having a
positive and realistic perception of oneself. Student self-confi-
dence in engineering is highly correlated with the retention
rate in engineering schools. Student self-confidence in solving
problems in engineering and science is a good predictor for
successfully graduating with a STEM degree (Leslie, Mc-
Clure, and Oaxaca, 1998). Self-confidence in college-level
math and science ability is another significant predictor for
both short-term and long-term persistence in engineering
(Burtner, 2005). If students have low confidence in their engi-
neering skills/knowledge and poor perceptions of their acade-
ic abilities, they are likely to switch from engineering to
other majors, despite their commendable academic standing
students with low self-confidence can be identified in time,
school counseling services can help them to change their self-
perception before attrition occurs.

c) Early Commitment: Another important affective indicator for
student persistence in engineering is the initial engineering career
aspiration (Astin and Astin, 1992, Shuman et al., 1999). Students
who are unsure about whether they can complete the engineering
program upon entering into engineering schools are likely to switch
to other majors. As Besterfield-Sacre et al. (1997, 1998) concluded,
students who left engineering in good academic standing often
started their undergraduate study with less commitment to
engineering than those who remained in the program. On the other
hand, the persistent engineering students are usually those who initially focused on engineering, worked hard academically, and had very few outside diversions. Since engineering majors usually attract almost no newcomers and mainly retain the old adherents at the later stage along the engineering educational pipeline (Hilton and Lee, 1988; Ohland et al., 2008), in order to maintain a good graduation rate, it is important to encourage more students to commit to engineering majors in the early stage when curricular options are still available and mobility is not discouraged.

4) **Demographic Characteristics:** Demographics refer to selected population characteristics such as age, gender, ethnicity, socioeconomic status, home background, school type, and religion. Student learning performance has a strong correlation with the characteristics of the population they belong to. The classification structure for demographic characteristics is shown in Figure 4. The solid lines with double arrows indicate interactions between characteristics within this category. The dashed lines with double arrows refer to interactions between characteristics from different categories. The meaning of the dashed lines with single arrows will be explained in the section regarding the future improvements in measurement content.

Among the long list of the characteristics in the demographic category, impact of gender and ethnicity on engineering educational outcomes has received the most attention in the current literature. Other impacts on socioeconomic status (SES) and home and school background (HSB) have also widely been addressed.

**a) Gender:** A large number of research studies have addressed gender issues in STEM education for the past two decades. Several general conclusions can be drawn from these research findings. The first conclusion is that female students have always been much less likely to select STEM majors. Data by Hilton and Lee (1988) showed that nearly four times as many male students than female students aspired to do mathematics, science, and engineering (MSE) majors in 1972. They found that this discrepancy held through enrollment in graduate school. The same data resource showed that the proportion of female engineering majors doubled in 1982, but males still out-numbered females by two to one. By 1996, females received 55 percent of all bachelor's degrees. However, only 18 percent of those received engineering degrees (Hill, 1999). In more recent years, the number of female engineering students has decreased, along with a decrease in the overall number of engineering students. In 2002, only 9,345 females planned to major in engineering, representing a twelve-year low of 18 percent (Noeth, Cauce, and Harmston, 2003). Secondly, although females represent a smaller percentage of all engineering majors, they are among the better-prepared students and do not fall behind academically (NCES, 2000). As Noeth et al. (2003) showed in their ACT policy report, a greater percentage of freshmen female engineering students were certain of their choice of majors, had higher GPAs and ACT scores, and took more advanced mathematics and science courses. Females' ratings on study skills are also higher than their male counterparts (Besterfield–Sacre et al., 2001).

The third conclusion about females' persistence rate in engineering has prompted disagreement. Some findings suggest that females do better than males in program switching and degree completion (NCES, 2000; Zhang et al., 2004). For example, Hilton and Lee (1988) reported that females had a higher persistence rate in MSE majors. Meanwhile, males had a 29 percent loss rate and females had 14 percent. However, other results indicate that females are slightly more likely to defect from engineering majors and careers across all ethnic groups (Astin and Astin, 1992; Felder et al., 1995; Smyth and McArdle, 2004), with female African-American, American-Indian, and Hispanic students exhibiting the largest dropout rate in STEM majors (Bonous–Hammarr, 2000).

Many external influences are responsible for the underrepresentation of females in science and engineering. From the community perspective, many girls get messages from their families and schools that boys are inherently superior in mathematical reasoning and visual–spatial abilities (Benbow and Stanley, 1983). This may explain why a gender gap in mathematics is small and inconsistent among younger students but becomes more evident among older students (Corbett, Hill, and Rose, 2008). The stereotypical perception that girls lack ability to do well in science and engineering has discouraged them from even thinking about entering STEM fields (Bar–Haim and Wilkes, 1989; Yaşar et al., 2006). Furthermore, the general impression that engineering is a “boys’ club” where...
guys tinker with machines disconnects female students from seeing their own potential relevance to society through engineering (Adelman, 1998; Baker et al., 2007). From the college environmental perspective, the absence of female role models in engineering colleges is also a barrier faced by female students (NSF, 2005; Murphy et al., 2007). Furthermore, although engineering has significant societal impact and communication is often more important for career success than technical knowledge, these ideas are not well delivered in the traditional engineering curricula. The relatively impersonal nature of the current engineering curricula is also likely a cause of women staying away from engineering (Einaron and Santiago, 1996; Felder, Felder, and Dietz, 2002). As a result of all these negative external influences, many female students no longer consider engineering as a suitable major and career choice, because they are led to believe that it is neither compatible with their interests and abilities nor socially relevant to their gender role (Adelman, 1998; Baker, 2007; Besterfield-Sacre et al., 1997, 2001; Meinholdt and Murray, 1999; Seymour and Hewitt, 1997).

The commonly observed differences in cognitive and affective characteristics between males and females are also responsible for the low enrollment and high attrition of females in engineering. Female students usually exhibit a low self-efficacy in their overall STEM abilities (Besterfield-Sacre et al., 1997, 1998, 2001; Baker et al., 2007; Bramard and Carlin, 1998; Grandy, 1994; McIlwee and Robinson, 1992; Noeth, Cruce, and Harmston, 2003). They tend to have a low tinkering self-efficacy due to their lack of experience in using tools and machinery, taking things apart, and putting components together (Baker, 2007; McIlwee and Robinson, 1992). They also have a low technical self-efficacy in believing in their ability to learn and apply engineering knowledge and skills (Grandy, 1994; Baker et al., 2007). Furthermore, their self-assessment as technical problem solvers and future engineers has also shown to be lower than their male counterparts (Grandy, 1994).

The other disturbing observation is that female students usually show a much higher anxiety level than their male counterparts, despite the fact that they are better prepared academically, have better study skills, and are more motivated (Felder, Felder, and Dietz, 2002). Many female students appear to be feeler type learners who prefer that instructors show appreciation of their efforts. Feelers usually respond more positively to a classroom environment focused on cooperation rather than competition. The traditional engineering instructional mode stresses individual work in a competitive grading system, which could heighten the anxiety level in female students (Felder, Felder, and Dietz, 2002).

Although most research findings suggest that females are less interested and less successful in current science and engineering education, some female students possessing special characteristics are found to have a great likelihood of majoring and succeeding in science and engineering. For example, a female student with a high SAT math score and a strong science orientation is a good indicator for enrollment of an engineering major (Astin and Astin, 1992). A female student with the motivation of making a theoretical contribution to science (Sax, 1996) or with high self-confidence and a positive feeling about science (Baker and Leary, 1995) is the best predictor of enrollment of a STEM graduate degree. Furthermore, a female student with parents having a high level of educational attainment and high expectations for their child’s college education is also a significant predictor for enrollment of a science and engineering major (Baker and Leary, 1995; Felder et al., 1995; NCES, 2000).

Losing female students in STEM majors leads to a loss of valuable talents in U.S. industry and academia. In order to attract more females into science and engineering, reform of the current engineering education is necessary. Through well-designed intervention programs, female students’ tinkering and technical self-efficacy as well as their belief in societal relevance of engineering can be increased to make a difference in their attitudes toward STEM study (Baker et al., 2007). By increasing the visibility of women faculty, strengthening the power of personal invitation, and providing personal attention and support, the School of Industrial Engineering at the University of Oklahoma has demonstrated that they have achieved parity of the genders at the undergraduate level (Murphy et al., 2007). Early encouragement also needs to be instilled in the engineering education pipeline. Activities may include exploration of engineering in middle school and affirmation of the value of mathematics and science coursework in high school (Noeth, Cruce, and Harmston, 2003).

b) Ethnicity: Minority students remain an underrepresented group in engineering education. During the 1990s, African-Americans, American-Indians, and Hispanics comprised only 10 percent of the engineering graduating class, although these groups constituted 30 percent of the college-age population (Georges, 1999). This situation has not improved in the twenty-first century. As a National Science Foundation report indicates, only 5.1 percent of the engineering bachelor degrees were awarded to African-Americans in 2003 (NSF, 2005). This percentage was considerably lower than the 12.2 percent of the population made up by African-Americans in 2001. Hispanics only earned 5.4 percent of bachelor degrees in engineering, compared to their 13 percent of the population in 2001.

Twenty years ago, minority students demonstrated less interest in science and engineering majors at the high school level (Hilton and Lee, 1988). This number has further dropped in recent years. As ACT data reports, the actual number of African-American and American-Indian engineering majors was lower in 2002 than in 1991 (Noeth, Cruce, and Harmston, 2003). After entering college, minority students are found to be less successful in STEM educational persistence, indicated by outcome measures of degree completion and switching out of STEM fields (NCES, 2000; Seymour and Hewitt, 1997; Smyth and McArdle, 2004). In particular, female African-American, American-Indian, and Hispanic students exhibit the largest dropout rate in STEM majors, while male students in these ethnic groups experience the second largest dropout rate (Bonous-Hammarth, 2000).

Many external and internal characteristics of disadvantaged minority students have limited their success in science and engineering. The external societal characteristics discouraging minority students from joining science and engineering include their lack of family support, lack of awareness of an engineering career path, and lack of financial resources (NCES, 2000; NSF, 2005). The stereotype asserting that minorities are “incapable” in studying engineering also prevents them from joining engineering (Yaşar et al., 2006). The social pressure on minority students after they enter college can be great. Minority students who matriculate at predominantly white institutions are more likely to experience prejudice, disrespect and isolation, get involved in less social activities, and face the additional challenge of adapting to another culture (Van Aken, Watford, and Medina-Borja, 1999). The absence of minority role
models within the alumni, faculty, and industry also makes the minority students feel unattached to the engineering field (NSF, 2005).

It is interesting to notice that African-American and Hispanic students exhibit the highest positive impression about engineering among all ethnic groups upon entering engineering study (Besterfield-Sacre et al., 1998, 2001). African-American students demonstrate a significantly higher perceived level in communication and computer skills than the majority students (Besterfield-Sacre et al., 2001). Hispanic students are more favorable of teamwork than other groups (Besterfield-Sacre et al., 1998, 2001). However, these students’ self-assessments of their engineering abilities decrease significantly during the first year of college, and a high attrition rate is likely to occur among these groups (Besterfield-Sacre et al., 1998, 2001). The substantial misalignment between their aspiration and preparation could be the main reason responsible for their failure. Although many minority students are determined to study engineering, they may not have adequate academic preparation when graduating from high school (Van Aken, Watford, and Medina-Borja, 1999; Noeth, Cruce, and Harmston, 2003; NSF, 2005). They appear to have significantly lower overall GPAs, specifically mathematics and science GPAs, in high school. Many of them have not completed core course requirements including calculus and physics. Furthermore, most minority students also need assistance in improving their study skills (Noeth, Cruce, and Harmston, 2003).

Among all ethnicity groups, the characteristics of the Asian-American group are particularly noteworthy. Their high enrollment rate indicates that this group expresses strong interest in STEM majors (NCES, 2000). Hilton and Lee (1988) reported that 27 percent of Asian-American high school graduates planned a major and career in science and engineering, while only 11 percent of the overall population planned to do so. This group also has the lowest attrition rate in engineering (Astin and Astin, 1992; Hilton and Lee, 1988; Smyth and McArdle, 2004). Parents of Asian-American students usually have high expectations for their children’s college education. These students also appear to have higher motivation to study STEM and often have acquired adequate academic preparation before entering into college. These characteristics can explain Asian-American students’ success in science and engineering education.

The changing demographics of the United States will see significant growth in minority groups in the twenty-first century. Losing minority engineering students means we will not have enough new engineers to meet the future demand. Various initiatives must be developed in order to attract and retain underrepresented minority students in engineering. Early encouragement can take place in middle and high schools. Strategies may include providing students with opportunities to explore engineering and offering remedial classes to improve student academic preparation. Retention strategies can help to keep minority students in the engineering program. Activities may include providing academic advice to help academically underprepared students, offering personal counseling to help minority students feel at home at a predominantly white institution, and offering financial aid to support these students (Hermond, 1995).

c) Socio-Economic Status (SES): SES is a measure of an individual or family’s relative economic and social ranking (NCES, 2008). Research has indicated that family income level is positively associated with academic performance from elementary to secondary education. Students from low SES families have the lowest average scores on tests such as NAEP, SAT, and ACT. An incremental rise in family income is associated with a rise in test scores (Corbett, 2008). Students with lower SES are therefore underrepresented in general higher education, particularly at four-year colleges and more selective universities (McDonough, 1997). In the field of engineering education, however, family SES is negatively correlated with student academic performance (Donaldson, Lichtenstein, and Sheppard, 2008). Students from the low SES quartile are found to have higher fulfillment with engineering extracurricular activities and higher professional persistence in engineering than their high SES counterparts. Low SES students also demonstrate greater financial motivation in attaining an engineering degree. Nevertheless, high SES students usually receive greater encouragement from their families to study engineering than their low SES counterparts.

d) Home and School Background (HSB): In the general areas of higher education, students from rural areas are found to be more likely to drop out of college than urban students, and students from small high schools tend to show higher attrition rates in college than students from large high schools (Brown, 1985). In the field of engineering education, urban students surpass rural students in almost every measure of academic performance. As compared to rural counterparts, the urban students show higher scores on college entrance examinations, earn better GPAs, and have lower dropout rates (Felder et al., 1994). These disparities between urban and rural groups are significantly correlated with the socioeconomic factors associated with the students’ home and school backgrounds (Brown, 1985; Felder et al., 1994). The rural students are typically from families with lower SES and receive less academic and cognitive support from parents than their urban counterparts. These students also have more geographic isolation and less access to role models in engineering. Students from research/rural colleges tend to have higher grades than students from urban colleges, and urban college students have higher grades than suburban college students (Padilla et al., 2005). With respect to the relationship between total SAT score and cumulative GPA, urban colleges demonstrate a stronger correlation than rural and suburban colleges. In addition, research colleges also show a higher correlation than non-research colleges (Padilla et al., 2005). The above findings indicate that engineering students enrolling in urban colleges with rural/small town backgrounds need more assistance than their peers.

C. Data Collection and Analysis Methods Applied

Apart from identifying significant engineering student characteristics for the prediction of college enrollment and retention, raising meaningful research questions and searching for the right answers, the other critical tasks in the measurement of student characteristics involve designing proper methodologies for data collection and applying suitable statistical tools for data analysis. The frequently applied data collection and analysis methods in the current literature are summarized in this section. For a succinct presentation purpose, only representative examples are referenced in each method.

1) Data Collection Methods: In social science research, the typical data collection methods are focus groups, open-ended surveys and closed-form questionnaires. These methods are usually not applicable in solving deterministic types of engineering problems where no randomness is involved. However, when dealing with
research issues in the area of engineering education, where measurement of attitude, perspective, ability, and motivation is involved, these methods are appropriate and have so far been widely applied.

a) Focus Group: The focus group is a commonly used method for collecting exploratory and exhaustive information about a particular issue (Krueger, 1988). There are several advantages of using the focus group method. First, it allows researchers to capture the “real-life” data by providing an environment for face-to-face discussion with participants. Second, a particular issue can be discussed in depth through the flexible structure of this method, while this is usually not possible in a fixed structure design. Third, this research method costs less and generates results more efficiently as compared to other measurement methods. However, the focus group method is not applicable when statistics are needed because it typically prompts qualitative data. When the research topic involves emotional issues, this method is not suitable either because the interviewee may express biased subjective opinions. Further, the first hand data is not always obtainable because some members in the focus group may not express their honest opinion in the presence of others. Last but not least, the measurement results cannot be generalized to the whole population due to the limited sample size.

Many research studies reviewed in this paper have the applied focus group method for data collection. For example, Besterfield-Sacre et al. (1998) used this method for the identification of student attitudes toward engineering and student perceptions about their engineering abilities. Ohland et al. (2004a) applied this method for the measurement of student perspectives on their experience of taking the new engineering entrepreneurship program.

b) Open-Ended Survey: An open-ended survey allows respondents to answer questions in their own words. There is no definite answer to an open-ended survey question. When the subject of concern is complex with a number of avenues to explore, the open-ended survey method is more suitable for data collection because it allows more in-depth information to be obtained in a private setting. However this method is more time and effort consuming as compared to focus group or closed-form questionnaire methods because it involves qualitative analysis. Similar to the focus group method, it is difficult to statistically analyze data obtained via the open-ended survey method. Qualitative summaries are usually produced with little or no generalizable statistics. An example utilizing this method is the attitude assessment study by Besterfield-Sacre et al. (1998) which applied this method to uncover the reasons why students chose to leave engineering programs. Students were required to complete an open-ended exit survey as part of the process of transferring out of engineering programs. Seymour and Hewitt (1997) applied the open-ended survey to measure various characteristics of engineering students, such as reasons for leaving STEM, intrinsic interests in learning STEM, and learning styles.

c) Closed-Form Questionnaire: If statistical inference results are desirable, the closed-form questionnaire method is a practical and efficient measurement instrument. This method adopts rating scales, check lists, and semantic differentials to measure respondent opinions about a particular subject. As compared to the focus group and open-ended survey, the closed-form questionnaire is less expensive and time consuming. It is therefore suitable for analysis that requires a large data set. Due to the limitation of the response choices, however, this method usually provides less detailed data. Therefore it is not suitable for exploration of complex issues. Most research studies reviewed in this literature survey adopted the closed-form questionnaire method to measure various characteristics of engineering students and draw statistical inference results accordingly.

2) Data Analysis Methods: Many data analysis methods have been applied in this research area. Since most studies in the literature focus on finding significant characteristics for the prediction of college enrollment and retention which exhibit a dichotomous outcome, logistic regression and multiple regression are thus the most frequently adopted methods. Due to the progressive nature of education, another method often applied is longitudinal data analysis. Other effective data analysis methods existing in the literature are also summarized below.

a) Logistic Regression: The status of college success can usually be coded as a dichotomous variable, i.e., success (i.e., enrolled/retained/graduated) = 1, failure (i.e., not enrolled/not retained/not graduated) = 0. Logistic regression is thus an appropriate data analysis method. The hypothesized significant characteristics are normally fitted into a logistic regression model as independent variables, where college success is coded as a dichotomous dependent variable, like the study presented by French, Immekus, and Oakes (2005). Moller-Wong and Eide (1997) extended their analysis a step further from the normal logistic regression. They predicted the probability of a student belonging to a particular status category. Instead of predicting the dichotomous status of success or failure, their model can predict the probability of a student’s status.

b) Stepwise/Hierarchical Multiple Regression: Predicting college success usually involves a large amount of variables. In order to identify the most significant variables, stepwise and hierarchical multiple regressions are commonly used. In stepwise or hierarchical multiple regression, groups of characteristic variables are entered into the regression model sequentially as blocks according to their logic or sequence of occurrence until no additional variables are capable of producing a significant reduction in the residual sum of squares \( R^2 \) of the dependent variable (Cohen et al., 2003). In stepwise regression, the focus is on maximizing \( R^2 \) with a minimum number of predictors. In hierarchical regression, however, the focus is on the change in \( R^2 \) associated with predictors entered later in the analysis over and above that contributed by predictors entered earlier in the analysis. Besterfield-Sacre et al. (1997) applied stepwise multiple regression to find the significant indicators predicting GPA. French et al. (2005), applied hierarchical multiple regression to examine the influence of variables like gender, SAT scores, motivation, and institutional integration on GPA.

c) Longitudinal Data Analysis: Education is a progressive process. With cross-sectional data, it is difficult to monitor student growth. Longitudinal data analysis facilitates investigation on student change and growth. In the current literature, longitudinal data analysis is widely used in predicting college success based on student characteristics measured at different points of time. For example, Bernold et al. (2007) recorded student background data like ACT and SAT scores, and high school ranking when they first entered into college. At the end of the first semester or the first year, student academic performances like GPA and number of credits enrolled in each term were measured again. Data collected at these different times were then used in a longitudinal data analysis for the prediction of student academic performance and final educational outcome.

d) Covariate Adjustment: Student college success depends on two main factors: the college program they are in and the preparation
they have received at entry level. Different college programs take students who differ in their preparation; therefore, the final results of college success may not necessarily reflect the differential impact of various college programs, but simply the differences in the characteristics of students. If a study is to objectively examine the success of a college program, student entry factors need to be partialed out as covariates. Application of covariate adjustment can be found in studies by Astin and Astin (1992) and French, Immekus, and Oakes (2005).

c) Two-Step Design: When one analyzes a large set of data containing numerous variables from different categories, two-step design provides an efficient means to simplify data analysis. The first step in this design involves applying basic statistical tests to the data set to identify the most consistent predictive indicators among a large group of variables. In the second step, the identified indicators are then used as inputs in a more sophisticated model for further identification of significant predictors for the dependent variables. Nicholls et al. (2007) analyzed a large data set including approximately 300 variables using the two-step design method. In the first step, they successfully identified variables that consistently had statistically significant differences between STEM and non-STEM students across gender and ethnicity subgroups. In the second step, they focused on the similarities between STEM or non-STEM students across these subgroups and revealed the subtle differences between STEM and non-STEM students.

d) Exploratory Factor Analysis: Measuring engineering student characteristics involves many latent constructs. For example, constructs like parental influence and motivation are not directly measurable. The behavior of these latent variables can only be indirectly estimated through their impacts on their manifest variables. Exploratory factor analysis provides an effective tool to reveal the construct structure from the observable manifest variables. This method is especially suitable when researchers have no hypotheses about the nature of the underlying construct structure of their measure (Thompson, 2004). Li et al. (2008) applied this method to study the perspectives about engineering among college students. Their exploratory factor analysis result led to a four-construct structure of the observed data. The construct “interest” found to exhibit the most significant difference between engineering and non-engineering students.

e) Structural Equation Modeling: Structural equation modeling is a statistical technique for testing and estimating causal relationships using a combination of statistical data and qualitative causal assumptions. It provides an effective tool for the estimation of a structural model in a complex measurement situation when latent constructs are involved (Kline, 2005). Cabrera, Nora, and Castaneda (1993) established a structural equation model to predict the commitment and persistence to institution via latent constructs on environmental facts, academic integration, social integration, and financial attitudes. French, Immekus, and Oakes (2003) developed a structural equation model to predict GPA and institution/major enrollment based on latent constructs like faculty-interaction and motivation, as well as measurable constructs like high school ranking and SAT scores.

f) Discriminant Analysis: Discriminant analysis is a statistical technique to classify objects into mutually exclusive and exhaustive groups based on a set of measurable object features (Klecka, 1980). The purpose of this analysis is to classify objects into one of two or more groups based on a set of features that describe the objects. Burtner (2005) applied this method to predict student membership into three groups, namely, Stayer, Switcher, and Leaver. In this discriminant analysis, persistence in engineering was treated as the dependent variable, four attitudinal factors reflecting expectation of engineering profession, assessment of personal attributes, and confidence were predictors.

i) Classification Tree: The classification tree method can be used to predict membership of an object in the classes of dependent variables based on its measurement on predictor variables. A classification tree is constructed by partitioning measurement data into separate regions in which the predicted classifications is consistent within each region. The tree modeling building process selects the best covariates by considering all possible binary splits on the variable list. The final tree model is constructed based on the best set of branches that minimizes the misclassification rate. Mendez et al. (2008) applied the classification tree method to identify the significant factors associated with persistence in STEM majors. Their findings indicate that cumulative GPA is most highly associated with STEM persistence, while SAT quantitative exam score and number of STEM courses taken in freshmen year are positively associated with persistence. Among all factors, total hours enrolled in freshmen year and SAT verbal exam score exhibit negative association with persistence.

III. AREAS FOR FUTURE RESEARCH

Since both environmental traits and personal characteristics can simultaneously affect student attitude and ability toward learning engineering, measurement of student characteristics that affect their educational success is a complex issue. The large amount of research effort spent in the past two decades has led to great progress in identifying many important influencing characteristics. However, several research issues need to be further explored.

A. Improvements to Be Made in Measurement Content

The previous section classified all the characteristics studied in the literature into three broad categories: external characteristics, internal characteristics, and demographic characteristics. Although most significant characteristics in these three categories have been included in the existing research, some important content is missing.

In the external characteristic category, the impact of societal influence on students’ attitudes toward studying engineering has not been well-studied. This missing component is indicated by the dashed line in Figure 2. Our society at large does not have an accurate perception about the nature of engineering (NSB, 2007). People usually associate engineering with construction, manufacturing, design, and defense, but less so with health care, environment, and improving quality of life. Engineers are generally perceived by the public as “nerds” with poor interpersonal skills (NSF, 2007), or specialists with highly technological skills (Yurtseven, 2002; Chisholm, 2003). Influenced by these public perceptions, it is reasonable to make a strong hypothesis that only students who are good at math and science as well as those interested in making “things” are attracted to engineering, while those who prefer teamwork and an emphasis on solving social problems will not find engineering attractive. Further study is needed to test this hypothesis and examine how significantly these societal influences can affect students’ attitude towards studying engineering.
More important content is missing in the internal characteristic category, as indicated by the dashed lines in Figure 3. For example, it is widely recommended that students should be introduced to the excitement and relevance of engineering and research early in the educational pipeline (Cantrell et al., 2006; NSB, 2007; Mehali, Doppelt, and Schuun, 2008). To make this early exposure possible, K-12 teacher training must be provided (Yaşar et al., 2006). How does this experience improve students’ knowledge in engineering? How does the experience change their impression about the engineering profession? As a consequence of these improvements and changes, how will it affect the enrollment and retention data in engineering school? All these questions remain to be answered.

The impact of many personality characteristics like temperament, energy expenditure, mood, focus of attention, social sensitivity, interpersonal competence, and coping strategies on educational outcomes has been addressed in general education (Messick, 1979). However, limited attention has been focused specifically in the field of engineering education (Brown and Cross, 1993). For example, as previously mentioned, discussion of the influence of motivation on educational outcomes has been restricted on personal goal setting. How motivation influences student characteristics like persistence and resilience, focus of attention, and time management skills in the context of engineering education has not been well studied.

In the demographic category, more effort needs to be placed on measuring the effect of SES on engineering education. As Donaldson, Lichtenstein, and Sheppard (2008) pointed out, most current research on SES effects has focused on elementary and secondary education. They developed a new survey instrument to measure the impact of SES on engineering education. Unfortunately no conclusive results can be drawn from their study yet. Future studies are especially needed in finding how low SES might result in disadvantages for students preparing for engineering. In addition to the traditional properties involved in this category, the impact of globalization also needs to be investigated. In this new era of globalization, the number of engineering jobs outsourced is ever growing, and many well trained foreign engineers are joining the U.S. industry. It is very important to explore how this global supply dynamics and complexity affect our students’ decision to study engineering.

B. Improvements to Be Made in Measurement Methods

One common weakness of most research studies reviewed in the literature is that they treated student characteristics as independent variables. Although some studies did investigate the impact of many characteristics across different categories simultaneously, they neglected the interaction effect among these variables. In reality, none of these characteristics are independent to each other. They have either correlation or causal relation with other characteristics. For example, SES is a characteristic highly correlated with ethnicity, meanwhile it is also highly correlated with home and school background. The interactions in this example are illustrated by the solid lines with double arrows in Figure 4. To obtain a more accurate measurement result, interactions among characteristics must be included in a measurement model.

In the current literature, most research conclusions were drawn based on basic statistical data. For those research studies that used measurement models for data analysis, usually a limited number of characteristics were included in their models. Measuring only a small number of characteristics from a complex system considered in this study can lead to a problematic prediction. While one characteristic may be identified as a significant predictor among a small group of variables, it may appear to be non-significant in a large pool of variables. In order to more accurately predict the most important characteristic indicators for college success in engineering education, it is necessary to develop a comprehensive model that can include as many variables as possible from all the three categories.

Figure 5 proposes a comprehensive structural model for the identification of important characteristics predicting enrollment and retention in engineering. All three characteristic categories are considered in this model, where the dashed lines represent the correlation or causal relation among characteristics in these categories.

IV. CONCLUSION

In order to maintain the global competitiveness of the United States engineering workforce, we must attract more qualified students to study engineering. Students with certain characteristics are more likely than others to join engineering schools and to choose engineering as a profession. One important topic in the field of engineering educational research is the development of advanced measurement instruments that can accurately model the relationship between student characteristics and their enrollment and retention probabilities in engineering. Despite many research efforts spent on this topic in the past, it lacked a universally agreed upon structure for the classification of engineering student characteristics. This paper proposes a standardized categorical classification system.
which groups student characteristics into external, cognitive, affective, and demographic categories. A thorough literature review has been conducted based on the proposed classification system.

The literature review reveals that the characteristics in these categories are either correlated or causally related with one another. The review results also unveil that both cognitive and affective characteristics of engineering students have equivalent significant impact on enrollment and retention. In order to provide our students with adequate engineering preparation, it requires an endeavor joining educational efforts from external, internal, and demographical aspects. In particular, much effort needs to be spent in areas of instilling positive societal influence, implementing early engineering exposure plans, modifying current engineering curricula, improving instruction approaches in engineering college, and understanding the impact of globalization. These educational elements are currently less emphasized along the engineering educational pipeline. Their impacts on the educational outcomes are not well understood yet. Many existing research conclusions are derived using basic statistical analysis. When a measurement model is needed for analysis, logistic multiple regression, stepwise/hierarchical multiple regression, longitudinal data analysis, and factor analysis are the mostly applied methods. However, the interaction effects among characteristics on educational outcomes are missing in the current research. Furthermore, due to the absence of a standardized classification structure for engineering student characteristics, impacts of various characteristics have not been studied concurrently in a complete framework. In the future, we will implement the comprehensive measurement model proposed in this paper to study the effect of student characteristics on enrollment and retention in engineering.

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