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# Evaluation of a Conceptual Model of Student Retention at a Public Urban Commuter University

Hoa Khuong

Loyola University Chicago, khuong.hoa@gmail.com

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LOYOLA UNIVERSITY CHICAGO

EVALUATION OF A CONCEPTUAL MODEL OF STUDENT RETENTION AT A  
PUBLIC URBAN COMMUTER UNIVERSITY

A DISSERTATION SUBMITTED TO  
THE FACULTY OF THE GRADUATE SCHOOL  
IN CANDIDACY FOR THE DEGREE OF  
DOCTOR OF PHILOSOPHY

PROGRAM IN RESEARCH METHODOLOGY

BY

HOA T. V. KHUONG

CHICAGO, IL

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## ABSTRACT

A new conceptual model of student retention was developed and evaluated for first-year retention and for second-year retention of students at an urban, mid-western commuter university. The model captured the joint effects of academic engagement and environmental factors on academic performance and persistence of commuter students in their first two years of college attendance. The academic engagement and environmental factors incorporated into the model included: pre-college academic achievement, Deep Learning, Study Time per Week, College Math Readiness, Major Selection, Hours of Employment, receiving (or not receiving) a Pell Grant Award and Financial Concerns. Structural equation modeling techniques were utilized to simultaneously assess the quality of the theoretical construct known as Deep Learning and to test the hypothesized causal paths linking the engagement and environmental factors to the college grades and student retention. Results indicated that when controlling for precollege academic achievement, Deep Learning, Study Time per Week, and College Math Readiness had positive effects on First-year Grades. Working outside campus 21 or more hours per week negatively impacted First-year Grades. First-year Grades and Pell Grant Award were significantly related to First-year Retention, but Financial Concerns were found to have a negative effect on retention. When applied to second-year students, Deep Learning and Major Selection were found to have significant effects on Second-year Grades. Factors that positively influenced Second-year Retention were Grades, Major Selection

and Pell Grant Award, while Financial Concerns lowered the likelihood of Second-year Retention. Based on these results I suggest that institutional efforts in engaging students in a deep learning-based curriculum, encouraging major and career exploration, and providing college-financing resources can create pathways to greater academic success and persistence among commuter students..

## CHAPTER ONE

### INTRODUCTION

#### **Student Retention and Graduation Imperative**

Leaving college without completion can present personal setbacks for students, not just in terms of time and money spent but also because of unfulfilled promises and lost opportunities. In contrast, persistence pays off as college graduates can enjoy tangible benefits such as higher income levels, higher employment rates, better health and longer life expectancy in comparison to those with a high school diploma or less (National Center for Health Statistics, 2013; Zaback, Carlson, & Crellin, 2012). While graduating from college is an aspiration for over a million students every year, the road to the finish line might be too challenging for many. Data from a national sample of undergraduates who began their postsecondary education for the first time in the 2003-04 academic year shows that only about half of all first-time postsecondary students persisted to earn a degree or certificate and over a third dropped out of college without a degree or certificate within six years of entry (National Center for Education Statistics, 2011). In the last 20 years the six-year graduation rate, as measured for first-time degree-seeking students who enroll in and graduate from the same 4-year institution, is in the range of 55 to 59 percent (National Center for Education Statistics, 2012). This rate varies widely among American colleges and universities, ranging from 31 percent at open admission institutions to 88 percent at highly selective institutions (Aud et al., 2013). Similarly, the annual institutional retention rate of first-time students at four-year

institutions also differs substantially in the institutional selectivity spectrum, where 62 percent of students are retained at open admission public institutions in comparison to 95 percent retained at highly selective public institutions (Aud et al., 2013). The difference in retention and graduation rates between open admission and selective admission institutions reflects differences in the diversity of student populations and institutional characteristics. It also indicates that most non-selective higher education institutions face challenges in educating students well and getting them to graduate in a reasonable time.

Improving student retention and graduation rates is at the core of the major reform movement in higher education, known as the “college completion agenda”. Spurred by President Obama’s “American Graduation Initiative”, which calls for America to have the highest proportion of college graduates in the world by 2020, numerous national, state, and philanthropy foundation-led efforts have been geared towards providing institutions with incentives to increase the graduation rates and close the inequalities in college attainment by race/ethnicity and income level (Russel, 2011). Twenty seven states currently have incorporated or are developing an outcomes-based funding component, which is tied to performance metrics such as retention and graduation rates, in their financial support for colleges (Jones, 2013).

At the institutional level the task of identifying the early symptoms of student failure and dropout and designing targeted strategies to support student retention and degree completion is an ongoing concern for all stakeholders. How do institutional researchers and practitioners identify the students who are prone to drop out in order to support them and help them fulfill their potentials? Are there patterns of student

behaviors that lead to failure where retention-targeted programming activities can make an impact and change these behaviors? How can commuter students who spend limited time on campus be reached and engaged? Which “high-impact” educational practices really work to increase student learning and retention at the institution? What are the effects of financial aid on student persistence? Researchers and practitioners in higher education continue to wrestle with these and many other questions to develop a better understanding of the factors that lead to college student persistence and ultimately to develop and implement effective programs to enhance retention and degree attainment.

In the last four decades since Tinto’s (1975, 1993) seminal work on student departure, research on college student retention has become one of the most prolific topics in higher education. However, given the “ill-structured” nature of the student departure problem, developing solutions requires research from multiple theoretical perspectives – educational, sociological, psychological, organizational and economic. There will not be a one-size-fits-all solution to the problem as “no template of a successful retention program exists” (Braxton, Hirschy, & McClendon, 2004). To advance the body of knowledge in college student retention, researchers are encouraged to develop and test hypotheses that incorporate multidisciplinary theories that explain the process of student retention and graduation in different types of institutions, such as residential and commuter universities, liberal arts colleges and two-year colleges (Braxton et al., 2004; Melguizo, 2011).

## **Research on Commuter Student Retention**

Research on commuter students who, as a group, account for a large majority of students on campuses across the nation (Jacoby, 2000) is needed because there are few theoretical frameworks that are directly targeted to them (Baum, 2005). The lack of in-depth examinations of commuter students means that there is still much to learn about the interactions and involvement of students in the college environment. Such studies may reveal valuable results to help guide institutions in meeting the retention needs of commuter students as well as those of sub-populations such as the academically under-prepared or specific minority groups.

Commuter students are a heterogeneous group in terms of demographic backgrounds and developmental needs. In comparison to residential four-year colleges and universities, commuter institutions tend to have greater proportions of economically and/or academically disadvantaged student populations because of lower tuition costs and closer proximity to their work and home communities.

Research on the impact of commuting on student retention indicates that residential students tend to have higher retention rates than the commuter students (Pike, 1999; Pike, Schroeder, & Berry, 1997). However, as Beal and Noel (1980) point out, while being a commuter student is a risk factor for dropout behavior, it is not as significant as other factors such as low academic achievement, limited educational aspirations, indecision about major/career goal, inadequate financial resources, economic disadvantage, or being a first-generation college student. Thus, while there are common factors that could promote or hinder retention of both residential and commuter students,

the challenge is to capture the unique aspects of the experiences of commuter students and develop a model that links these aspects to the process of retention and completion.

### **Overview of the Conceptual Framework for the Study**

For this study I have developed a model of student retention in commuter colleges and universities. The model was based on the theoretical foundations advanced by Tinto's (1975, 1993) longitudinal theory of student departure and Bean and Metzner's (1985) nontraditional student attrition model.

Tinto's theory has emerged as the most influential theoretical perspective among the theories and conceptual frameworks developed in the last four decades to explain college student departure process (Braxton et al., 2004; Melguizo, 2011). In his theory, Tinto posited that the levels of academic and social integration, developed through the interactions between students and institution norms and culture, influence departure or retention decisions. Tinto's theory has maintained its paradigmatic position in the field even though the theory has modest empirical support in retention research and that leading researchers in the field have advocated for either major revisions of the theory or the development of a new theory (Braxton, 2000; Braxton, Sullivan, & Johnson, 1997; Melguizo, 2011). Braxton and associates (2004) argue that Tinto's theory fails to serve as a "grand theory" of student departure process because its propositions were not supported by strong evidence when tested in different types of colleges and universities and among different student populations. In a major appraisal of college student departure studies, Braxton and Lien (2000) determined that the cornerstone proposition in Tinto's theory regarding the influence of academic integration on student retention is only modestly

supported in single-institutional studies in all institutional types. Because the academic integration construct was measured inconsistently across studies, which might be the cause of the modest results, Braxton and Lien (2000) made recommendations for future research to broaden Tinto's academic integration construct to include dimensions of good fit to the academic environment of the institution, such as students finding a suitable major field of study or choosing intellectually stimulating courses.

Tinto's academic integration construct was defined differently in Bean and Metzner's (1985) nontraditional student attrition model. For Bean and Metzner, the academic dimension of college experience is formed by students' academic behaviors and their perceptions of academic support through academic advising and course scheduling. Academic outcomes, such as grades, are then the results of the academic integration process.

In developing the model used in this research, I incorporated Bean and Metzner's idea that academic behaviors drive academic achievement with the concept that student engagement is linked to student development and success in college (Kuh, Cruce, Shoup, Kinzie, & Gonyea, 2008; Pascarella & Terenzini, 2005; Tinto, 1993). The academic engagement variables that were incorporated into the model are: (a) college readiness in mathematics (by completing math remediation or by test scores), (b) the amount of time spent studying, (c) deep learning behaviors, and (d) selection and declaration of a major or a pre-major. These engagement behaviors are universal to beginning college students as they go through the process of adjustment by navigating the academic system of a campus and finding a good fit to their personal and career goals. How engaged students



are in the academic processes could tell us a lot about their commitment to the goal of degree completion, as well commitment to the institution as their alma mater. As will be discussed throughout this dissertation, students who are more academically prepared and engaged in their academic studies are more likely to have better performance and remain in the institution.

Among the measures of academic engagement, “deep learning” is a composite measure based on 12 questions from the National Survey of Student Engagement (NSSE) which measure higher order learning (4 items), integrative learning (5 items) and reflective learning (3 items). Deep learning is differentiated from surface learning. Learners use surface learning to remember, reproduce and apply information in doing course assignments, while deep learning is used in creating a new understanding of reality or in perceiving things in a more meaningful way (Marton & Säljö, 1976). Deep learning has been found to produce a positive impact on students’ academic performance and overall learning experience by helping students to bridge the gap between classroom and out-of-class experiences, and make connections to the external communities (Fenollar, Román, & Cuestas, 2007; Malie & Akir, 2012; Simons, Dewitte, & Lens, 2004).

In addition to the academic engagement variables, the current research aimed at examining the influence of environmental factors on students’ performance and retention outcomes in the first two year of college. The environmental factors have been given prominent roles in the major theoretical models of commuter student persistence (Bean &

Metzner, 1985; Braxton et al., 2004). In this research the environmental factors were: (a) hours of employment, (b) Pell grant award, and (c) financial concerns.

Using structural equation modeling, the current research analyzed a model that integrates student entry skills, academic engagement, environmental factors, and their effects on GPA and retention of commuter students.

### **Purpose of the Study and Research Questions**

The purpose of this study was to evaluate the adequacy of a new conceptual model of commuter student retention. This was done by examining the causal paths linking pre-college academic achievement, academic engagement behaviors, employment, Pell grant award and financial concerns to academic performance and retention outcomes in first-time students at a public urban commuter university. In particular, the study addressed the following four questions:

- 1: How well do pre-college academic performance, academic engagement behaviors and hours of employment predict first-year grade point average?
- 2: How well do first-year grade point average, Pell grant award and financial concerns predict first-year retention?
- 3: How well do pre-college academic performance, academic engagement behaviors, and hours of employment predict second-year grade point average?
- 4: How well do second-year grade point average, major selection, Pell grant award and financial concerns predict second-year retention?

### **Significance of the Study**

The investigation of student retention in commuter colleges and universities is of great importance to faculty, administrators, policymakers, students and other stakeholders who are concerned with issues of quality, equity, learning and accountability in higher education. The current research contributes to the research knowledge base on student retention by defining and evaluating a conceptual model which captures the joint effects of academic engagement, academic performance and environmental factors on retention of commuter students in their first two years of college.

The current research study was conducted at a public urban commuter university in the Midwest, and it focused on first-time full-time undergraduate students. Research has shown that the heaviest toll of attrition usually takes place among incoming students as they begin the journey into higher education. Adjusting to a college environment and to the academic requirements can be a challenging process for first-time students and many of them are able to develop appropriate coping mechanisms for this transition. However, not all students are able to stay the course until degree completion. The dropout rate is greatest in the first year and it gradually decreases through the following years. Because of this, institutions understand that the first year is the most critical time period to make an impact on the students. Thus, the first-year experience curriculum and other targeted support services are geared toward building a supportive academic and social environment for new students to enhance their engagement in the campus's intellectual and social lives. These first-year curriculum courses or seminars often include skill-building components such as time management, note-taking, study and library research

skills and career exploration. As students become engaged in the educational activities and in campus life, they are more likely to enjoy their college experience, have better grades and continue their enrollment at the institution. Understanding students' academic engagement behaviors in the first year of college and how the academic dimension of student experience affect their retention is a necessary first step for institutions to implement intentional and targeted activities and programs to impact those behaviors.

This study offers further insight into the student retention puzzle by introducing an integrated model that examines the effects of pre-college academic achievement, engagement behaviors, employment and finance-related issues on the college experience and outcomes of first-time students.

While the current research study examines the unique institution-specific characteristics of a commuter student population, the findings from this study will likely prove applicable to other institutions with similar student populations and program offerings.

### **Potential Limitations**

Generalizability of this study may be limited to similar institutions (public urban commuter universities) because the research was conducted on a single institution. In addition, the study sample was based on the students who enrolled continuously in the first year and participated in the NSSE and, thus, may not reflect the risks of all students in the target population.

## **Definitions of Key Terms**

### **Academic Engagement**

Academic engagement is defined as the amount of time and efforts students put in academic activities to produce desirable learning and intellectual development outcomes. The concept of academic engagement used in this study points to the activities and behaviors of the individual student as an active agent in the educational process. Forms of academic engagement are measured by the items from the National Survey of Student Engagement (NSSE) and by the enrollment behaviors captured in institutional records.

### **Commuter Students**

The Council for the Advancement of Standards in Higher Education (CAS) defines commuter students as those who do not live in university-owned housing facilities (Jacoby, 1989). These students account for over eighty percent of college students in the U.S. (Jacoby & Garland, 2004) and are present at all types of higher educational institutions from private residential colleges and public state universities to community colleges and urban four-year institutions.

### **Retention**

The term retention, also known as “institutional retention”, was used in this study to indicate the process of student retention from the perspective of the institution where students enroll. “Retention” is distinguished from the term “persistence” which refers to the perspective of the student and indicates the process of enrollment in the higher education system irrespective of whether the student remains at the institution or transfers to another institution.

## CHAPTER TWO

### REVIEW OF THE LITERATURE

This chapter reviews the theoretical foundations of and the empirical support for a number of models of student retention in higher education. A lack of extensive research on the college experience of commuter students in four-year institutions presents opportunities for developing a better understanding of the complex processes that lead to retention in this student population. Building new models that account for the forces shaping students' decisions to stay and persist may help inform institutional actions towards increased commuter student retention.

#### **Theories of College Student Retention**

##### **Tinto's Longitudinal Theory of Institutional Departure**

Tinto's (1975, 1993) theory of student departure, also known as the Student Integration model, is among the most widely discussed and cited theories in higher education (Braxton, Sullivan, & Johnson, 1997; Melguizo, 2011). It has gained a near-paradigmatic status in student persistence research thanks in a large part because it established "a workable and testable foundation" for analyzing factors involved in student departure (Rendón, Jalomo, & Nora, 2000). Tinto's theory was originally derived from Durkheim's theory of suicide and later drawn upon Van Gennep's "rites of passage" study in the social anthropology field. The theory sought to explain the longitudinal and interactive process and forces that account for voluntary individual student departure

from the institution prior to degree completion (Tinto, 1988). The theory posits that students' background characteristics and pre-college academic achievement directly influence their initial commitment to the goal of graduation and to the institution. Upon entering college environment students interact with and integrate at various degrees into the diverse social and academic communities of the institution. Students are active participants in the integration process, and both the individual and institutional actions continually shape the college environment. Tinto uses the term "integration" to describe the internalization process where the individual integrates and incorporates the values and norms of the college environment into his or her own value system (Tinto, 2012). Successful social and academic integration influences subsequent commitment to the goal of degree completion and commitment to the chosen institution, thus affecting the decision to leave or continue at the institution. A voluntary decision to leave the institution might indicate unsuccessful integration into social or academic life at the college.

Tinto's theoretical model was designed to describe the departure process "within an institution of higher education" (Tinto, 1993), and not the departure from higher education system. As such, the model requires validation when being applied at various types of higher education institutions. Tinto (1993) noted that students at commuter colleges and universities often have limited opportunities for social integration in comparison to those at residential institutions. He argued that the classroom is the primary educational community and the "gateway" for commuter students to establish

academic and social connections. Therefore, the students who fail to create meaningful relationships with peers and instructors in the classroom might have difficulties in their academic progress. Given the lack of well-defined and –structured opportunities for making social connections on commuter campuses, these students would feel further isolated and disengaged from the campus life.

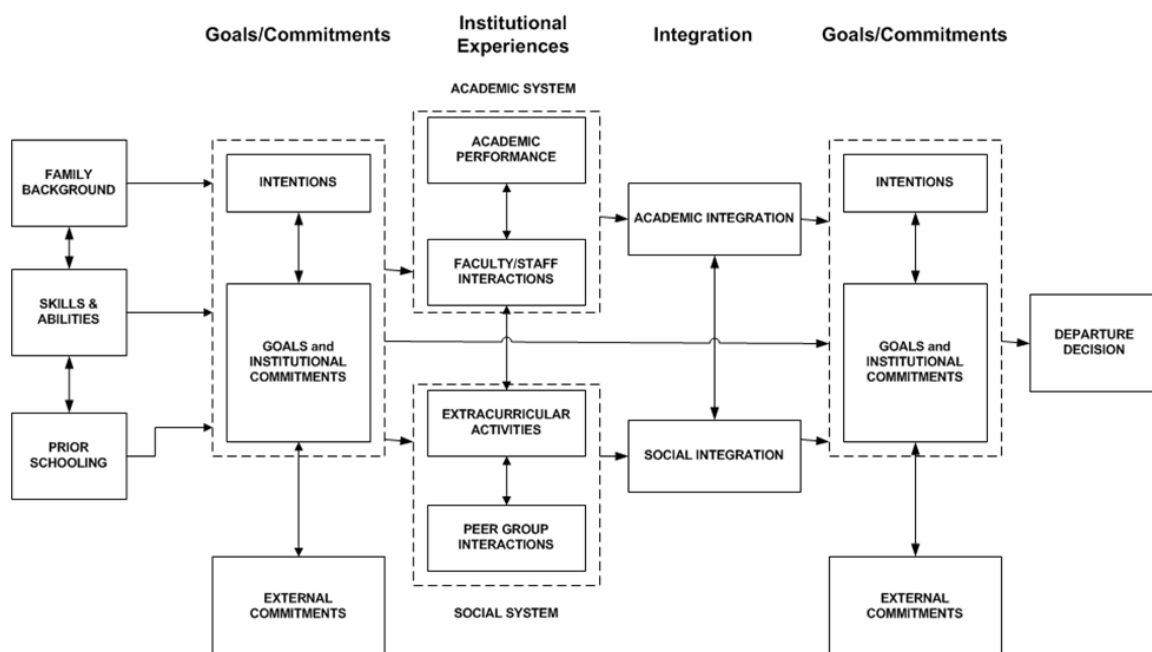


Figure 1. Tinto's (1993) Longitudinal Model of Institutional Departure

The “social integration” construct has given rise to much debate among higher education scholars, such as Tierney, Attinasi, Hurtado and others. Tierney (1992) argued that the construct of “social integration” implies conformity and recognition of the prevailing culture or environment, and that an alternative model where diversity of cultures is celebrated would be preferable in examining persistence and retention of



minority groups. Attinasi (1989) also criticized the model for its implication that “moral consensus” with the dominant groups is required for students to persist in colleges.

In their study on how Latino students adjusted to college and developed a sense of belonging, Hurtado and Carter (1997) found that minority students, especially those from marginalized and underrepresented groups in higher education, relied on the ease of separation and maintenance of relationships with their families and external communities while making the transition to college. They argued that while Tinto’s model did not describe and include important aspects of the transition-to-college experience, its construct of academic and social integration implied that students of minority cultural and ethnic backgrounds would need to develop normative congruence and assimilate themselves to the dominant culture in order to be accepted and integrated. In fact, the findings from their research indicated that the development of students’ sense of belonging to the institution reflected their “subjective sense of cohesion” during the process of interacting with the academic and social systems of college. The researchers postulated that the sense of belonging may be the key to understand how college experiences impact students of minority and underrepresented groups. In a recent interview, Tinto acknowledged that Hurtado and Carter’s research on Latino students’ transition to college had influenced his views on the student departure model (Wolf-Wendel, Ward, & Kinzie, 2009). He believed that the term “integration” is problematic, as has been pointed out by Tierney, Hurtado, and others (Wolf-Wendel, Ward, & Kinzie, 2009).

In the decades since Tinto's theory was introduced, the research community has conducted multiple tests and extensive analyses of the model. Braxton, Sullivan and Johnson (1997) reviewed empirical support for Tinto's theory based on published research studies that used a single-institutional or multi-institutional design, residential or commuter two-year and four-year settings. They determined that there was strong empirical support for five out of thirteen key propositions derived from the theory when applied to residential universities. Four out of these five propositions, as illustrated in Figure 2, formulate a logically connected narrative in the following form. The initial level of commitment to goal of graduation has a strong association with the level of social integration which, in turn, significantly affects the subsequent commitment to the institution. Subsequent institutional commitment then influences persistence. The initial commitment to the institution also influences subsequent institutional commitment.

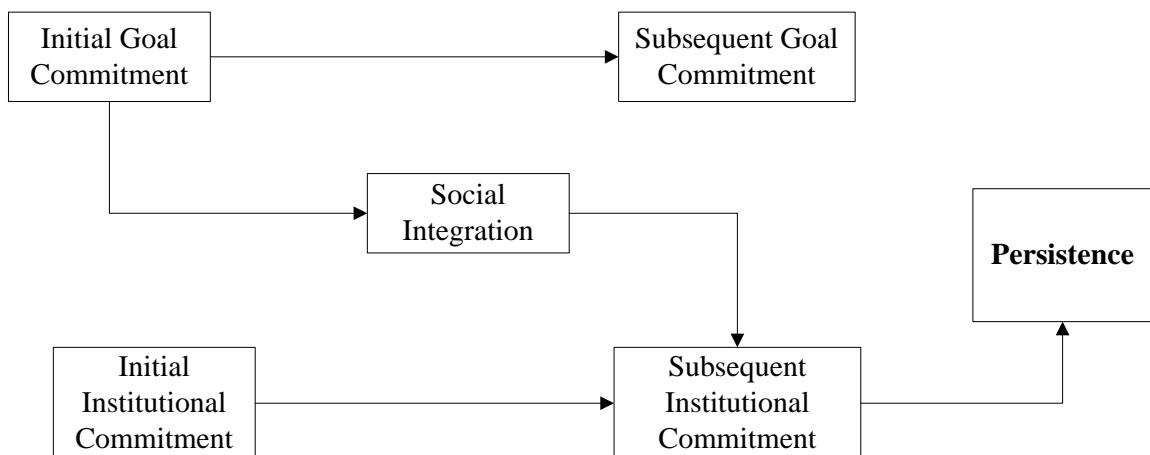


Figure 2. Supported propositions of Tinto's model in residential institutions (Braxton et al., 1997).

Tests of Tinto's model in commuter institutional settings indicated strong support for two out of thirteen propositions (Braxton et al., 1997). These propositions, as depicted in Figure 3, suggest that student individual entry characteristics affect the level of initial commitment to the institution, and that the initial institutional commitment influences the subsequent level of commitment to the institution.

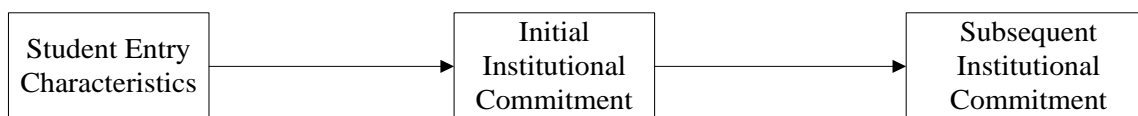


Figure 3. Supported propositions of Tinto's model in commuter institutions (Braxton et al., 1997).

In another review of empirical support for Tinto's theory, Braxton and Lien (2000) determined that academic integration has a significant effect on subsequent institutional commitment of commuter students. The reviews by Braxton and associates (1997, 2000) indicated that Tinto's model of student departure, as a whole, failed to adequately account for the factors that contribute to retention of commuter students. The lack of empirical support for the majority of the propositions in Tinto's theory of student departure makes it clear that revisions or new conceptual frameworks are needed to explain the forces influencing college student retention.

### **Bean's Longitudinal Student Attrition Model**

Bean first introduced a theoretical model of student attrition in 1980, drawing on studies of turnover in work organizations, such as the research of Price (1977), to explain student departure in higher education. As in Tinto's model (1975), attrition is described

as a longitudinal process, where the interactions between students and the institution result in educational and attitudinal outcomes that lead to student retention. In addition to measuring the integration of students into the campus environment through objective measures such as academic performance and participation in campus organizations, Bean's (1980) model also includes subjective measures such as the perceived practical value of education and the quality of the institution which influence students' satisfaction and commitment to the institution.

Bean (1982, 1985) further improved the model by including the environmental factors that have a direct impact on student retention. These factors come from students' personal conditions and circumstances, including lack of finances to cover educational and living costs, family and work responsibilities, opportunities to transfer, or the desire to follow significant others to another school. The environmental factors are important for commuter students who spend limited time on campus and have fewer opportunities for developing interpersonal relationships on campus than residential students. These factors certainly should be included in the model of commuter student retention.

Bean's (1990) Student Attrition Model is an integrative model that addresses the departure puzzle from multiple perspectives: sociological (background characteristics, academic and social integration of the student with the institution, work and family responsibilities), economic (student finances), organizational (admissions, rules and regulations, course scheduling and offering, academic advising, and financial aid), and psychological (attitudes, self-beliefs and academic intent). Bean hypothesized that factors

affecting how students integrate academically and socially would shape their self-confidence, development, as well as their perceptions of the utility of college education.

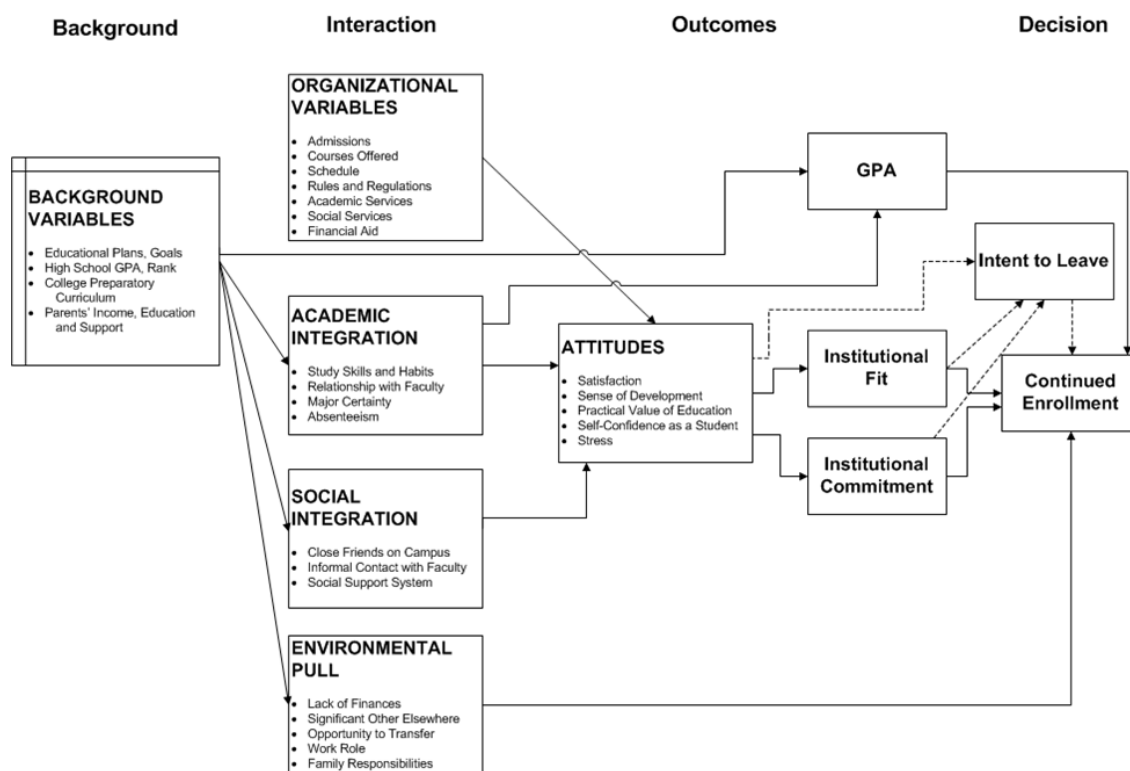


Figure 4. Bean's (1990) Longitudinal Student Attrition Model

There is considerable overlap in Bean's Student Attrition Model and Tinto's Longitudinal Theory of Student Departure, as both models include academic and social integration, institutional fit and commitment constructs. The emphasis on the role of environmental factors and the view of college grades as an outcome variable instead of an indicator of academic integration are two distinguishing features in Bean's conceptual model. In a study testing the validity of both Tinto's and Bean's conceptual models, Cabrera, Castaneda, Nora, and Hengstler (1992) reported that Tinto's Student Integration model was more robust than Bean's model based on the number of validated hypotheses

(70 percent versus 40 percent), but Bean's model explained more of the variance in student persistence (44 percent versus 38 percent). The researchers contended that the higher proportion of variance explained in the Student Integration model was due to the significant effects of the external factors such as parental encouragement, support from friends and finances, on both the intent and the decision to stay at the institution.

### **Bean and Metzner's Nontraditional Student Attrition Model**

In 1985 Bean and Metzner introduced a model of the dropout process for nontraditional undergraduate students who were defined as commuter, part-time, or older than 25 years. The model was based on behavioral theories (Fishbein & Ajzen, 1975) and models of student attrition, such as Bean (1982), Pascarella (1980), and Tinto (1975). The structure of the model (Figure 5) indicates that a decision to leave or continue in college is directly influenced by four set of variables: background and defining characteristics (age, gender, race/ethnicity, high school performance, educational goals, and hours enrolled), academic performance (college grades), intent to leave which is influenced by academic and psychological factors, and environmental variables (finances, hours of employment, family encouragement, etc.).

Bean and Metzner (1985) posited that environmental variables, or pull factors, can support or hinder retention of nontraditional students. In case of environmental support, its positive impact might compensate for the negative impact from academic variables. For example, students receiving strong environmental support such as parental encouragement, or convenient commute and work schedule, will remain in college

despite poor academic support. However, good academic support might not compensate for weak environmental support, because attrition of nontraditional students is expected to be most influenced by the factors outside of the campus.

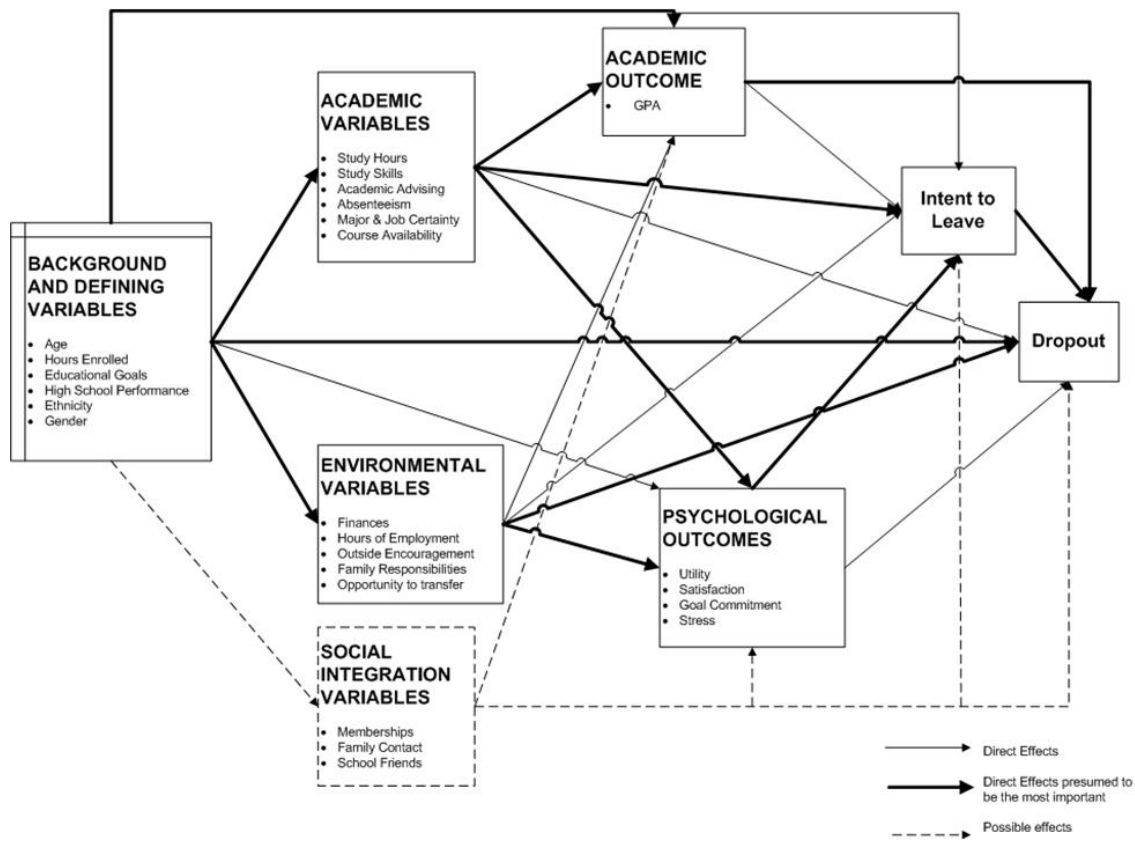


Figure 5. Bean and Metzner's (1985) Nontraditional Student Attrition Model

Bean and Metzner's (1985) model also described a second compensatory effect between the academic outcome (GPA) and the psychological outcomes of the college experience. Positive outcomes in both aspects should encourage students to continue enrollment, and positive psychological outcomes may compensate for the effects of low GPAs. However, high levels of stress, or perceptions of low levels of utility or satisfaction may negatively impact retention despite high GPAs.

Bean and Metzner (1985) postulated that for nontraditional students the decision to stay would be greatly influenced by their academic behaviors and interactions with the academic system of the institution, instead of the interactions with the social environment of the institution. Findings from research studies on commuter students indicated strong empirical support for the link between academic behaviors and college grades (Metzner & Bean, 1987), as well as between grades and student retention (Nora & Cabrera, 1996).

This model of attrition has been applied successfully to diverse populations of college students, including students at two-year community colleges (Brown, 2007; Metzner & Bean, 1987; Stahl & Pavel, 1992).

#### **Cabrera, Nora, and Castaneda's Ability-to-Pay Model**

Student finances were identified as an important environmental factor in Bean's (1985, 1990) Student Attrition Model and in Tinto's (1993) Student Integration Model. Tinto (1993) argued that the impact of financial stress on persistence was often "conditioned" by other noneconomic factors, such as the character and the psychological outcomes of students' interactions within the institution. Findings from a study conducted at a public urban commuter institution by Cabrera, Nora and Castaneda (1992) supported Tinto's argument for the indirect nature of finances in supporting students' adjustment and integration in college. The researchers found that students' finance attitudes as expressed through their satisfaction with the amount of financial support received for college positively influenced their academic and intellectual development. In addition, the reception of financial aid was found to have positive impacts on students' academic



performance, on their relations with peers, and to subsequently increase their intent to persist in college. Findings from this study substantiated the direct effects of finances on persistence behavior as well as the indirect effects of financial aid on student persistence through affecting other factors. The ability-to-pay model, drawn from Cabrera et al.'s study, represented a successful merged approach between the economic-impact perspective and the theoretical frameworks on student persistence, based on Tinto's Student Integration model and Bean's Student Attrition model.

### **St. John, Paulsen, and Starkey's College Choice-Persistence Nexus Model**

While the determinants of success in college have been found to be significantly related to pre-college attributes and academic preparation (Pascarella & Terenzini, 2005), factors that influence the choice of college were often omitted from the analysis. The college choice-persistence nexus model, proposed by St. John, Paulsen, and Starkey (1996), integrates the choice of college, of major, and the college experience as factors that affect decisions to continue in college. In this model students are viewed as "choice makers" who weigh the costs and benefits of attending and of persisting at the chosen institutions. These choices are made in the context of academic, social and financial issues. Their initial commitment to the chosen institution is formed by their perceptions of academic quality and future opportunities, potential social relationships and affordability.

St. John et al. (1996) found that the finance-related reasons for college choice had both a direct and indirect influence on students' persistence. The study suggested that the

way students responded to prices and financial aid was related to the financial reasons why they chose to attend college in the first place. These findings provide support for the proposition that there exists a nexus between college choice and persistence in college, particularly in the context of finance-related reasons for choosing a college.

### **Student Learning Experience and Retention**

The link between student learning experience and retention was “virtually ignored” in the theories of student attrition advanced by Bean (1980, 1983, 1990) and Tinto (1975, 1987, 1993), as noted by Tinto (2000). Empirical evidence supporting the validity of the academic and social integration constructs in these theoretical models often relied on the perceptual component of student experience, instead of their actual learning behaviors and interactions with peers and faculty both inside and outside the classroom (Milem & Berger, 1997). Issues of model specification aside, a resurging interest in the quality of student efforts and of their engagement in learning has stimulated interests in investigating the effects of learning experience on student retention.

The concepts of involvement and engagement are closely related and can be used interchangeably in research on student development and learning. Astin’s (1984) theory of involvement was drawn from of a longitudinal study of persistence which indicated that the levels of students’ involvement in the college experience significantly influenced their decision to persist. Astin (1984) defined involvement as “the investment of physical and psychological energy that the student devotes to the academic experience” (p. 298).

In this sense Astin (1984) emphasized the behavioral aspects of involvement and suggested that the quantity and quality of involvement had direct effects on student learning and development in college.

Milem and Berger (1997) found that various forms of involvement, such as involvement with peers through discussing course content or participating in organized study activity and/or interactions with faculty, influenced students' perception of institutional and peer support, which in turn impacted their commitment to the institution. Other researchers (Kuh, Schuh, Whitt, & Associates, 1991) provide examples of the "involving colleges" where supportive organizational and academic structures were established to promote active involvement on the part of students in campus life and learning, and where students are more likely to be satisfied with their education and feel a sense of loyalty to their institution.

While the classroom space has evolved from the traditional brick-and-mortar physical meeting place for students and faculty to include virtual discussion forums and social media networks over the last decade, classroom behaviors remain an important component of a student's interaction with peers and faculty. In a study of the impact of active-learning behaviors in the classroom on student persistence, Braxton, Milem, and Sullivan (2000) reported that involvement in class discussions and higher order thinking activities had significant direct and indirect effects on students' social integration. This, in turn, influences their subsequent commitment to the institution and persistence decisions.

Evidence of the linkage between learning and persistence can also be evaluated based on the impact on persistence of cognitive abilities and perceived gains in learning-related and affective skills (Nora, Cabrera, Hagedorn, & Pascarella, 1996). Other dimensions of learning, such as socially responsible leadership, intercultural effectiveness, inclination to inquire and lifelong learning, moral reasoning, and course mastery can also positively impact persistence (Wolniak, Mayhew, & Engberg, 2012). Nora et al. (1996) observed that cognitive abilities and gains in affective skills were significant contributors to persistence among minority students. Similarly, Wolniak et al. (2012) reported that content mastery (as measured by college grades) and learning in leadership development had a positive and significant influence on the student persistence decisions. However, the other dimensions of student learning, including intercultural effectiveness, need for cognition, and moral reasoning, were not significant in influencing the persistence among entering first year students (Wolniak, Mayhew, & Engberg, 2012).

### **Braxton, Hirschy and McClendon's Theory of Commuter Student Departure**

Braxton et al.'s (2004) Theory of Student Departure in Commuter Colleges and Universities is an important theoretical advancement in retention research as it conceptualizes the multitude of economic, organizational, psychological and sociological forces which influence commuter students in their persistence in college.

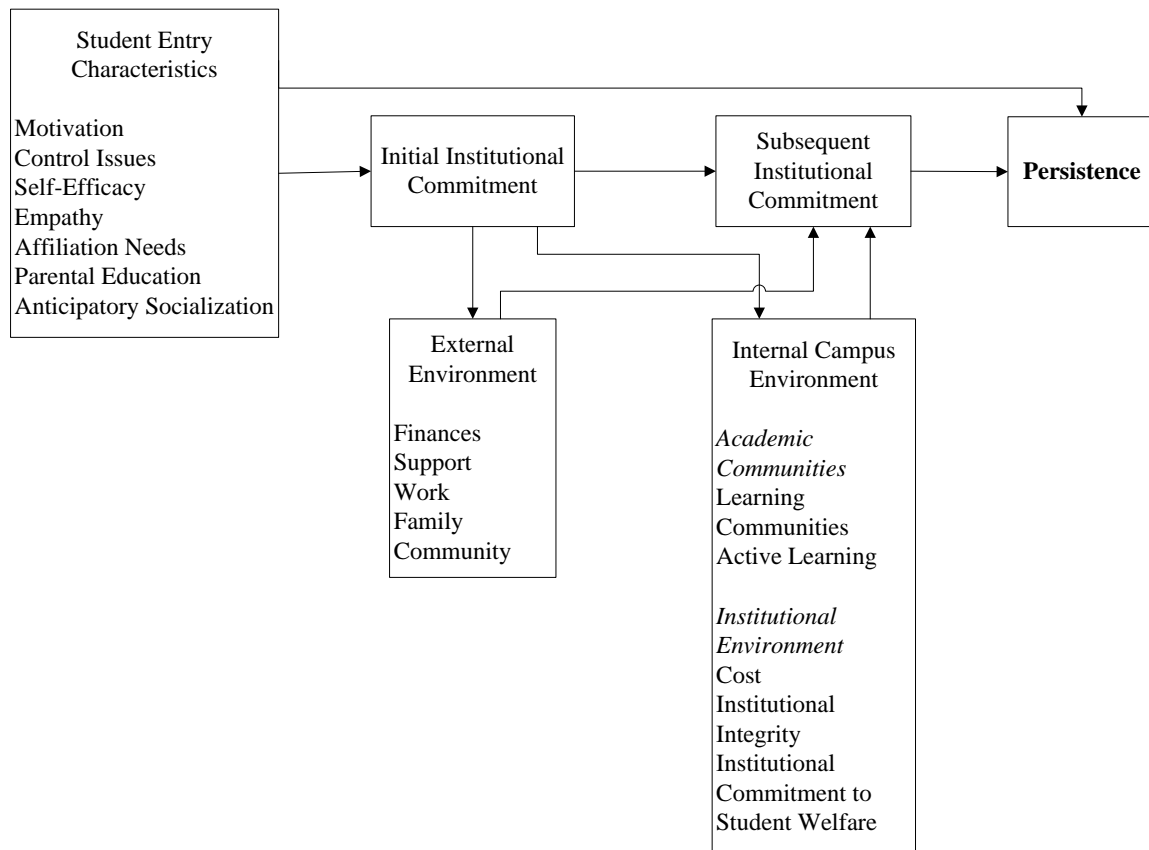


Figure 6. Braxton, Hirschy, and McClendon's (2004) Student Departure Model

In addition to the economic factor (costs of college attendance), Braxton et al.'s model includes five psychological factors (degree motivation, locus of control, self-efficacy, empathy, and need for affiliation), four sociological constructs (parental education, support from significant others, participation in learning communities, and engagement in anticipatory socialization), two organizational constructs (commitment to the welfare of students, and institutional integrity) and four factors which are drawn from Tinto's model (student entry characteristics, initial and subsequent institutional commitment, and academic integration). Combined together, the sixteen propositions in

Braxton et al.'s Theory of Student Departure in Commuter Colleges and Universities form a comprehensive theoretical model that can contribute substantially to our understanding of the process of student departure at commuter institutions. In particular, the importance of both the internal campus environment and the life circumstances outside campus in influencing student persistence is emphasized in Braxton et al.'s model.

One of the key differences between Braxton et al.'s (2004) model and Bean and Metzner's (1985) nontraditional student attrition model is the description of the academic dimension in the college experience of students. Bean and Metzner's (1985) model provides a detailed description of the academic integration process, which is defined through the causal paths linking academic preparation and readiness, to academic behaviors and to academic outcome (college grades), and ultimately to student retention. On the other hand, Braxton et al.'s (2004) model describes participation in academic communities as a central construct for explaining the mechanisms that connect the academic experience to student persistence in college. Braxton et al. posit that the more students participate, involve and engage in academic activities and learning communities, the less likely they are going to leave the institution. This proposition is well supported by the research evidence on student involvement and engagement (Astin, 1984; Kuh et al., 2005; Kuh, Schuh, Whit, & Associates, 1991; Tinto, 1997).

### **Integrated Model of Student Retention in Commuter Universities**

The model of student retention developed in this study focuses on the role of academic and environmental factors as major determinants of retention of commuter students. The model is based on Bean and Metzner's (1985) Nontraditional Student Attrition Model and it also incorporates more recent critiques as discussed in the previous discussion. Both Bean and Metzner's (1985) and Braxton et al.'s (2004) models emphasize the role of academic behaviors, work, and finances on retention of commuter students. Due to the lack of well-defined and -structured social communities the crucial bonds that commuter students form with the institutions are predominantly those of an academic nature. Thus, central to this study is the question of how aspects of academic engagement influence academic performance and retention outcomes among beginning college students, controlling for previous academic achievement such as high school grade point average and standardized test scores. A second important question is how much the environmental factors influence persistence and academic success of commuter students. Thus, the model of student retention developed in the study is an integrated model that examines the paths linking pre-college academic achievement, academic engagement, and environmental factors to academic performance and retention outcomes.

#### **Pre-college Academic Achievement**

Measures of pre-college academic achievement such as high school grade-point average (GPA) and college admissions test scores (SAT or ACT) represent the academic background characteristics of the entering student class. These variables have

traditionally been used as predictors of academic success in college, especially of grades during the first years of college (Pascarella & Terenzini, 2005). In a study estimating the nontraditional student attrition model with a commuter student sample, Metzner and Bean (1987) found that high school performance, as measured by the high school class rank, was one of the best predictors of college grades, but was not significantly related to first-year retention. Consistent with prior research, high school grade point average and ACT Composite scores were included in this study as indicators of pre-college academic achievement. These variables were hypothesized to have direct impacts on grade performance of entering freshmen and indirectly influence their retention decisions.

### **Academic Engagement**

The factors of academic engagement that were incorporated into the retention model are: (a) college readiness in mathematics (by completing remediation or by test scores), (b) the amount of time spent studying, (c) deep learning behaviors, and (d) selection and declaration of a major or a pre-major. Behaviors of academic engagement are particularly important because they directly influence the quality of students' learning and are significant contributors of retention.

The concept of student engagement is grounded on the theory of student involvement (Astin, 1984) and quality of student efforts (Pace, 1980). Astin (1984) defines involvement as “the amount of physical and psychological energy that students devote to the academic experience” (p. 297), and posits that the quality and quantity of student involvement has direct impact on their learning and personal development in



college. The concept of “student engagement”, made popular in higher education research and practice after the introduction of the National Survey of Student Engagement (NSSE) in 2000, is essentially the same as Astin’s “student involvement” (Wolf-Wendel, Ward, & Kinzie, 2009). The NSSE survey questionnaire explores different facets of student engagement in educational activities, such as preparing class assignments, writing and reading activities, engaging in service-learning and community-based projects, participating in classroom-based activities, collaborating with classmates, and interacting with faculty. Beside the wide range of student engagement measures, the survey assesses institutional features that promote student learning. NSSE’s main purpose is to produce “diagnostic and actionable data” that can help institutions assess the quality of undergraduate education and make improvements to support student learning and development (McCormick & McClenney, 2012).

Academic engagement behaviors can be developed through learning experiences on or off campus. As noted by Tinto (1997), the classroom environment serves as an important gateway for students to participate in the academic and social communities on a college campus. The learning communities established inside the classroom environment could be the make-or-break factor for college persistence of commuter students (Tinto, 1997). With limited time resources commuter students might spend most of their time on campus attending classes. By engaging students in the learning materials and class discussions faculty members provide commuter students the key ingredients of the academic experience. Students feeling supported in the classroom environment may

invest psychological energy in joining the broader academic life of an institution and expand interactions with other students and academic communities on campus.

The aspects of academic engagement behaviors examined in the current study include two measures based on NSSE survey items (Amount of Time Spent Studying and Deep Learning) and two measures based on students' registration records (College Math Readiness and Major Selection).

**College math readiness.** The level of academic preparation for college is a significant determinant of college success (Adelman, 2006). However, as reported by the testing company ACT, the reality of college readiness remains an area of concern for the public. Over half of college-going students need to take developmental courses in math and about a quarter of all students need to take English courses (ACT, 2013). Research studies on the effects of developmental education enrollment on grades, credit hour accumulation and persistence are often based on community college student population, as many 4-year public and private universities do not offer developmental education. Campbell and Blakey (1996) found that students who completed developmental course requirements during the first year of enrollment persisted at a higher rate than those who delayed enrollment in remediation. Weissman, Silk, and Bulakowski (1997) discovered that the students who had completed remediation had the similar number of earned credit hours but lower GPAs than the college-level students after the first two and a half years of enrollment. However, the students who had not remediated during that period had remarkably lower academic performance outcomes in comparison to both the remediated

and college-level students. Given the widespread remedial needs in math among the first-time commuter students and the role of remedial courses in providing important preparation for college-level courses, the study sought to examine the influence of college math readiness achieved through successful remediation or by proof of competency such as ACT test scores on the cumulative GPAs.

**Amount of time spent studying.** The amount of time students spent studying per week, obtained from a NSSE survey item, was used in this study as a quantitative measure of what Astin (1984) called the amount of “physical time and energy” that students put into their academic studies. In his theory of student involvement Astin (1984) emphasized the importance of student time as a resource and posited that student achievement is “a direct function of time and efforts”.

Research studies indicate conflicting evidence of the influence of time spent studying on academic performance of college students. In a study of the effects of student engagement on first-year outcomes, Kuh and associates (2008) discovered that the total study time influenced first-year grades, and that the direct effects of time spent studying on GPA varied by ACT score. Another study by Nonis and Hudson (2010) also provided evidence that the amount of time spent studying (an indicator of academic behaviors) had a significant impact on the academic performance when the interaction between study time and ACT score (an indicator of pre-college ability) was included in the analysis.

In this study, the amount of time spent studying was hypothesized to have a direct relationship with Deep Learning engagement and with college grades. In other words, the

students who to put more efforts and more time into academic activities were expected to be more engaged in Deep Learning and have better academic performance.

**Major selection.** Selecting an academic major is equivalent to setting up educational and professional goals for most college students. St. John et al.'s (2004) research indicated that major fields could play a role in influencing retention of Black and White students. In particular, the researchers discovered that White students who were undecided about their majors were less likely to persist. The current study uses selection of a major as an indicator of academic engagement, because many beginning college students are exploratory or uncertain about their academic majors. Having established specific academic and career goals would provide students with a focus for their learning process and influence their retention. The Major Selection variable used in this study is operationalized by a binary variable, where value of 1 indicates whether students have selected a major or a pre-major during the first two years of enrollment.

**Engagement in deep learning.** As noted by Leamson (1999), learning is done “internally” and, even though the learning process can be inspired and encouraged by others, the actual process of learning resides in the person and requires learners to engage their minds in the process. By studying engagement behaviors I hoped to understand the relationships between engagement and learning, as well as between engagement and other student outcomes, such as college grades, and retention. Research using national-level data from the NSSE indicated that student engagement in educationally purposeful behaviors, which was constructed as a global measure of engagement, was positively

related to first-year grades and persistence to second year of beginning college students (Kuh et al., 2008). Of particular interest to the current study are the Deep Learning scales in the NSSE, which measure engagement in activities and experiences that help students develop valuable skills such as integrative, higher order and reflective thinking skills.

The concept of “deep learning” stems from early qualitative research by Marton and Saljo (1976). The researchers discovered through a series of studies that the levels of information processing were related to the levels of student learning outcomes, or what was learned. Based on these findings, they established the conceptualization of surface and deep levels of approach to learning, where the former referred to efforts to memorize and reproduce, while the latter indicated efforts aimed at understanding the meaning of the information provided. An academic environment which emphasizes deep orientation to learning among other effective educational practices is conducive to greater expectations and higher quality of student learning (Prosser, Ramsden, Trigwell, & Martin, 2003).

According to Laird, Shoup and Kuh (2006), the NSSE-based Deep Learning construct is measured by three scales representing students’ engagement behaviors in integrative learning, high-order learning and reflective learning. The Integrative Learning scale addresses the activities (e.g., “Worked on a paper or project that required integrating ideas or information from various sources”) that help students make meaningful connections among ideas, life experiences and academic knowledge. The Higher Order Learning scale assesses how students are engaged in developing higher-

order thinking levels, which include the skills of analysis, synthesis, evaluation and application of existing knowledge to new situations. The Reflective Learning scale examines the learning process through developing metacognitive skills (e.g., “Examined the strengths and weaknesses of your own views on a topic or issue”). NSSE researchers have tested and validated the psychometric properties and the factorial structure of the three Deep Learning scales and of an omnibus Deep Learning scale combining these scales (Laird et al., 2006). Appendix A lists the NSSE items included in the Deep Learning construct.

Previous studies have demonstrated the link between NSSE-based Deep Learning scale and students’ perceptions of learning gains, college grades and satisfaction with college (Laird, Shoup, Kuh, & Schwarz, 2008; Reason, Cox, McIntosh, & Terenzini, 2010). In the current study the NSSE-based Deep Learning construct was included as a measure of students’ engagement behaviors in the learning process. This study sought to find the evidence for the effects of Deep Learning on college grades among commuter students.

### **Environmental Factors**

**Financial concerns.** The impact of finances, or having adequate financial means to cover college costs, was left out of the Tinto model of student departure, as Tinto (1987, 1993) posits that students could use finances as a “polite” excuse for dropping out. However, in the environment of declining federal and state aid and rising tuition costs, students and their families are aware of their financial constraints and the challenges of

finding adequate funds for college costs. Many students juggle between work and school to be able to go to college. Students consider these factors in both the college choice and persistence processes. In fact, there is evidence that student perceptions of their ability to pay for college have an influence on their academic and social experiences in college (Cabrera, Nora, & Castañeda, 1992, 1993). In the conceptual model of commuter student retention students' concerns for meeting college-financing needs were expected to have direct influence on college retention of first-time students.

The "financial concerns" factor was measured by a survey item which asked students to estimate the likelihood that financial problems will delay their degree completion. The single-item measure used a 5-point scale (1 = very unlikely to 5 = very likely). The survey item was included in the NSSE online questionnaire based on an agreement between the NSSE administration and a consortium of urban participating higher education institutions.

**Hours of employment.** National statistics indicate that working for pay while enrolling in college is a persistent and prevalent trend among college students (Horn & Nevill, 2006; Horn, Peter, & Rooney, 2002). In the 2003-04 academic year nearly 75 percent of all undergraduate students and 70 percent of the full-time students worked while enrolling in college (Horn & Nevill, 2006). The relationships between student employment, academic performance and persistence in higher education have been investigated in the last few decades, but the results have been mixed and inconsistent (Riggert, Boyle, Petrosko, Ash, & Rude-Parkins, 2006). In his seminal research on

factors influencing college student outcomes Astin (1993) reported the negative effects of working full-time and part-time off campus on college GPA, on interpersonal skills, and on college degree completion. However, Astin found that having a part-time job on campus was positively associated with student cognitive and affective growth, degree completion, satisfaction, and campus involvement. Astin attributed these positive effects on college outcomes to greater student involvement in the campus environment and more frequent interactions with peers and faculty. The examination of the impact of employment by Pascarella and associates (1998) uncovered different patterns of influence. They found that while work did not have any influence on first-year students' cognitive development, part-time work of up to 15 or 20 hours per week had a positive impact on critical thinking skills of third-year students. Some other researchers did not find the evidence for the impact of employment on college outcomes, such as on GPA (Canabal, 1998) or on student persistence (Metzner & Bean, 1987). In a study using NSSE survey data collected from a wide range of universities, Kuh and associates (2004) discovered that working 21 or more hours off campus had a negative influence on college grades of first-year students while working 20 hours or less off campus was not a significant determinant of grades. In the current study Hours of Employment was hypothesized to have direct effects on academic performance (grades) of first-year students. The variable was measured by a NSSE survey item on the number of hours per week that students spent on a job outside campus.



**Pell grant award.** Federal Pell grant program is a need-based financial aid program geared toward supporting low-income postsecondary students (Wei & Horn, 2009). Pell awards have been found related to increase student persistence in college (Cabrera, Nora, & Castaneda, 1992). While a Pell grant award can be considered as a socioeconomic status (SES) indicator of the recipients, the variable was used in the study to estimate the effect of a Pell grant award on the likelihood of student persistence. The variable was obtained from the student financial aid records, and it indicated whether or not the student had received a Pell grant award each of the first two years of college enrollment.

### **Outcome Variables**

**Academic outcome.** Literature reviews indicate that academic outcome, as measured by college grades, has strong impact on year-to-year persistence (Cabrera, Castaneda, et al., 1992; Johnson, 1997; Kuh et al., 2008; Mallette & Cabrera, 1991; Murtaugh, Burns, & Schuster, 1999; Tinto, 1997). Researching commuter students, Nora, Barlow, and Crisp (2005) discovered that how students perform in the first semester carried strong implications for subsequent persistence decisions, especially among minority students. In the present study academic outcome was operationalized by the cumulative grade point average (GPA) values of the study participants at the end of the first two years of college.

**Retention outcome.** Retention outcome is operationalized in this study by the students' enrollment status in the fall term of the second year (First-year Retention) and

in the third year (Second-year Retention) of college. Retention is defined as a binary variable (code 0 indicating “did not enroll”, and code 1 indicating “enrolled”).

### Models of Student Retention for the Study

As Nora, Barlow, & Crisp (2005) noted, even though a wealth of research on college student persistence had been produced in the last few decades, much attention was focused on the first-year student persistence or on graduation. The current study aimed to make contributions to retention research by investigating factors influencing student retention in the first year and the second year of college.

The first-year student retention model (Figure 7) examines the effects of pre-college academic performance, academic engagement and hours of employment on the First-year GPA, and of First-year GPA and environmental factors on First-year Retention.

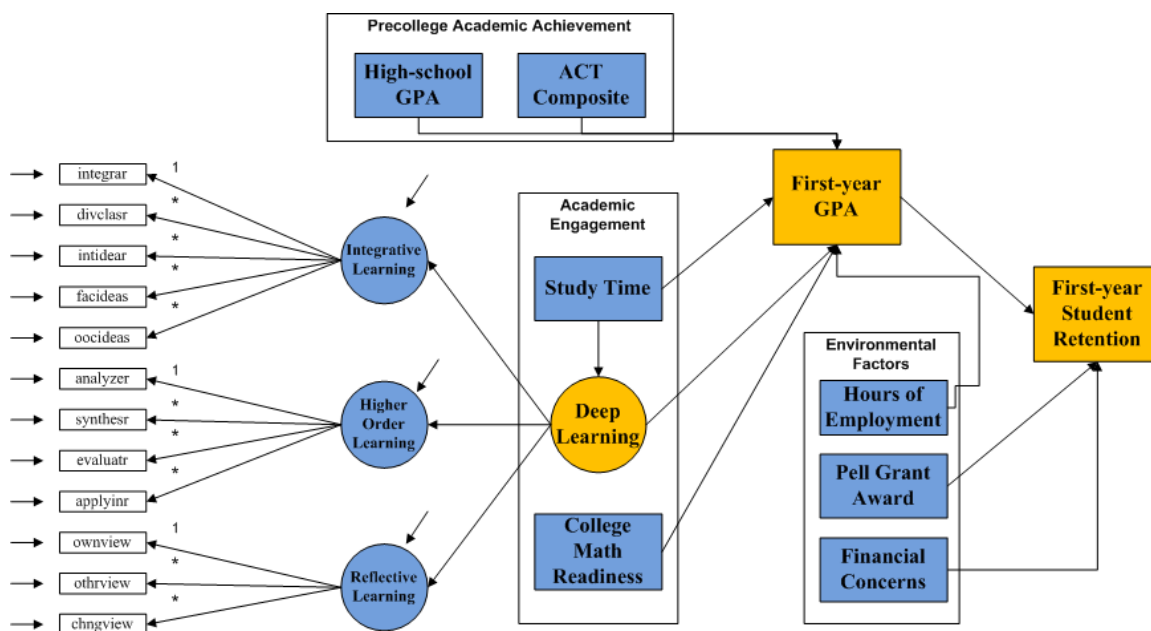


Figure 7. Model of First-Year Student Retention

The Second-year Retention Model developed in the present study examined the impact of student characteristics, academic engagement behaviors and environmental factors on academic performance and retention outcomes after the first two years of college. In comparison to the First-year Retention model two new structural relationships, one between Major Selection and Second-year GPA and the other between Major Selection and Second-year Retention, were added to the Second-year Retention model.

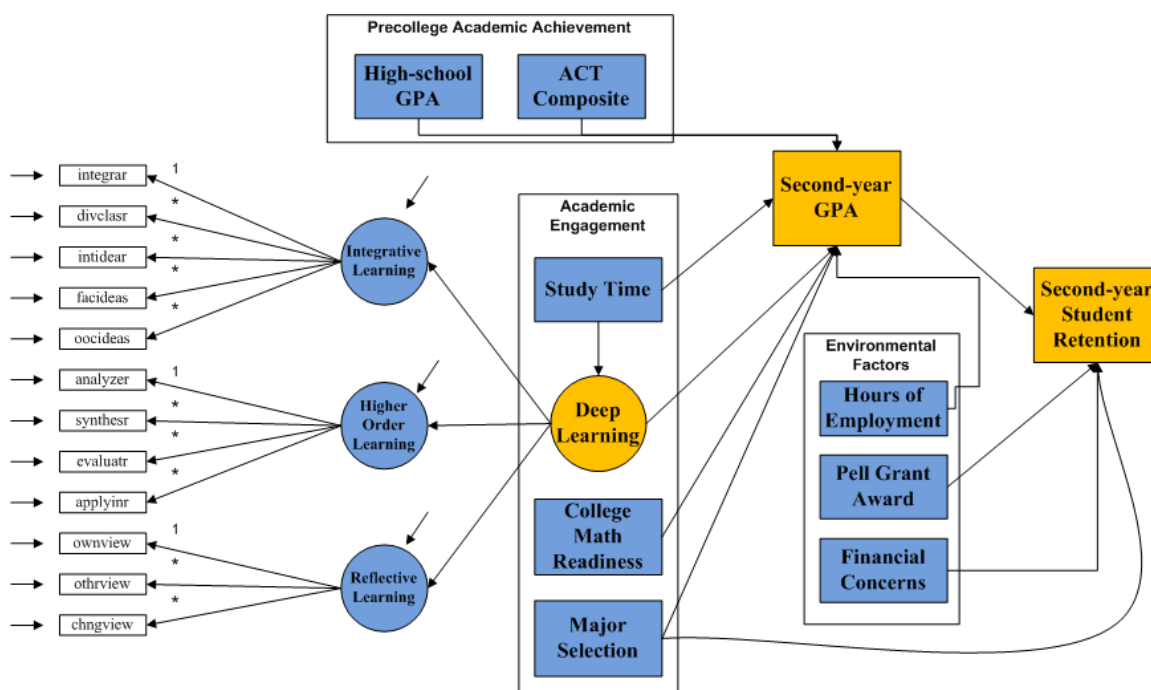


Figure 8. Model of Second-Year Student Retention

Because students at the focus institution are not required to declare a major until they have completed their first 49 credit hours, the selection of an academic major or a pre-major can be seen as a milestone in a student's academic career. Major selection may represent a commitment to educational and professional goals and a potential match between the individual's interests and the academic program that the institution offers.

In the second-year student retention model (Figure 8) the cumulative Second-year GPA was hypothesized to be influenced by pre-college academic performance, academic engagement variables including Major Selection, and by Hours of Employment. Second-year Retention is hypothesized as a function of Second-year GPA, Major Selection, Pell Grant Award and Financial Concerns.

### **Model Testing with Structural Equation Modeling**

Structural equation modeling (SEM) was used to test the hypotheses about the relationships among student entry skills, academic engagement, environmental factors, academic outcome, and retention of commuter students.

SEM-based techniques are considered “a second generation of multivariate analysis” (Fornell & Larcker, 1987) because of the flexibility a researcher has in assessing the validity of theoretical variables and evaluating hypotheses regarding their relationships in a structural theory. SEM techniques have historical roots in path analysis methods, which were originally developed by Sewall Wright (1930) as the methods of decomposing correlations between two variables into a sum of single and compound paths, enabling the researcher to measure the direct and indirect effects between variables, and estimate the magnitude of the causal relationships in the theoretical model. Karl Joreskog’s research in the 1970s, combining path analytic modeling with principles of psychometrics in a single model, has significantly contributed to the development of SEM as a popular statistical methodology in modern social and behavioral sciences (Klem, 2000). While traditional path analysis models only deal with observed variables

and, thus, are unable to allow for measurement errors, SEM procedures provide the flexibility of constructing unobserved (i.e. latent) variables and estimating errors in measurements for observed variables (Maruyama, 1997). A full structural model offers the unique advantage of simultaneously assessing the quality of theoretical constructs and testing the hypothesized causal effects among them (Klem, 2000).

In the current research the hypothesized model can be described as a full SEM model, because it comprises both a measurement model and a structural model. The measurement model, to be tested by confirmatory factor analysis (CFA) procedure, depicts the underlying latent variable structure that includes three dimensions of deep learning approaches – high-order learning (four items), integrative learning (five items), and reflective learning (three items). The structural model specifies regression structure among the latent variables and other observed variables in the hypothesized model.

SEM methodology has been used as a standard approach to testing research hypotheses in the social and behavioral sciences in the past few decades. Some examples of the application of the SEM approach in retention research are discussed next.

Cabrera, Nora, and Castaneda (1993) developed and tested an integrated model of student retention that incorporated Tinto's (1975, 1987) Student Integration Model and Bean's (1983) Student Attrition Model. In a single-institution study design, using a sample of beginning college students at a large southern urban institution, Cabrera et al. (1993) determined that the integrated model was a good fit to the data, accounting for 45 percent of the variance observed in students' reenrollment status in the second year of

college. Cabrera et al.'s research study suggested that student intention to reenroll and college GPA were the most important predictors of persistence, and that environmental factors may have significant influence on goal commitment, as well as on socialization and academic experiences of the students.

Based on Cabrera et al.'s (1993) integrated model of student retention, Nora and Cabrera (1996) examined the role that perceptions of discrimination and prejudice play in persistence. The structural model evaluated in the study specifies the causal relationships among the seven composite variables, which are: (1) Perceptions of Prejudice-Discrimination, (2) Parental Encouragement, (3) Academic Experiences, (4) Social Integration, (5) Academic and Intellectual Development, (6) Goal Commitment, and (7) Institutional Commitment, and a measure of Institutional Persistence. Data for the study was collected from a sample of entering freshman students at a major public, commuter, predominantly white, doctoral-granting university in the Midwest. Model evaluation indicated good fit to the data as the causal model accounted for 42 percent of minority student persistence. One of the unexpected findings of the study is that, while perceptions of discrimination and prejudice were not significant predictors of persistence of minority students, these perceptions exert both total and indirect effects on persistence decisions of nonminority students.

The concept of student-institution fit is central to Tinto's (1975, 1993) longitudinal theory of institutional departure, where successful integration is hypothesized to be dependent on individual perceptions of fit with the academic and

social environments of the campus. Bowman and Denson (2014) developed the Student–Institution Fit Instrument (SIFI) to assess fit based on students’ perceptions of their current institution and their ideal institution in academic, social, cultural, physical, athletic, religious, socioeconomic, and political dimensions. The researchers administered the instrument at two distinctively different institutions to examine the predictive power of fit on social and academic outcomes and on students’ intent to persist. Structural equation modeling (SEM) analyses provided evidence that student–institution fit was associated with greater college satisfaction and had a positive, indirect effect on intent to persist.

## CHAPTER THREE

### METHODOLOGY

#### **Introduction**

The current study examined the causal paths linking pre-college academic achievement, academic engagement behaviors and environmental factors to academic performance and retention outcomes of first-time students at a public urban commuter university. The study used structural equation modeling (SEM) to address the following research questions:

#### **Question One**

How well do pre-college academic performance, academic engagement behaviors and hours of employment predict first-year grade point average?

#### **Question Two**

How well do first-year grade point average, Pell grant award and financial concerns predict first-year retention?

#### **Question Three**

How well do pre-college academic performance, academic engagement behaviors, and hours of employment predict second-year grade point average?

#### **Question Four**

How well do second-year grade point average, major selection, Pell grant award and financial concerns predict second-year retention?



## Data Sources

The data used in this study came from a combination of self-reported measures of college experiences collected from the National Survey of Student Engagement (NSSE), as well as student-level data from institutional records, such as demographic and academic background characteristics, college grades, and enrollment status.

In spring 2012 the National Survey of Student Engagement was administered online to all freshman and senior level students enrolled at the institution. NSSE staff coordinated with the participating institution in the preparation and delivery of the online survey. NSSE also provided a secure web-portal for uploading files and managing survey administration details from start to finish. To improve student participation in the survey the institution employed the use of in-class announcements and of promotional materials such as banners, posters, and flyers in high-traffic areas on campus. Survey participants were also entered in drawing for cash prizes, gift cards, institution-branded trinkets and other small-value prizes. Approximately 3,500 first-year and senior-level students at the institution were invited to participate in the survey. The overall response rate was thirty-five percent (35%). The response rate among the first-time full-time students was twenty-nine percent (29.3%). The final study sample contained 260 first-time full-time students who began their postsecondary education in fall 2011 and participated in the NSSE survey in spring 2012. All data, including demographic and academic variables of the first-time full-time students who completed the questionnaire, were obtained through the Institutional Research Office following the approval from the Institutional Review Board.

### **Site Institution**

The study was conducted at a public urban commuter university with an ethnically and culturally diverse student body. The institution was founded in 1867 as a teacher training institution and continued its mission as a teachers' college serving a large metropolitan area in the Midwest until the 1980s when it was transformed into a 4-year university offering programs in arts and sciences, education and business. Today the institution is classified as one of the Master's colleges and universities (larger programs) based on the basic Carnegie classification schema (Carnegie Foundations for the Advancement of Teaching, 2014). This institution enrolls 11,000 undergraduate and graduate students each year, and prides itself on the high quality and affordability of its academic programs, a faculty excelling in teaching and research, a small student-to-faculty ratio and its emphasis on building strong partnerships with local high school and community networks.

In the last decade the institution has transformed into one of the most ethnically diverse institutions in the Midwest, providing access to higher education for large numbers of minority and low-income students. Students of Hispanic or Latino origin account for over half of the first-time students entering the institution each fall term. Among the first-time college students many are the first in their families to attend college or are from low-income backgrounds. Supporting new students in their transition to higher education has become the push for curriculum transformation and implementation of targeted and student-centered programs and services. The First Year Experience

program was created as a cohesive colloquium of discipline-based introductory courses that embeds student learning and self-discovery within the local environment context, supported by peer mentoring and learning skills enhancement activities. New student and family orientation, summer transition program, co-curricular programs such as student government, community service, Leadership Academy Outdoor Adventure and Freshman Leadership Institute are some of the important initiatives that offer engaging opportunities to incoming students.

### **Study Variables**

The goal of this study was to evaluate two models of student retention in which student entry characteristics, academic engagement and environmental factors were hypothesized to influence academic outcome, such as GPA, and student retention. Academic engagement variables used in this study reflect the intensity of academic efforts (amount of time spent studying, deep learning engagement) and academic behaviors as expressed through successful completion of math developmental courses in the first year and major selection in the second year. In the model of first-year student retention, the academic outcome was operationalized as First-year GPA which is hypothesized to be influenced by a student's pre-college academic achievement (high school grade point average and ACT Composite score), academic engagement behaviors and hours of employment. Retention outcomes of the first-year students were hypothesized to be influenced by academic outcome (first-year college GPA) and the environmental factors (hours of employment, Pell grant award, financial concerns).

Retention outcome of the second-year students was hypothesized to be influenced by academic outcome (second-year college GPA), the environmental factors (hours of employment, Pell recipient, financial concerns) and academic engagement (major selection).

During the data screening process, seven of the NSSE Deep Learning items were recoded to reduce the level of negative skewness. These variables were *integrar*, *divclar*, *intidear*, *analyzer*, *synthesr*, *evaluatr*, and *applyinr*. The Study Time variable was recoded to reduce level of positive skewness. In addition, the hours of employment off campus variable (*workof01*) was recoded as a binary variable to indicate the students who worked 21 or more hours per week off-campus. Table 1 presents the types, definitions and measurements of the study variables.

Table 1. Variable Definitions and Measures

<b>Variable/Factor</b>	<b>Name</b>	<b>Variable Definition and Measure</b>
Gender	GENDER	0 = Male, 1 = Female.
Race/Ethnicity	ETHNIC	Hispanic=0, Black=1, Asian = 2, White=3, Others=4.
Age at college entry	AGE	Age at entry to college on a ratio scale.
ACT Composite score	ACTCOMP	The Composite score of the ACT tests (Scale: 1 to 36 units)
High School Grade Point Average (GPA)	HSGPA	High school cumulative grade point average (Scale: from 0.00 to 4.00)
Study Time per Week	STUDYTM	Hours per 7-day week spent preparing for class (Scale: 1=5 hours or less; 2=6 to 10 hours; 3=11 to 15 hours; 4=16 or more hours;)

<b>Variable/Factor</b>	<b>Name</b>	<b>Variable Definition and Measure</b>
Integrative Learning		During the current school year, about how often have you done each of the following? (Scale: 4=Very often; 3=Often; 2=Sometimes; 1=Never). Note: Recoded scale for integrar, divclar, intidear: 3=Very often; 2=Often; 1=Sometimes or Never.
	INTEGRAR	Worked on a paper or project that required integrating ideas or information from various sources
	DIVCLASR	Included diverse perspectives (different races, religions, genders, political beliefs, etc.) in class discussions or writing assignments
	INTIDEAR	Put together ideas or concepts from different courses when completing assignments or during class discussions
	FACIDEAS	Discussed ideas from your readings or classes with faculty members outside of class
	OOCIDEAS	Discussed ideas from your readings or classes with others outside of class (students, family members, co-workers, etc.)
High-Order Learning		During the current school year, how much has your coursework emphasized the following mental activities? (Recoded scale: 3=Very much; 2=Quite a bit; 1=Some or Very little)
	ANALYZER	Analyzing the basic elements of an idea, experience, or theory, such as examining a particular case or situation in depth and considering its components
	SYNTHESR	Synthesizing and organizing ideas, information, or experiences into new, more complex interpretations and relationships
	EVALUATR	Making judgments about the value of information, arguments, or methods
	APPLYINR	Applying theories or concepts to practical problems or in new situations
Reflective Learning		During the current school year, about how often have you done each of the following? (Scale: 4=Very often; 3=Often; 2=Sometimes; 1=Never)

	OWNVIEW	Examined the strengths and weaknesses of your own views on a topic or issue
	OTHRVIEW	Tried to better understand someone else's views by imagining how an issue looks from his or her perspective
	CHNGVIEW	Learned something that changed the way you understand an issue or concept
College Math Readiness	MATHPASS	Successful completion of math developmental courses during the first year or ACT Math score greater than 21 (Scale: 0=Not at college-level math;1=Prepared at college-level math)
Major Selection	YR1MAJOR	Selection of a major or pre-major program of study by the end of the first year (Scale: 0=Did not select a major/pre major; 1=Selected a major/pre major)
	YR2MAJOR	Selection of a major or pre-major program of study by the end of the second year (Scale: 0=Did not select a major/pre major; 1=Selected a major/pre major)
Financial Concerns	FINANCE	How likely is it that financial problems will delay you in completing your undergraduate education? (Scale: 1=Very unlikely; 2=Somewhat unlikely; 3=Not sure; 4=Somewhat likely; 5=Very likely)
Hours of Employment	WORKIND	Number of hours per week that students spent on working off campus. (Scale: 0.00 = "0 up to 20 hours", and 1.00 = "More than 20 hours")
Pell recipient in Year 1	PELLREC1	Indicator of Pell grant award in the first year in college. (Scale: 0=Not awarded; 1=Awarded)
Pell recipient in Year 2	PELLREC2	Indicator of Pell grant award in the second year in college. (Scale: 0=Not awarded;1=Awarded)
First-year Grade Point Average	YR1GPA	Cumulative grade point average at the end of the first year in college. (Scale: from 0.00 to 4.00)
Second-year Grade Point Average	YR2GPA	Cumulative grade point average at the end of the second year in college. (Scale: from 0.00 to 4.00)
First-year Retention	INYR2	Enrollment status in the fall term of the second year. (Scale: 0=Not enrolled; 1=Enrolled)
Second-year Retention	INYR3	Enrollment status in the fall term of the third year. (Scale: 0=Not enrolled; 1=Enrolled)

### **Statistical Procedures**

Sample statistics were calculated using IBM SPSS version 20. Mplus software version 7.2 (Muthén & Muthén, 1998-2012) was employed in testing the proposed model of student retention because the software can analyze complex structural equation models (SEM) when the data are continuous, ordinal, binary observed dependent variables, or a combination of these (Muthén & Muthén, 1998-2012). In addition, the software includes a multiple imputation procedure for dealing with missing data.

### **Assumptions in Structural Equation Modeling**

**Sample size.** Determining an appropriate sample size for latent variable modeling studies is not an easy research design question (Fabrigar, Porter, & Norris, 2010). There is common belief that structural equation modeling techniques require large sample size to estimate accurate parameters and establish stable model results (Maruyama, 1998). Various rules of thumb on minimum sample size or minimum ratio of cases per measured variable have been proposed in the literature, such as at least 10 cases per measured variable (Bentler & Chou, 1987; Schumacker & Lomax, 1996), or at least 100 to 200 cases (Ding, Velicer, & Harlow, 1995). However, due to the lack of consistency in the recommended minimum sample size, these rules of thumb might create more confusion rather than clarity for those designing research. Also, it should be borne in mind that these rules are based on relatively little theoretical or empirical evidence (MacCallum, Browne, & Sugawara, 1996). Examining the sample size question from the perspective of accuracy and stability of parameter estimates, MacCallum et al. (1999) found that both

the level of communalities among indicator variables and the number of indicators per factor need to be considered in determining minimum satisfactory sample size.

The three latent variables representing dimensions of the Deep Learning construct have 3 or more indicator variables and high level of communalities, as evidenced by the psychometric analyses done by Laird, Shoup and Kuh's (2006) using nation-wide survey data from the NSSE administrations in 2004 and 2005. The condition of high communalities and strongly determined factors achieved in the model is "optimal" in reducing inaccuracy and variability in parameter estimates (MacCallum et al., 1996). Thus, the sample size of 260 cases was considered adequate to achieve stable factor solution.

**Multivariate normality.** Data for a traditional SEM application are assumed to be continuous and have a multivariate normal distribution (Klem, 2000). When these assumptions are not met, the performance of the normal theory estimators, such as maximum likelihood and general least squares, may not be robust, resulting in incorrect or inefficient parameter estimates and other potential problems (West, Finch, & Curran, 1995). To remedy for multivariate non-normality Browne (1984) developed the asymptotically distribution free (ADF) estimator, a weighted least square estimator which requires very large samples to create stable estimates. While the ADF estimator produces unbiased parameter estimates and standard errors, its requirements for large sample size and small number of observed variables place significant practical limitations on research involving small and moderate sample sizes (Byrne, 2011). This is where the newer



weighted least square estimators, such as mean-adjusted WLS estimator (WLSM) and the mean and variance-adjusted WLS estimator (WLSMV), developed by Muthén and colleagues (Muthén, du Toit, & Spisic, 1997) provide major theoretical and practical advantages. The WLSMV estimator, available in Mplus 7.2 (Muthén & Muthén, 1998-2012), has shown robust results in modeling of categorical data or a combination of continuous, ordered categorical and nominal data in small and moderate sample sizes (Byrne, 2011).

Data used in the current study was a combination of continuous and ordered categorical outcome measures. In particular, the college GPA is treated as a continuous variable, while the NSSE survey items on the deep approaches to learning, measured on a 4-point Likert scale, and the dichotomous retention outcome are considered as categorical variables. WLSMV, the default estimator in Mplus 7.2 for analyzing categorical outcome measures, was used in this study.

**Missing data.** Missing data is a prevalent issue in survey research designs. Graham (2009) strongly discouraged the use of the “old” missing data methods, such as listwise deletion (“loss of power”), pairwise deletion (“no basis for estimating standard errors”) and mean substitution (“do not recommend”). The multiple imputation (MI) procedure is the preferred method of dealing with missing data issue (Graham, 2009). The MI procedure involves sampling  $M$  copies of the set of missing values,  $\mathbf{Y}_{\text{mis}}$ , from a conditional distribution  $f(\mathbf{Y}_{\text{mis}}|\mathbf{Y}_{\text{obs}}, \boldsymbol{\theta})$ , and then each copy fills in the missing part of the dataset to create  $M$  imputed datasets. For each imputed dataset, a complete-case analysis

would then be conducted to generate estimates of the model parameter  $\theta$  and the corresponding sampling covariances (Song, 2007).

In the current study there were four missing data cases in the ACT Composite scores and a varying range of missing data among NSSE survey items. The multiple imputation procedure was applied using Mplus 7.2 to create 10 datasets for data analysis. The multiple datasets were inspected to make sure that the imputed data values were within the original scale.

The strategy to handle the missing data issue in the dataset, which accounts for 1% to 14% missing in the input indicators, is to estimate the model with the complete dataset using listwise deletion method, and, after that, with imputed datasets using the multiple imputation procedure available in Mplus 7.2. The examination of parameter estimates would highlight any structural differences resulted from using the two missing data approaches and allow the researcher to determine whether including the imputations will improve the estimates.

### **SEM Implementation Steps**

**Specification.** The current study evaluated a full SEM model, as termed by Byrne (2011), which specifies inter-relationships among academic background, engagement, environmental variables and various outcome measures. The full SEM model can be decomposed into two sub-models: a measurement model and a structural model. The reason for assessing model fit in two separate steps (Anderson & Gerbing, 1988) is to examine the underlying latent variable structure apart from the structural component

which contains directional paths between the latent variables and other structural paths, thus allowing the researcher to identify separate sources of potential model misspecification (Hoyle, 2012).

The measurement model, also referred to as the confirmatory factor analysis (CFA) model (Hoyle, 2012), specifies the cause-and-effects relations between the latent variable and its indicator variables.

In this study the CFA model was the Deep Learning model, which hypothesizes a priori that (a) responses to the NSSE questions on “deep approaches to learning” can be explained by three first-order factors (Higher-order Learning, Integrative Learning, and Reflective Learning) and one second-order factor (Deep Learning); (b) each input indicator has a nonzero loading on the designated first-order factor and a zero loading on the other two first-order factor; (c) residuals associated with each input indicator are not correlated; (d) correlations among the three first-order factors are accounted for by the second-order factor. Justification for the hierarchical factorial structure of Deep Learning is based on research findings by Laird, Shoup, and Kuh (2006).

The structural models of this study were used to examine the predictive power of pre-college academic achievement, academic engagement and hours of employment on college GPA (Research Questions 1 and 3), the predictive power of first-year GPA, and environmental factors on first-year retention (Research Question 2), and of second-year GPA, environmental factors, and major selection on second-year retention (Research Question 4).

**Identification.** A SEM model is statistically identified when it has sufficient information, or data points, for parameter estimation. However, an over-identified model where the number of data points is greater than the number of freely estimated parameters is needed for model testing, because a just-identified model with no degrees of freedom can never be rejected (Byrne, 2011). Latent variable scaling by fixing one factor-loading parameter, or a regression path, in each congeneric set of loadings to a non-zero value, such as 1.0, is an approach used in the study to determine the scales of the unobserved variables and also to meet the requirements for model identification. In this SEM model, the latent variable structure is identified by 12 observed variables, and 4 continuous latent variables, of which there are 3 first-order factors and 1 second-order factor. The scale of the latent variables has been established by constraining the first factor-loading parameter in each first-order factors to a value of 1.0. On the other hand, all second-order factor loadings are freely estimated to provide the researcher with a full picture of the higher-order factor structure. To solve the issue of model identification some additional constraints were put in place with regards to the second-order factor, including fixing the second-order factor variance to 1.0 and the residual variance for the Integrative Learning to zero. The constraint of the residual variance of the Integrative Learning factor was used for this study because Laird, Shoup and Kuh (2006) found that the Integrative Learning factor was nearly perfectly predicted by the second-order factor and, thus, had a very small residual variance. These constraints were made to ensure that the model is over-identified (Byrne, 2011).

The measurement model and both structural models (of first-year and second-year retention) in the study are over-identified models, with 52, 165 and 177 degrees of freedom, respectively.

**Estimation.** As noted by Hoyle (2011), parameter estimation process aims at minimizing the discrepancy between the observed (or population) covariance matrix,  $\Sigma$ , and the predicted (or model) covariance matrix,  $\Sigma(\theta)$ . The model covariance matrix was generated through estimation. The null hypothesis for model testing is expressed as follows:

$$\Sigma = \Sigma(\theta)$$

Since the hypothesized model in this study employs both continuous and categorical data, WLSMV estimator was used to obtain parameter estimates of the statistical model. WLSMV estimator is the default estimator for categorical data in Mplus 7.2 computer program. As explained earlier, WLSMV is a mean- and variance-adjusted weighted least squared estimation method that is robust to conditions of nonnormality and violations of assumptions of continuous measurements. In addition, the sample size of 260 cases is sufficiently large to represent the population and produce valid parameter estimation.

**Evaluation of fit.** To evaluate whether the model is consistent with the observed data, also known as the omnibus fit (Hoyle, 2011), a set of three fit indices was used. The Comparative Fit Index (CFI) and the Tucker-Lewis Fit Index (TLI) are called incremental, or comparative, indices which measure the improvement in model fit by

comparing the specified model with the baseline model where zero covariation among the observed indicator variables were assumed (Byrne, 2011). As recommended by Hu and Bentler (1999), a CFI value of .95 or higher is indicative of a well-fitting model. The TLI index is customarily used in the same way as the CFI, with values of .95 or higher as the criterion of good fit (Byrne, 2011).

The root mean square error of approximation (RMSEA) is an absolute index of fit which, unlike the incremental fit indices, measures the discrepancy between the hypothesized model and the population covariance matrix. Browne and Cudeck (1993) provided the following guidelines in with regards to RMSEA values:  $\varepsilon$  equal or less than .05 indicates close fit,  $.05 < \varepsilon < .08$  represents fair fit,  $.08 < \varepsilon < .10$  indicates marginal fit, and  $\varepsilon$  greater than .10 indicates unacceptable fit.

## CHAPTER FOUR

### RESULTS

#### **Introduction**

Data used in this study were gathered from the institutional records and the NSSE survey data. The study sample was comprised of 260 first-time full-time students who began their postsecondary academic careers in fall 2011 and participated in the NSSE survey in spring 2012. The dataset variables included student demographic characteristics (gender, age, race and ethnicity), pre-college academic performance (ACT Composite Score, high school grade point average), academic engagement (amount of time spent studying per week, deep approaches to learning, college readiness in mathematics, major selection) and environmental factors (financial concerns, hours of employment, and Pell grant award), first-year and second-year outcomes (GPA and retention).

#### **Descriptive Statistics**

##### **Demographic and Academic Background Characteristics**

The sample was overrepresented by female participants in comparison to the population of first-time full-time students at the institution (61.9% versus 52.4%). The majority of the participants (88.5%) were aged 19 or younger. Participants ranged in age from 18 to 39, with a mean of 19 (SD = 1.80). The sample did not differ the population in terms of age distribution. Nearly half of the participants (48.8%) were Hispanic, 15% were Asian, 6% were African American, 25% were Caucasian, and 5% were of other or unknown racial and ethnic background.

Table 2. Demographic and Academic Background Characteristics

Student Characteristics	Study Sample		All Others	
	n	Pct.	n	Pct.
Number of Students	260	100%	626	100%
<b>Gender*</b>				
Male	99	38%	323	52%
Female	161	62%	303	48%
<b>Race/Ethnicity*</b>				
Hispanic	127	49%	319	51%
African American	16	6%	58	9%
Asian	39	15%	55	9%
Caucasian	65	25%	150	24%
Other/Unknown	13	5%	44	7%
<b>Age</b>				
19 or younger	230	89%	536	86%
20 and above	30	12%	90	14%
Mean (SD)	18.98 (1.8)		19.27 (3.08)	
<b>High-school GPA*</b>				
Above 3.0	130	50%	211	34%
2.01 – 3.0	113	44%	315	50%
2.0 or Lower	17	7%	83	13%
GPA Not Available			17	3%
Mean (SD)	3.01 (.637)		2.77 (.683)	
<b>ACT Composite Score*</b>				
Under 19	127	49%	278	44%
19 to 23	97	37%	286	46%
24 or Higher	32	12%	62	10%
ACT Not Available	4	2%		
Mean (SD)	18.96 (3.72)		18.30 (5.21)	
<b>Pell Recipient in Year 1*</b>				
Yes	190	73%	392	63%
No	70	27%	234	37%

\* Statistically significant



The majority of students, 73%, received a Pell grant award during the first year of college enrollment. In terms of pre-college academic performance, the mean high-school grade point average was 3.01 (SD = 0.64), and the average ACT Composite score was 18.96 (SD = 3.72).

The comparison group included all other first-time full-time students who did not participate in the NSSE survey in spring 2012. This group consisted of 626 students, or 70.6% of the target population. Table 2 displays demographic and academic background characteristics of the 260 participants in the study and of the comparison group. The two groups differed significantly in demographic and socioeconomic status variables: gender,  $X^2(1, N=886) = 13.463, p < .001$ ; race/ethnicity,  $X^2(4, N=886) = 10.235, p < .05$ ; Pell recipient,  $X^2(1, N=886) = 8.913, p < .01$ .

In terms of pre-college academic background, the participants had better high school grade point averages ( $M = 3.01, SD = .637$ ) than the comparison group ( $M = 2.77, SD = .683$ ),  $t(521.5) = -4.924, p < .001$ . They also have higher ACT Composite scores ( $M = 18.96, SD = 3.72$ ) than the comparison group ( $M = 18.30, SD = 5.21$ ),  $t(656.39) = -2.128, p < .05$ .

### **Academic and Retention Outcomes**

Two-thirds of the participants achieved college-level Math Readiness by the end of the first year, outperforming the comparison group:  $X^2(1, N=886) = 7.605, p < .01$ . The difference in first-year GPA of the study participants ( $M = 2.87, SD = 0.75$ ) and of the comparison group ( $M = 2.15, SD = 1.21$ ) was significant,  $t(878) = -8.98, p < .001$ .

A fourth of the study participants had selected a major by the end of the second year in college. As reported in Table 3, the study participants also were more likely to choose a major by the end of the second year than the comparison group,  $X^2(1, N=886) = 32.177, p < .001$ . They were also more likely to reenroll in the second year,  $X^2(1, N=886) = 54.76, p < .001$ ; as well as to reenroll in the third year of college,  $X^2(1, N=886) = 45.102, p < .001$ .

Table 3. Academic and Retention Outcomes

Student Characteristics	Study Sample		All Others	
	n	Pct.	n	Pct.
Number of Students	260	100%	626	100%
<b>Math Readiness by Year 1*</b>				
Yes	171	66%	349	56%
No	89	34%	277	44%
<b>First-year GPA *</b>				
Above 3.0	119	46%	166	27%
2.01 – 3.0	103	40%	208	33%
2.0 or Lower	38	15%	246	39%
No GPA	0	0%	6	1%
Mean (SD)	2.87 (.748)		2.15 (1.21)	
<b>First-year Retention*</b>				
Yes	209	80%	337	54%
No	51	20%	289	46%
<b>Major Selection by Year 2*</b>				
Yes	68	26%	69	11%
No	192	74%	557	89%
<b>Second-year Retention*</b>				
Yes	169	65%	252	40%
No	91	35%	374	60%

\* Statistically significant

## Missing Data

Prior to performing SEM analyses, a multiple imputation procedure was conducted to deal with the missing data. This procedure is considered as a “state of the art” technique because, while sampling variability is retained with the multiple imputed data sets, the accuracy and the power of the analyses are improved in comparison to other methods (Schafer & Graham, 2002).

While the demographic and academic background variables were complete, the ACT Composite scores had four (4) missing values, accounting for 1.5% of the dataset. Of the 15 survey items used in the analyses, the amount of missing data ranged from 1.2 to 14.2%. The distribution of missing data in the dataset was assumed to be at least missing at random (MAR), which meant that for a participant the probability of missingness in a variable might depend on the other observed data but not on the missing data (Schafer & Graham, 2002).

The multiple imputation procedure in Mplus 7.2 (Muthén & Muthén, 1998-2012) was used to generate 10 complete data sets, each of which contained different estimates of the missing values. Because the NSSE items measuring student engagement in Deep Learning were considered ordered categorical indicator variables and because the outcome variable *retention* is a dichotomous variable, the WLSMV estimator was used for both the measurement and structural model analyses. This estimation method was used for its robustness against violations of multivariate normality and its appropriateness for ordinal scale data (Byrne, 2011).

The strategy to handle the missing data issue in the dataset was to estimate the model with the complete dataset using listwise deletion method, and, after that, with the imputed datasets which were created by the multiple imputation procedure in Mplus 7.2 (Muthén & Muthén, 1998-2012).

## Structural Equation Modeling Analyses

### The Measurement Model

The measurement model in this study is a confirmatory factor model measuring student uses of deep approaches to learning, also known as the Deep Learning construct. The construct's psychometric properties were examined by Laird, Shoup and Kuh (2006), using national data from the 2004 and 2005 administration of the NSSE survey.

Table 4. Summary Statistics of the Deep Learning items (N=260)

Factor/Variable <sup>a</sup>	Mean	SD	Missing %
<b>Integrative Learning</b>			
INTEGRAR	2.17	0.74	1%
DIVCLASR	2.10	0.79	1%
INTIDEAR	1.86	0.78	4%
FACIDEAS	2.20	1.08	4%
OOCIDEAS	2.83	0.94	5%
<b>Higher-order Learning</b>			
ANALYZER	2.27	0.74	5%
SYNTHESR	2.11	0.77	5%
EVALUATR	2.10	0.79	6%
APPLYINR	2.15	0.75	5%
<b>Reflective Learning</b>			
OWNVIEW	2.48	1.01	8%
OTHRVIEW	2.77	0.96	8%
CHNGVIEW	2.93	0.92	8%

<sup>a</sup> Refer to Table 1 (page 50) for full variable names.

Based on Laird et al.'s (2006) findings, the model of Deep Learning, which was hypothesized to comprise three first-order factors (Higher-order Learning, Integrative Learning, and Reflective Learning) and a second-order factor (Deep Learning), was tested in this study on a sample of 260 first-year students at a commuter university.

**Model estimation using listwise deletion method.** When tested using the complete data set ( $N=226$ ), the model of Deep Learning provides a reasonable fit to the data, chi-square (52) = 85.854,  $p < 0.05$ , RMSEA = 0.054 (90% CI = 0.32 to 0.073, probability RMSEA  $< .05 = 0.362$ ), CFI = 0.988, TLI = 0.984). The estimated RMSEA value of 0.054 and the 90% confidence interval of RMSEA values are within the bounds of “a reasonable error of approximation” (Browne & Cudeck, 1992). The CFI and TLI values are both above .95, indicating that the model fits the data reasonably well. All first-order and second-order factor loadings are statistically significant ( $p < .05$ ). The fit statistics and the significant factor loadings, which are reported in section A of Table 5, provide strong evidence for the hierarchical factorial structure of Deep Learning. In the next step, I evaluate the CFA model of Deep Learning using 10 data sets, which were imputed in Mplus 7.2 based on the multiple imputation method for handling missing data.

**Model estimation using multiple imputation method.** Model testing using the multiple imputation method indicated that the hypothesized second-order factor model exhibited a fair fit to the data. The pooled model fit statistics, averaged over 10 data sets, were as follows: chi-square (52) = 98.861, RMSEA = 0.059, CFI = .985, and TLI = .981.

Table 5. Parameter Estimates of the Measurement Model of Deep Learning

Parameter	A. Estimation with Listwise Deletion					B. Estimation with Imputed Data Sets				
	Unstd. Est.	SE	P value	Std. Est.	Residual Variance	Unstd. Est.	SE	P value	Std. Est.	Residual Variance
<b>Integrative Learning</b>										
INTEGRA <sup>(1)</sup>				0.721	0.480				0.720	0.481
DIVCLASR	0.963	0.087	0.000	0.695	0.518	0.966	0.084	0.000	0.696	0.516
INTIDEAR	1.083	0.087	0.000	0.780	0.391	1.054	0.083	0.000	0.759	0.423
FACIDEAS	0.795	0.095	0.000	0.573	0.672	0.814	0.090	0.000	0.587	0.656
OOCIDEAS	0.894	0.090	0.000	0.644	0.585	0.887	0.085	0.000	0.639	0.592
<b>Higher-order Learning</b>										
ANALYZER <sup>(1)</sup>				0.882	0.221				0.892	0.205
SYNTHESR	1.005	0.046	0.000	0.887	0.213	0.967	0.044	0.000	0.862	0.257
EVALUATR	0.941	0.048	0.000	0.830	0.310	0.924	0.046	0.000	0.824	0.321
APPLYINR	0.963	0.049	0.000	0.850	0.277	0.968	0.045	0.000	0.863	0.256
<b>Reflective Learning</b>										
OWNVIEW <sup>(1)</sup>				0.817	0.332				0.836	0.301
OTHRVIEW	1.121	0.047	0.000	0.916	0.161	1.078	0.044	0.000	0.901	0.188
CHNGVIEW	1.065	0.041	0.000	0.871	0.241	1.056	0.038	0.000	0.883	0.221
<b>Deep Learning</b>										
Integrative Learning <sup>(2)</sup>	0.721	0.050	0.000	1.000	0.000	0.720	0.046	0.000	1.000	0.000
Higher-order Learning	0.643	0.046	0.000	0.728	0.456	0.639	0.047	0.000	0.716	0.487
Reflective Learning	0.516	0.053	0.000	0.632	0.620	0.544	0.052	0.000	0.651	0.576

Notes: (1) Parameter fixed at 1.0 to identify variance of latent variable. (2) Residual variance fixed at 0.

The RMSEA values were within the range of reasonable error of approximation (.05 to .08) as recommended by Browne and Cudeck (1992). In addition, the CFI and TLI values are above the .95 criterion, indicating that the model is correctly specified.

It is important to note that a method for pooling model fit indices such as RMSEA, CFI, and TLI from the imputed datasets has not been established. As such, the overall model fit was assessed in an ad hoc approach, based on the examination of an empirical distribution created by the 10 estimates of each of these fit indices (Enders, 2010).

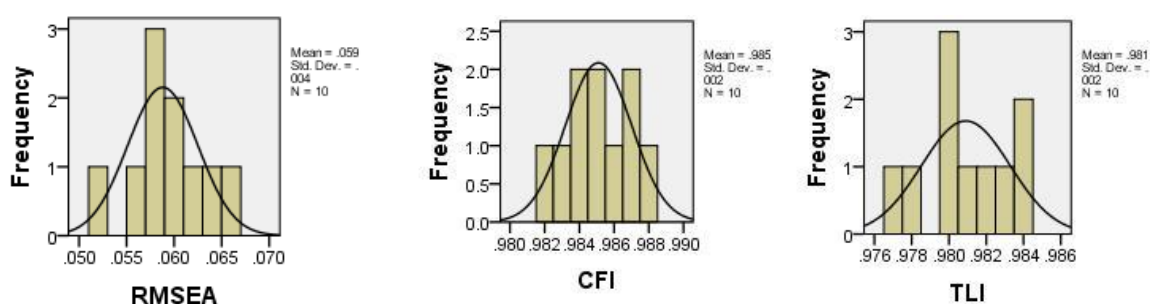


Figure 9. Deep Learning Factor Model - Histograms of Fit Indices

Results indicated that the RMSEA values were all below .07, while the CFI and TLI values were above .95 (Figures 9). Because high values of CFI and TLI are indicative of good model fit, it was found that the CFI and TLI values at the 5<sup>th</sup> percentiles of the distribution (.982 and .977, respectively) were well above the conventional cut-off values of .95. The evidence showed that the measurement model of the Deep Learning construct fits well to the data.

Results of the confirmatory factor analysis are indicative that the three Deep Learning scales (higher-order, integrative, and reflective) are three specific dimensions of

the higher-order Deep Learning construct as identified by Laird, Shoup and Kuh (2006).

As reported in section B of Table 5, the standardized first-order and second-order factor loadings are all significant and substantially higher than the conventional cut-off value of 0.3 (Floyd & Widaman, 1995). The second-order factor loadings are significant, providing evidence for the hierarchical structure of the Deep Learning construct.

Factor loadings and residual variances, as reported in Table 5, also show that results from the confirmatory factor analyses using the complete data set (the listwise deletion method) are similar to those using imputed data sets.

In summary, the analyses demonstrate that the model for the Deep Learning construct fits the data well.

**Measurement invariance analyses.** There are two methods for evaluating measurement invariance: CFA with covariates and multiple-group CFA. CFA with covariates, also known as multiple-indicators, multiple-causes (MIMIC) modeling, was used in the present study because this approach has smaller sample size requirements and is more parsimonious than the alternative method (Brown, 2006). To examine whether the Deep Learning factor structure is applicable across samples of male and female participants, the Gender variable (0 = male, 1 = female) was added as a covariate to the CFA model of Deep Learning and the model was estimated using the complete-case data. The path diagram of this MIMIC model is presented in Figure 10.



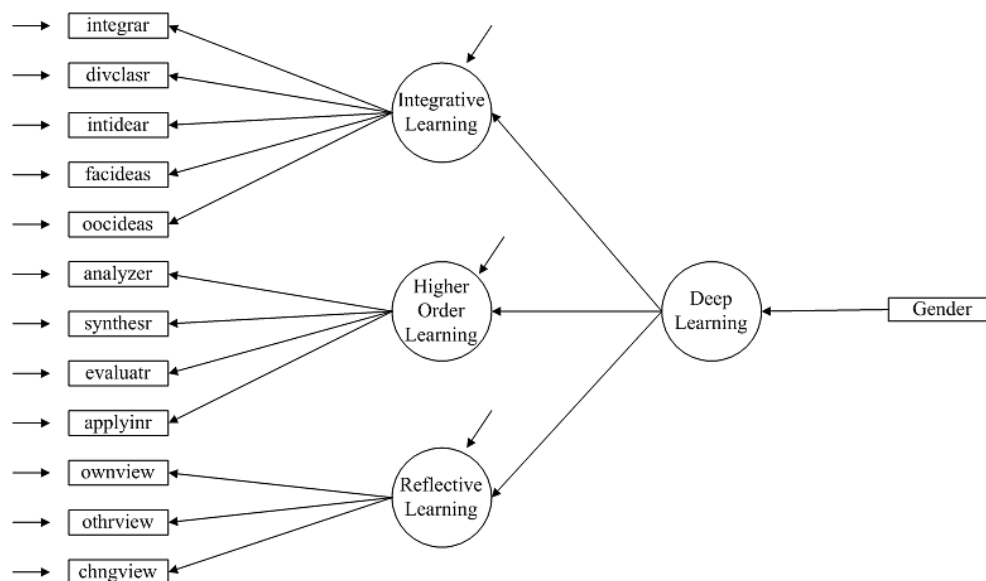


Figure 10. Deep Learning Factor Model with Gender as a Covariate

The MIMIC model provided an adequate fit to the data: chi-square (63) = 99.372, RMSEA = 0.051,  $CI_{90} = [.030, .069]$ , CFI = .98, and TLI = .984. With the inclusion of the Gender covariate, the factor structure remained stable and parameter estimates were similar to those in the original CFA solution. The regression coefficient of gender was not significant ( $p > .05$ ), indicating that male and female students did not differ with respect to Deep Learning factor mean.

A second measurement invariance analysis of the Deep Learning factor was conducted with ethnicity as a covariate. Because the Hispanic students accounted for nearly half of the sample, the ethnicity variable was recoded as a binary variable (0 = non-Hispanic, 1 = Hispanic) and was then added as a covariate to the CFA model of Deep Learning construct. The Deep Learning model with Hispanic as a covariate provided a good fit to the data (RMSEA = .055,  $CI_{90} = [.036, .073]$ , CFI = .985, and TLI

= .981). The regression coefficient for path from ethnicity to Deep Learning was significant ( $b = -.434$ ,  $SE = .151$ ,  $p < .05$ ). The results from this analysis indicated that the Deep Learning factor mean was lower for Hispanic students than for non-Hispanic students.

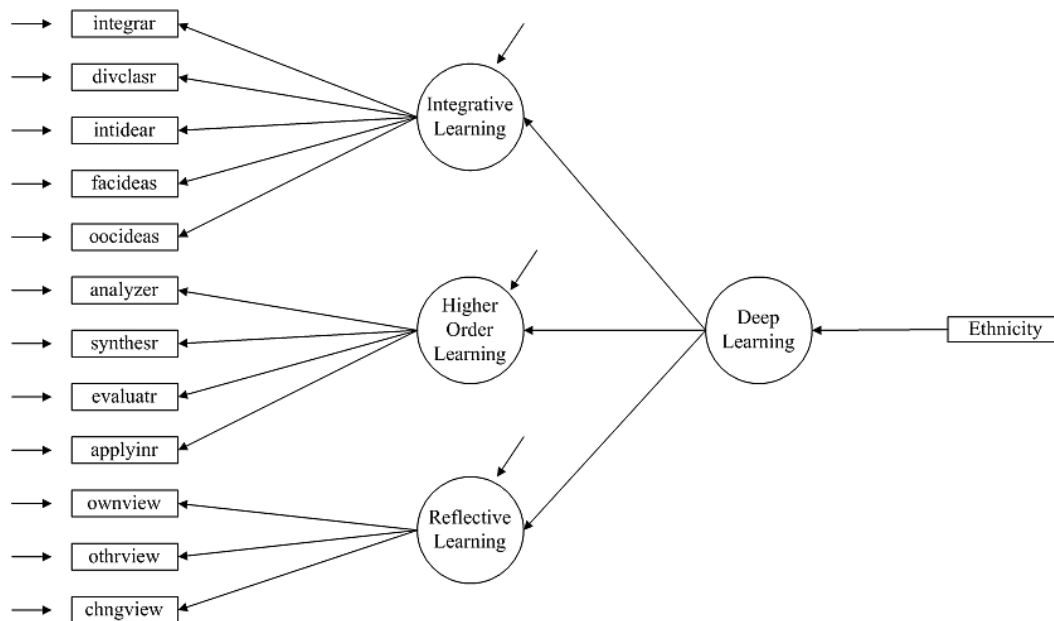


Figure 11. Deep Learning Factor Model with Ethnicity as a Covariate

### The Structural Models

While the measurement model focuses solely on the Deep Learning scales and their measured variables, the structural models in this study specify the regression structure relating Deep Learning and other explanatory variables, including student academic background, academic engagement, and environmental factors, to college grades and student persistence. Results from the structural model analyses, including model fit statistics, regression paths, standard errors and unique variances, are presented here.

**First-year retention model.** The structural model of First-year Student Retention was estimated in two ways, first, using the complete data set, and, then, using the 10 imputed data sets. Model fit statistics and parameter estimates produced by the two methods were compared in order to examine the stability of the model and the sensitivity of parameter estimates. Since the retention outcome is a dichotomous variable, the WLSMV estimator in Mplus 7.2 was applied for model estimation.

The estimation of the First-year Retention model using the complete data set ( $N = 205$ ) produces a chi-square statistic of 201.299 ( $df = 165$ ,  $p = .028$ ). Fit indices indicate the model fits the data well: RMSEA = .033 (90% CI = .12 to .047, CFI = .975), CFI = .986 and TLI = .984.

The pooled chi-square statistic produced by the multiple imputation analyses ( $N = 260$ ) is 217.544 ( $df = 165$ ), and the fit statistics, averaged over 10 data sets, indicate a good-fitting model: mean RMSEA = .035, CFI = .985, and TLI = .983.

The overall model fit of the First-year Retention model was assessed based on the empirical distributions created by 10 estimates of the model fit indices (Enders, 2010).

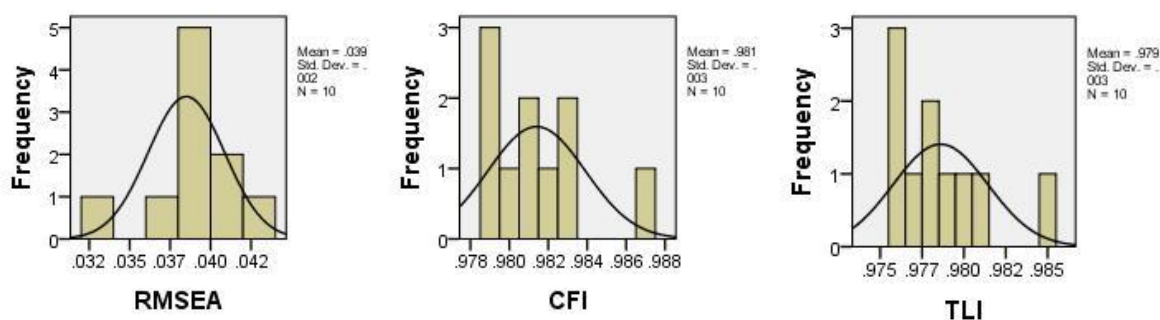


Figure 12. First-year Retention Model – Histogram of Fit Indices with the Imputed Data Sets

Histograms of the RMSEA, CFI and TLI estimates from 10 imputed data sets, as reported in Figure 11, show that all the CFI and TLI values are above .95 and all the RMSEA values were below .05, indicating a good fit.

Table 6 presents standardized and unstandardized parameter estimates for the structural model of First-year Retention produced by listwise deletion and multiple imputation approaches. Most of the estimated parameters are similar when compared across estimation approaches. However, the regression coefficient of Deep Learning on First-year GPA is notably higher using the complete date set ( $z = 2.36$ ) than with the imputed data set ( $z = 1.81$ ). Thus, under the listwise deletion approach Deep Learning was found significant at  $p < .05$  level in predicting First-year GPA, while under the multiple imputation method the path from Deep Learning to First-year GPA was not significant ( $p=.072$ ).

Because the results produced by the complete data set did not differ from the multiply-imputed ones except for the Deep Learning variable, the regression weights estimated under the listwise deletion approach were used to interpret the findings in the context of the research questions.

***Research question one: How well do pre-college academic performance, academic engagement behaviors, and hours of employment predict first-year grade point average?*** The results from testing the First-year Retention model show that pre-college academic performance, academic engagement behaviors, and hours of employment are significantly related to First-year GPA ( $p < .05$ ).

Table 6. Parameter Estimates for the Structural Model of First-year Retention

Parameter	A. Estimation with Listwise Deletion				B. Estimation with Imputed Data Sets			
	Est.	SE	P value	Std. Est.	Est.	SE	P value	Std. Est.
<b>Paths</b>								
Study Time → Deep Learning	0.339	0.076	0.000	0.362	0.287	0.069	0.000	0.312
Deep Learning → First-year GPA	0.111	0.047	0.017	0.158	0.076	0.042	0.072	0.108
ACT Comp → First-year GPA	0.037	0.014	0.009	0.187	0.033	0.013	0.013	0.165
High school GPA → First-year GPA	0.527	0.075	0.000	0.442	0.484	0.065	0.000	0.414
Study Time → First-year GPA	0.090	0.042	0.031	0.138	0.105	0.038	0.006	0.162
Math Readiness → First-year GPA	0.306	0.097	0.002	0.407	0.337	0.086	0.000	0.453
Employment Hours → First-year GPA	-0.257	0.111	0.021	-0.342	-0.207	0.096	0.031	-0.277
College GPA → First-year Retention	0.430	0.123	0.000	0.300	0.414	0.101	0.000	0.291
Financial Concerns → First-year Retention	-0.196	0.080	0.015	-0.234	-0.176	0.077	0.022	-0.217
Pell Grant Award → First-year Retention	0.581	0.239	0.015	0.540	0.483	0.213	0.023	0.455
<b>Residual Variances</b>								
First-year GPA	0.357	0.036	0.000	0.634	0.368	0.032	0.000	0.663
Integrative Learning	0.000	0.000		0.000	0.000	0.000		0.000
Higher Order Learning	0.351	0.059	0.000	0.441	0.411	0.058	0.000	0.506
Reflective Learning	0.417	0.053	0.000	0.605	0.427	0.052	0.000	0.584
Deep Learning	1.000	0.000		0.869	1.000	0.000		0.902

Notes: 1) Estimation results in (A) was based on the complete data set (N = 205). 2) Estimation results in (B) were averaged from 10 imputed data sets (N = 260). 3) Residual variance for the latent variable Integrative Learning was fixed at 0 and the Deep Learning factor variance was fixed at 1.0.

Among the factors which had a positive effect on First-year GPA, High-school GPA was the most significant predictor ( $\beta=.442$ ,  $SE = .057$ ,  $p<.001$ ), followed by College Math Readiness ( $\beta = .407$ ,  $SE = .129$ ,  $p<.05$ ), ACT Composite Score ( $\beta = .187$ ,  $SE = .069$ ,  $p < .05$ ), Deep Learning ( $\beta = .158$ ,  $SE = .066$ ,  $p < .05$ ), and Study Time per Week ( $\beta = .138$ ,  $SE = .065$ ,  $p < .05$ ). While pre-college academic performance and academic engagement variables exerted positive influence on first-year GPA, Hours of Employment had a negative effect on First-year GPA ( $\beta = -.342$ ,  $SE = .143$ ,  $p < .05$ ). Overall, 36.6% of variance in First-year GPA was explained by the predictor variables.

***Research question two: How well do first-year grade point average, Pell grant award and financial concerns predict first-year retention?*** Results indicated that all three predictor variables in the model were significantly related to First-year Retention. First-year GPA ( $\beta = .3$ ,  $SE = .084$ ,  $p < .001$ ) and Pell Grant Award ( $\beta = .54$ ,  $SE = .209$ ,  $p < .05$ ) had significant and positive direct effects on First-year Retention, while Financial Concerns ( $\beta = -.234$ ,  $SE = .090$ ,  $p < .05$ ) had a negative effect on student retention. Figure 12 displays the structural coefficients estimated in the First-year Retention model.

The model explained 19.4 % variance in first-year retention outcome of beginning college students. This finding is comparable to other retention research based on commuter students (Brown, 2007; Zhai, Monzon, & Grimes, 2005).

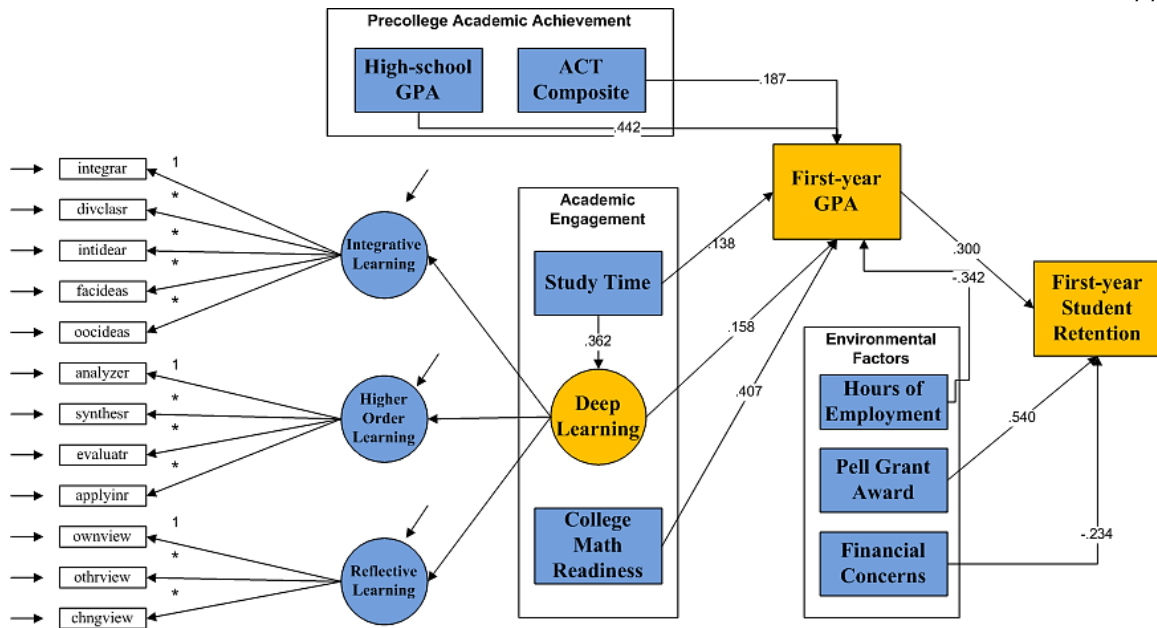


Figure 13. First-year Retention Model with standardized structural coefficients

**Total, direct and indirect effects in the first-year retention model.** The total, direct and indirect effects of the predictor variables on First-year GPA and First-year Retention, obtained from the listwise deletion approach, are reported in Table 7.

Indirect effect coefficients were estimated as the product of direct effects that comprise them (Kline, 2005). Total effects were calculated by summing all direct and indirect effects of each variable. Statistical significance tests of the unstandardized indirect effects and total effects in the first-year retention model were conducted.

Results indicated that Study Time per Week had a significant effect on First-year GPA. In addition, High-school GPA, ACT Composite score, Study Time and College Math Readiness had significant indirect effects on First-year Retention. However, the indirect effects of Deep Learning and Hours of Employment on First-year Retention were not found significant.

Table 7. Effect Decomposition for the First-year Retention Model (N = 205)

Outcome/Predictor Variables	Direct Effect		Indirect Effect		Total Effect	
	b	SE	b	SE	b	SE
<b><u>On First-year GPA</u></b>						
High School GPA	0.527***	0.075			0.527***	0.075
ACT Composite Score	0.037**	0.014			0.037**	0.014
Study Time per Week	0.090*	0.042	0.038*	0.018	0.128**	0.040
Deep Learning	0.111*	0.047			0.111*	0.047
College Math Readiness	0.306**	0.097			0.306**	0.097
Hours of Employment	-0.257*	0.111			-0.257*	0.111
<b><u>On First-year Retention</u></b>						
High School GPA			0.226**	0.069	0.226**	0.069
ACT Composite Score			0.016*	0.007	0.016*	0.007
Study Time per Week			0.055*	0.023	0.055*	0.023
Deep Learning			0.048	0.026	0.048	0.026
College Math Readiness			0.131*	0.057	0.131*	0.057
Hours of Employment			-0.110	0.058	-0.110	0.058
First-year GPA	0.430***	0.123			0.430***	0.123
Pell Grant Award	0.581*	0.239			0.581*	0.239
Financial Concerns	-0.196*	0.080			-0.196*	0.080

Note. b – unstandardized path coefficient; SE – standard error. \*p < .05; \*\*p < .01; \*\*\*p < .001.

Based on the standardized parameter estimates, the largest total effect on First-year Retention was accounted for by First-year GPA, followed by Pell Grant Award and Financial Concerns.

**Second-year retention model.** The structural model of Second-year Retention was analyzed under the listwise deletion approach (N = 205) and the multiple imputation approach using 10 imputed data sets (N = 260). All analyses were conducted using the WLSMV estimator in Mplus 7.2 (Muthén & Muthén, 1998-2012). Model testing with the complete-case data produced a chi-square value of 218.084 (p=.0193), while the



multiply-imputed data produced a pooled chi-square value of 228.409. The fit indices, estimated using the complete-case data (RMSEA = .034 (90% CI = 0.015 to 0.048, CFI = 0.974), CFI = .985, and TLI = .982) indicate that the Second-year Retention model provides close fit to the data. The fit indices produced by the multiply-imputed data (RMSEA = .033, CFI = .986, TLI = .984) also suggested that the Second-year Retention was a good-fitting model. The distributions of the fit indices produced by 10 imputed data sets, as seen in Figure 13, are approximately normal, where all the RMSEA values are below .05 and the CFI and TLI values are above .95.

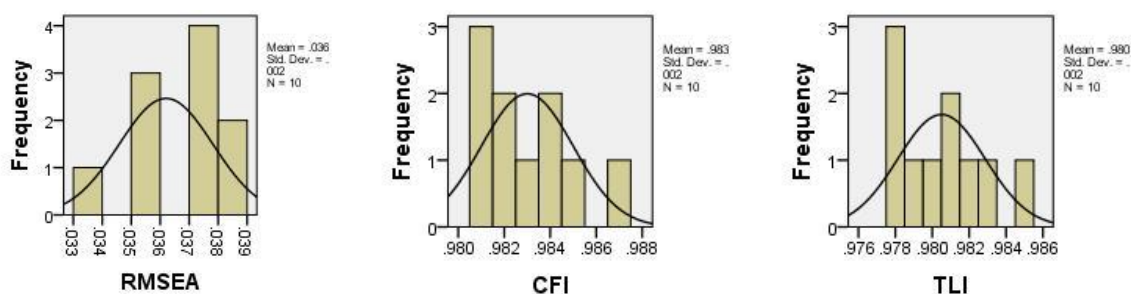


Figure 14. Second-year Retention Model - Histograms of Fit Indices with Imputed Data Sets

Once the model fit has been examined and satisfied, the latent variable structure, the regression weights and other parameter estimates were reviewed. All loadings for the first-order and second-order Deep Learning factors are significant ( $p < .001$ ) and their values are closely convergent in the listwise deletion and multiple imputation estimation. The results indicate that the latent variable structure for Deep Learning is well preserved in the Second-year Retention model.

Standardized and unstandardized parameter estimates for the structural model of Second-year Retention are reported in Table 8. The majority of the parameter estimates produced by the listwise deletion and multiple imputation approaches were similar. One main difference between the two approaches was that the College Math Readiness was found significantly related to Second-year GPA in the analysis using the multiply-imputed data ( $p < .05$ ), and not in the complete data set ( $p < .10$ ). Another notable difference was that the coefficient of the path from Major Selection to Second-year Retention was lower in the complete-case results ( $\beta = .598$ ) than in the multiply-imputed ones ( $\beta = .809$ ).

In summary, both listwise deletion and multiple imputation approaches produced a good overall model fit and approximately similar parameter estimates, except for the path between College Math Readiness and Second-year GPA and from Major Selection to Second-year Retention. Based on the similarity in findings, parameter estimates generated from the listwise deletion approach are next reviewed in the context of research questions three and four.

***Research question three: How well do pre-college academic performance, academic engagement behaviors, and hours of employment predict second-year grade point average?*** Major Selection was found to have a significant influence on Second-year GPA ( $\beta = .553$ ,  $SE = .153$ ,  $p < .001$ ). Major Selection was the most significant predictor of Second-year GPA, followed by High-school GPA. College Math Readiness also had a positive, but not significant, influence on Second-year GPA ( $\beta = .253$ ,  $SE = .133$ ,  $p = .058$ ).

Table 8. Parameter Estimates for the Structural Model of Second-year Retention

Parameter	A. Estimation with Listwise Deletion				B. Estimation with Imputed Data Sets			
	Est.	SE	P value	Std. Est.	Est.	SE	P value	Std. Est.
<b>Paths</b>								
Study Time → Deep Learning	0.334	0.076	0.000	0.357	0.286	0.069	0.000	0.311
Deep Learning → Second-year GPA	0.116	0.042	0.006	0.166	0.095	0.041	0.020	0.134
ACT Comp → Second-year GPA	0.048	0.013	0.000	0.244	0.045	0.012	0.000	0.224
High school GPA → Second-year GPA	0.498	0.072	0.000	0.417	0.430	0.063	0.000	0.369
Study Time → Second-year GPA	0.095	0.041	0.020	0.144	0.095	0.037	0.010	0.146
Math Readiness → Second-year GPA	0.190	0.099	0.054	0.253	0.214	0.087	0.014	0.288
Employment → Second-year GPA	-0.162	0.108	0.134	-0.216	-0.164	0.095	0.084	-0.221
Major Selection → Second-year GPA	0.416	0.121	0.001	0.553	0.385	0.105	0.000	0.519
Second-year GPA → Retention	0.575	0.141	0.000	0.326	0.385	0.127	0.002	0.219
Major Selection → Retention	0.795	0.336	0.018	0.598	1.054	0.301	0.000	0.809
Financial Concerns → Retention	-0.265	0.090	0.003	-0.256	-0.194	0.085	0.023	-0.194
Pell Grant Award → Retention	0.969	0.254	0.000	0.730	0.939	0.210	0.000	0.721
<b>Residual Variances</b>								
Second-year GPA	0.307	0.033	0.000	0.542	0.334	0.032	0.000	0.605
Integrative Learning	0.000	0.000		0.000	0.000	0.000		0.000
Higher Order Learning	0.350	0.059	0.000	0.438	0.410	0.058	0.000	0.505
Reflective Learning	0.419	0.052	0.000	0.613	0.431	0.052	0.000	0.589
Deep Learning	1.000	0.000		0.872	1.000	0.000		0.903

Notes: 1) Estimation results in (A) was based on the complete data set (N = 205). 2) Estimation results in (B) were averaged from 10 imputed data sets (N = 260). 3) Residual variance for the latent variable Integrative Learning was fixed at 0 and the Deep Learning factor variance was fixed at 1.0.

Both ACT Composite Score and Study Time per Week had significant effects on Second-year GPA ( $p < .05$  for both variables). The Deep Learning factor showed a significant influence on the Second-year GPA ( $\beta = .166$ ,  $SE = .06$ ,  $p < .01$ ). Since the Deep Learning behaviors were measured in the spring term of the first year of college, its significance on Second-year GPA indicated that academic engagement behaviors might produce a lagged time effect on the outcomes. Working more than 20 hours per week had a negative, but not significant effect on Second-year GPA.

The total amount of variance in Second-year GPA explained by the second-year retention model was 45.8%, an improvement of 9.2% from the first-year retention model.

***Research question four: How well do second-year grade point average, major selection, Pell grant award and financial concerns predict second-year retention?***

Second-year GPA, Pell Grant Award and Major Selection each had a positive influence on Second-year Retention while Financial Concerns had a negative impact on retention. All four variables were significant predictors. Pell Grant Award was the most significant predictor of Second-year Retention ( $\beta = .730$ ,  $SE = .180$ ,  $p < .001$ ), followed by Major Selection ( $\beta = .598$ ,  $SE = .235$ ,  $p < .05$ ), Second-year GPA ( $\beta = .326$ ,  $SE = .080$ ,  $p < .001$ ), and Financial Concerns ( $\beta = -.256$ ,  $SE = .08$ ,  $p < .01$ ). When combined, the four variables explained nearly half (49.3%) of the variance in Second-year Retention.

Figure 14 displays the standardized structural coefficients of the second-year retention model estimated using the complete-case data.

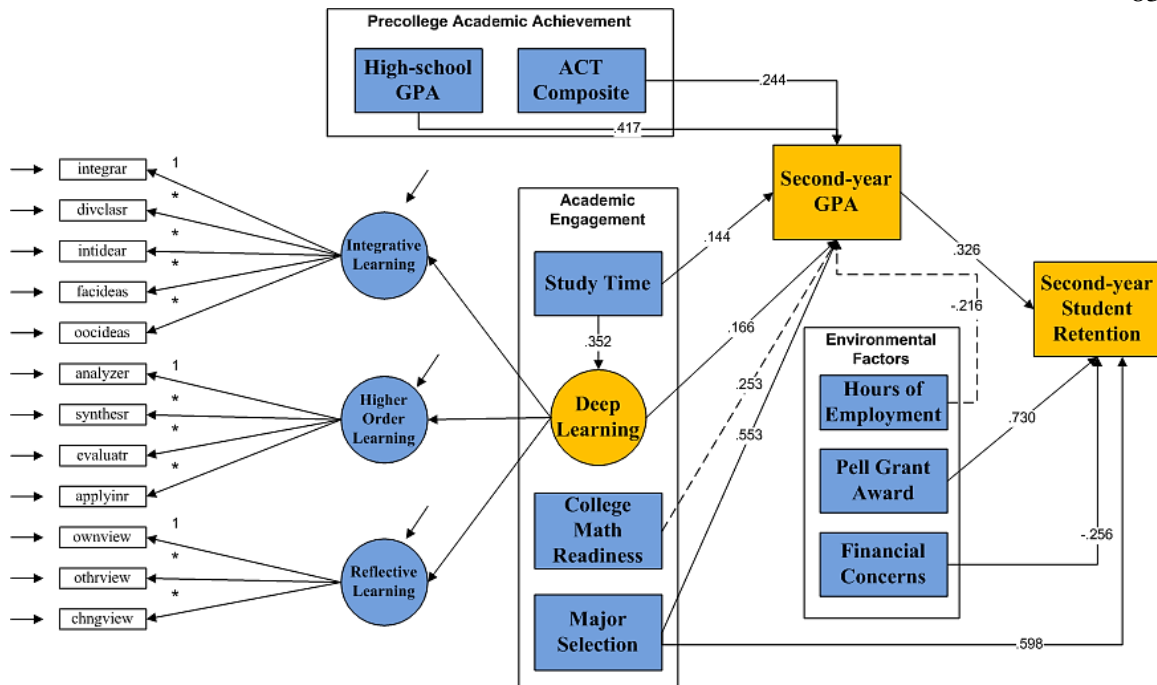


Figure 15. Second-year Retention Model with standardized structural coefficients

**Total, direct and indirect effects in the second-year retention model.** The total, direct and indirect effects of the predictor variables on Second-year cumulative grade point average (GPA) and Second-year Retention are reported Table 9. The product of coefficients strategy (MacKinnon, Lockwood, Hoffman, West, & Sheets, 2002) was used to measure the extent and significance of the indirect effects of the predictor variables.

The results, which were obtained from the complete-case analysis, indicated that High School GPA and ACT Composite Score not only directly influence Second-year GPA, but also had significant indirect effects on Second-year Retention. This finding suggests that academic performance and achievement in high school has a positive

influence on academic performance and persistence in college beyond the first year of studies.

Deep Learning and Study Time both exhibited a significant influence on Second-year GPA and indirectly on Second-year Retention ( $p < .05$ ). In addition, Major Selection demonstrates a strong influence on both Second-year GPA and Retention. College Math Readiness and Hours of Employment, however, were not found to have a significant effect on either GPA or Retention.

Table 9. Effect Decomposition for the Second-year Retention Model (N = 205)

Outcome/Predictor Variables	Direct Effect		Indirect Effect		Total Effect	
	b	SE	b	SE	b	SE
<b><u>On Second-year GPA</u></b>						
High School GPA	0.498***	0.072			0.498***	0.072
ACT Composite Score	0.048***	0.013			0.048***	0.013
Study Time per Week	0.095*	0.041	0.039*	0.016	0.134**	0.039
Deep Learning	0.116*	0.043			0.116*	0.043
College Math Readiness	0.190	0.099			0.190	0.099
Hours of Employment	-0.162	0.108			-0.162	0.108
Major Selection	0.416**	0.121			0.416**	0.121
<b><u>On Second-year Retention</u></b>						
High School GPA			0.286***	0.081	0.286***	0.081
ACT Composite Score			0.028**	0.010	0.028**	0.010
Study Time per Week			0.077**	0.029	0.077**	0.029
Deep Learning			0.067*	0.029	0.067*	0.029
College Math Readiness			0.109	0.064	0.109	0.064
Hours of Employment			-0.093	0.065	-0.093	0.065
Second-year GPA	0.575***	0.141			0.575***	0.141
Major Selection	0.795*	0.336	0.239**	0.092	1.034**	0.317
Pell Grant Award	0.969***	0.254			0.969***	0.254
Financial Concerns	-0.265**	0.090			-0.265**	0.090

Note. b – unstandardized path coefficient; SE – standard error. \* $p < .05$ ; \*\* $p < .01$ ; \*\*\* $p < .001$ .

Measures of pre-college academic achievement (High-school GPA and ACT Composite score) and of academic engagement (Study Time per Week and Deep Learning) had significant indirect effects on Second-year Retention. Among these four variables the indirect effect on retention from High-school GPA was the highest ( $b = .286, p < .001$ ). The indirect effects on retention from the other three variables were small.

The direct effects from Second-year GPA, Major Selection, Pell Grant Award and Financial Concerns on Second-year Retention were found significant. Major Selection also had a significant indirect effect on retention. Based on the standardized coefficients of the direct effects, Pell Grant Award ( $\beta = .730, SE = .180, p < .01$ ) was the most significant predictor of Second-year Retention ( $\beta = 1.034, p < .01$ ), followed by Major Selection ( $\beta = .598, SE = 0.235, p < .05$ ), Second-year GPA ( $\beta = .326, SE = .08, p < .001$ ) and Financial Concerns ( $\beta = -.256, SE = .08, p < .01$ ).

CHAPTER FIVE  
DISCUSSION AND CONCLUSION

**Introduction**

The current study aimed at examining the impact of academic engagement behaviors and of environmental factors on academic performance and retention of first-time students in non-residential institutional settings. Grounded in the research conducted by Astin (1993), Bean and Metzner (1985), Pascarella and Chapman (1983) and Tinto (1975, 1993), the conceptual model of student retention in this study focuses on how student engagement variables such as the amount of time spent studying, deep approaches to learning, college-level readiness in math and major selection, as well as employment and finance-related issues influence outcome measures.

At the heart of this study was the question of how academic engagement behaviors, employment and finance-related factors influence academic performance and retention outcomes among beginning college students, while controlling for previous academic achievement (high school grade point average and standardized test scores). The study utilized the data on student engagement from the NSSE, one of the most prominent student surveys in higher education, and supplemented with the academic and financial aid data from institutional records to answer this question. The study focused on the academic engagement and environmental factors, because these factors have been found to play essential roles in the college experience of commuter students.



## **Summary of the Study**

The study explored whether the pathways through deep engagement in the academic life and processes of the institution would be the key to academic achievement and continuous enrollment in college. The study findings provide empirical evidence for the predictive power of academic engagement on college grade point averages and retention of beginning college students.

### **Deep Learning Engagement**

The Deep Learning construct was included in the study of student retention as an important academic engagement factor because deep learning engagement behaviors were linked to students' gain in general knowledge, skills, sense of personal development, college grades and overall satisfaction of college experience (Laird, Shoup, Kuh, & Schwarz, 2008). Deep learning behaviors are distinguished from rote memorization and other types of surface learning. In the models of student retention developed in this study, Deep Learning in combination with prior academic achievement and other academic engagement variables, such as Study Time per Week, College Math Readiness and Major Selection, were postulated to directly influence first-year and second-year GPA. Moreover, Major Selection was hypothesized to have direct influence on students' reenrollment decisions.

The study results provided evidence for the validity of the Deep Learning construct which was measured by engagement behaviors in integrative, higher-order and reflective learning activities. The goodness-of-fit statistics of the measurement model

indicated that the Deep Learning construct fit the data reasonably well. The results from the First-year Retention model indicated that Deep Learning was significantly related to the grades of first year students ( $p < .05$  in the analysis with the complete-case data, and  $p < .10$  with the multiply-imputed data).

Of interest is the question whether the deep learning engagement behaviors have a lasting impact on student performance throughout the first two years of college. The findings from the Second-year Retention model showed that deep learning engagement behaviors had a positive influence on the cumulative second-year GPA ( $p < .05$  in the analysis with the complete case data, as well as with the multiply-imputed data). The results suggest that as students actively engage in the learning process by incorporating integrative, reflective and higher-order learning activities in their studies, their grade performance would also improve. In other words, engagement in learning in the early years of college might help students develop the competencies needed for academic success in the later years. The study findings on deep learning among beginning college students offer insights into how students become engaged learners and how to promote academic success.

### **Academic Preparation, Engagement and Grade Performance**

Research studies show that pre-college academic performance measures, such as standardized test scores (SAT, ACT) and high-school grade point averages, are significant indicators of performance in college, especially in the early years (Adelman, 2006; Belfield & Crosta, 2012). Results from this study provide additional evidence for

the predictive power of pre-college academic achievement in both the first-year and second-year cumulative GPAs. The study indicates that high school GPA is highly predictive of grade performance in the first two years of college. ACT Composite Score was also found a significant predictor of college GPA, however, its magnitude of effect is much smaller in comparison to the High-school GPA.

In the transition from high school to college the academically under-prepared students are usually termed at-risk students, because of the extra efforts and commitment that they need to make to catch up with other students and to make satisfactory progress in their academic studies. Being ready for college-level math coursework has proven to be a strong predictor of academic performance and on-time graduation (Adelman, 2006). In this study college readiness in math was measured by successful completion of developmental math coursework in the first year of college or by standardized test scores. The study findings provide evidence for a significant impact of college readiness in Math on first-year and second-year GPA ( $p < .05$ ).

Similar to findings from previous research (Kuh, Cruce, Shoup, Kinzie, & Gonyea, 2008; Pace, 1982), the amount of time spent studying was also confirmed as a significant predictor of academic performance. The regression path between the Study Time per Week and the Deep Learning factors is also significant, signaling that students spend more time studying when they are engaged in purposeful, intentional and meaning-making level of studies.

While the latent variable Deep Learning was found to have a relatively small positive relationship to First-year and Second-year GPA, Major Selection, as an academic engagement factor, was strongly significant in predicting Second-year GPA. The finding indicates that, compared to undecided students, those who have selected a major program of study might be on track to develop a good fit in the academic communities at their chosen institution. Finding a suitable major field can lead to enhanced self-confidence, goal commitment and engagement to academic studies.

Holding a job outside of campus was found to have negative impact on many aspects of student experience, including grade performance (Astin, 1993; Kuh et al., 2008). The study findings provided corroborative evidence for the significant impact of employment on academic performance of first-year students, notably among those who worked more than 20 hours per week.

### **Predictive Factors of First-year and Second-year Retention**

At the core of the study was the investigation into the predictive power of the academic and environmental factors on retention outcomes of beginning college students in their first two years of college.

**First-year retention.** The findings from the analysis suggest a number of general conclusions. First, finance-related factors play a significant role in influencing student persistence. Of all the predictors, receiving a Pell grant award has the largest effect on First-year Retention. This finding is consistent with previous research on the role of need-based aid in increasing enrollment among lower income populations (Bettinger, 2004).

Financial Concerns also directly and negatively impact students' reenrollment decision. This finding indicates that students who are more concerned with college-financing issue are less likely to re-enroll at the institution. The significance of this variable is consistent with the extant research on retention (Cabrera, Castaneda, Nora, & Hengstler, 1992; St. John, Hu, Simmons, Carter, & Weber, 2004). The finding is not a surprise considering that the study is set at an urban commuter institution, which, like other similar institutions, tends to attract low-income, first generation students. The importance of financial concerns also indicates a need for affordability and equal access to higher education among the college-going population.

A second finding is that college grades, as an indicator of academic achievement, ability and motivation of beginning college students, exert a significant influence in students' reenrollment decision in the second year. The positive regression weight suggests that the students with higher GPA would be more likely to continue enrolling at the institution. This finding is consistent with previous research findings (Cabrera, Nora, & Castaneda, 1993; Kuh et al., 2008; Metzner & Bean, 1987).

**Second-year retention.** The first major finding of the Second-year Retention model analysis is the role of a Pell grant award as the most significant predictor of retention. As previously found in the analysis of the First-year Retention model, students who received a Pell grant award would be more likely to persist than those who did not. The finding is consistent with the prior research on the role of a Pell grant in reducing dropout rates (Bettinger, 2004).

Another key finding is that Major Selection plays an important role in influencing students' reenrollment decision. By choosing a major students indicate an interest in a subject area which might lead to a future career, and a level of commitment to the degree attainment goal. Leppel (2001) discovered that among college freshmen the "undecided" students had lower GPA and were less likely to persist to the following year than the students who had selected a major. St. John and associates (2004) also came to a similar conclusion in a study of the influence of major fields on persistence among White and African American college freshmen. They found that White freshmen students who were undecided or had a major in social sciences were less likely to persist. In addition, African American sophomores enrolling in the high-demand major fields such as Business, Health, or Engineering/Computer Science persisted at higher rates. The role of Major Selection in student retention has important implications for institutional practice, especially in new student orientation and academic advising activities. This result indicates that early guidance and support for beginning college students to establish major and career directions help them "fit in" and find their footing in the academic life of the institution.

Second-year GPA accounts for a significant portion of the variance in Second-year Retention. This finding is consistent with previous research in assertions that academic performance is a key factor in retention decisions of students at commuter colleges and universities (Pascarella & Chapman, 1983).

Lastly, Financial Concerns have a strong negative effect on Second-year Retention. This finding is consistent with previous research (St John, Paulsen, & Carter, 2005) on college costs and student retention and highlights the issue of equity and access to higher education.

### **Implications for Public Policy and Institutional Practice**

The study provided empirical evidence for the role of academic engagement behaviors and environmental factors in grade performance and retention outcomes of beginning college students in the first two years of studies. While the academic factors take center stage in the study design, working off campus, receiving a Pell grant and financial concerns were also found to play significant roles in shaping students' retention decisions. Aspects of social integration and other environmental factors were not included in the estimated model of student retention due to sample size limitations. The study findings point to a number of recommendations for policy and practice, especially applicable to urban commuter colleges and universities.

### **Academic Preparation**

Rigorous coursework at high school level has been found as the most significant predictor of college success by previous research (Adelman, 2006). In the conceptual model tested in this study high school GPA and ACT Composite score were used as indicators of pre-college academic achievement. Even though high school GPA does not reflect the differentiating effect of academic rigor, the findings from this study point out that high school grade point average has the highest impact on the first-year GPA and

continues to significantly impact second-year GPA. This finding is in line with previous research.

In addition to high school GPA, ACT score and college readiness in Math also have significant predictive values on college GPA and retention in the conceptual model of student retention.

The findings from the study strongly support the importance of academic preparation for college and academic readiness among high school graduates. At urban universities, often the school of choice for first-generation students, students from low-income families and racial/ethnic minority groups, incoming students may need to take multiple courses in developmental Mathematics, English and Reading. In order to provide support to academically at-risk students as they transition to college, institutions should identify and implement innovative approaches in developmental education, including early diagnostic placement exam, summer refresher courses, supplemental instruction, linked session between developmental course and a college-level course, and module-based developmental courses.

### **College-financing Resources**

Having adequate financial resources for college is a critical factor to college access, persistence and success, as evidenced in the findings of this study and many others (Cabrera, Nora, & Castaneda, 1992; St John et al., 2005). College-financing worries might lead to drop-out or stop-out behaviors if students do not have the ability to pay for college. Thus, financial aid policies and practices at federal, state and institutional



levels have been found to have significant effects on student persistence in college, particularly among students from low-income families. The findings of the current study provided corroborative evidence for the role of Pell grant in increasing enrollment among beginning college students in a public urban commuter university.

At the institutional level, financial literacy education and early identification of students having financial difficulties can provide students with the support they need to be on the right track with their educational budget and help them find the right financial resources for college. Institutions should provide guidance and clear instructions on financial resources for students through website, financial workshop and communication materials to students, including financial aid award letters (Perna & Steele, 2011). In addition, colleges can improve affordability by minimizing tuition rate increases and increasing institutional need-based aid to qualified students.

Institutions also need to develop new approaches in obtaining federal and state resources and finding matching funds to increase support to those students in needs.

### **Early Intervention for At-risk Students**

College GPA, used as a proxy for the level of academic integration in the current study, was found to be predictive of retention in the first two years of college. This is not an unexpected finding, as one of the most cited reasons for student attrition is poor academic performance. Students facing the demands of college-level coursework and who are learning new time management and study skills might have difficulty keeping up with their studies. Thus, by early identification of at-risk freshmen through analysis of

application materials, freshmen survey and student background characteristics, the support for student success needs to take place as soon as students enter the institution. Tracking student performance and attendance behaviors in the first-term courses, especially the study skills and first-year experience seminars, can lead to checking in with an advisor and referrals to appropriate support services. The level of intentional and engaged support for at-risk students upon campus arrival is especially important for non-residential students because, due to the lack of time and resources, they often do not have the opportunity to develop deep connections with social and academic communities on campus.

### **Major Advising**

The study highlighted the role of learners taking an active role in learning by setting goals and engaging in the learning process. For beginning college students the process of selecting and declaring a major indicates a commitment to educational and professional goals that would provide learners with not only the motivation to study, but also a path to achieve these goals.

### **Support for Deep Learning**

In the current study deep learning engagement was found to have a significant effect on grade performance of students in their first two years of college.

**Faculty support.** Deep learning demands elaborate efforts on the part of the learners as they discover relationships among concepts, develop new perspectives in problem solving or link course content to real life issues (Leamson, 2002). Deep

learning is active learning, often in interactions with others. This cooperative aspect of deep learning needs to be embedded in coursework requirements, through group work or out-of-classroom assignments that are part of a meaningful sequence of the deep learning approach (Millis, 2010). To encourage deep approaches to learning faculty need to engage students in active learning and facilitate the process of finding personal meaning and making connections between ideas and constructs, and align course expectations with fair and consistent assessment of student learning.

**Institutional support.** Deep learning is fostered through engagement in an academic environment that is intentional in creating effective educational practices that engage and encourage students to learn across disciplines, develop skills to apply learning to answer big questions and complex challenges. Institutions play a major role in establishing the bridge between the ivory tower and the real world by helping students achieve the learning they need for future life and work. Institutions can create formal and informal channels of support through curricular improvements, faculty development, and reward systems to promote deep learning practices.

### **Study Limitations**

The limitations inherent in the research design aspects such as the study setting, the target population and the sample size may have impacted the generalizability of the study findings. The study was conducted at an urban commuter university in the Midwest, which may share representative characteristics with other urban universities, for examples, having a student body with diverse race and ethnic, economic, social and

academic backgrounds. However, due to the myriad of differences in institutional characteristics, resources and cultures, the findings from a single-institution study might not generalize well to other institutions.

While the target population for the study is a cohort of first-time full-time students who began college in fall 2011, the study sample was selected based on a subset of the original cohort including those who participated in the spring 2012 administration of the National Survey of Student Engagement at the study site. The overall representativeness of the sample was impacted by the survey nonresponse rate and by the timing of the survey administration because a portion of the first-time full-time student cohort was not enrolled in the term when the survey was conducted.

The research design and analytic procedures in the study permit the latent variable Deep Learning, measured by students' academic behaviors and beliefs at a single point in time, to function as a time independent variable. As one can expect that the quality of student engagement changes over time and relative to the conditions of the academic environment, the findings related to the relationship between Deep Learning and the cumulative grade performance, Second-year GPA, may have limited generalizability.

Structural equation modeling procedures, and especially SEM models employing categorical variables, usually require large data sets to ensure non-biased parameter estimates. Due to the sample size limitation the study design was focused on a limited number of potentially significant intervening variables such as academic engagement, performance and financial concerns. Other intervening variables which were identified as

pertinent in extant retention and persistence research, such as academic motivation, sense of mattering/belonging, financial support, advising, student-faculty interactions, social activities, family emotional support, campus climate and others were not included in the estimated model of retention. As a result, the omission of potentially significant variables in the model impacts the generalizability of study findings.

### **Directions for Future Research**

The current study examines the structural relationship among prior achievement, academic engagement, environmental factors and student outcomes in the first two years in college. As noted previously, the study design may have omitted many potentially significant variables in influencing student retention at commuter 4-year institutions. Thus, future studies may benefit from exploring the effects of academic advising, mentoring, learning communities, student organizations, campus climate and institutional support, and of financial aid on the retention of beginning college students in commuter campus settings. Data from well-known national student surveys, such as the NSSE survey, Noel-Levitz's Student Satisfaction Inventory, UCLA-based Higher Education Research Institute's CIRP Freshman Survey and from others may help assess the importance of different factors on student success and persistence in college.

Student engagement in college has been identified as the key to success. However, how to promote engagement and help student stay engaged remain key questions in the educational research agenda. Institutions facing tightening budgets and

controlling costs are often not able to innovate and implement experiments to improve the teaching and learning processes. Localized initiatives need to scale up to be effective.

As the results of the study indicate, student retention is significantly impacted by goal commitment evidenced by major selection. One aspect of retention and persistence research is to examine factors affecting first-generation and economically disadvantaged students. The inclusion of social capital attributes such as parental education, socio-economic status, and resources, such as family emotional support, mentoring, in retention model will further enhance our understanding of the balancing act between drop-out risk and persistence.

The exploration of retention and persistence factors using national data sample benefits from the hierarchical design with unit of analysis at student and institutional levels. This type of research study can provide valuable insights into the departure question based on the interactions of students and institutions.

### **Conclusion**

After decades of research the student departure question remains a complex issue in higher education, especially for non-residential urban institutions serving transient student populations. The present study offers an integrative framework in understanding the influence of precollege academic preparation, academic engagement behaviors and environmental factors on college grade performance and retention decisions. By highlighting the variables that are found to be the strongest predictors of retention the study results suggest that concerted efforts in advising and engaging students in academic

skills development, major selection, deep processing through integrative, higher-order and reflective learning activities, can provide pathways to higher grade performance and strengthen student motivation for continuing studies at the institution.

The success of the institution in providing beginning college students with intensive and intentional advising and mentoring programs, and in creating organizational structures and practices promoting deep learning engagement will most likely improve retention efforts. These initiatives at the institutional level reflect not only the commitment of the institutions in supporting student success of college achievement, but also reflect the approaches that empower students to become self-aware and purposeful in their studies and take charge of their future.

APPENDIX A  
DEEP LEARNING SCALES AND ITEMS



High-Order Learning Activities	<p>During the current school year, how much has your coursework emphasized the following mental activities?</p> <ul style="list-style-type: none"> <li>• Analyzing the basic elements of an idea, experience, or theory, such as examining a particular case or situation in depth and considering its components</li> <li>• Synthesizing and organizing ideas, information, or experiences into new, more complex interpretations and relationships</li> <li>• Making judgments about the value of information, arguments, or methods, such as examining how others gathered and interpreted data and assessing the soundness of their conclusions</li> <li>• Applying theories or concepts to practical problems or in new situations</li> </ul>
Integrative Learning Activities	<p>In your experience at your institution during the current school year, about how often have you done each of the following?</p> <ul style="list-style-type: none"> <li>• Worked on a paper or project that required integrating ideas or information from various sources</li> <li>• Included diverse perspectives (different races, religions, genders, political beliefs, etc.) in class discussions or writing assignments</li> <li>• Put together ideas or concepts from different courses when completing assignments or during class discussions</li> <li>• Discussed ideas from your readings or classes with faculty members outside of class</li> <li>• Discussed ideas from your readings or classes with others outside of class (students, family members, co-workers, etc.)</li> </ul>
Reflective Learning Activities	<p>During the current school year, about how often have you done each of the following?</p> <ul style="list-style-type: none"> <li>• Examined the strengths and weaknesses of your own views on a topic or issue</li> <li>• Tried to better understand someone else's views by imagining how an issue looks from his or her perspective</li> <li>• Learned something that changed the way you understand an issue or concept</li> </ul>

(Source: National Survey of Student Engagement 2012)

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## VITA

Hoa Khuong was born and raised in Hanoi, Vietnam. She earned a Bachelor of Arts in Russian from the Hanoi Pedagogical College, with Distinction, in 1991. From 1996 to 1998, she attended the University of Wisconsin in Madison, where she received a Master of Business Administration. Before attending Loyola University Chicago, she attended the Northeastern Illinois University, where she earned a Master of Science in Computer Science in 2004.

Currently, Khuong is an Associate Director of Institutional Research and Assessment at Northeastern Illinois University in Chicago, Illinois.

