FINDING THE RIGHT MIX: TEACHING METHODS AS PREDICTORS FOR STUDENT PROGRESS ON LEARNING OBJECTIVES

by

JACOB I. GLOVER

B.S., Manhattan Christian College, 1995
M.S., Fort Hays State University, 2007

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Special Education, Counseling and Student Affairs
College of Education

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Abstract

This study extends existing student ratings research by exploring how teaching methods, individually and collectively, influence a minimum standard of student achievement on learning objectives and how class size impacts this influence. Twenty teaching methods were used to predict substantial or exceptional progress on each of 12 learning objectives. Analyses were conducted in four class-size groups, Small (between 10-14 students), Medium (between 15-34 students), Large (between 35-49 students), and Very Large (50 or more students). Archival data were over 580,000 classes of instructors and students who responded to two instruments within the IDEA Student Rating of Instruction system: Instructors completed the *Faculty Information Form*, and students responded to the *Student Ratings Diagnostic Form*. Significant progress, for the purpose of this study, means students indicated they made either substantial or exceptional progress on learning objectives the instructor identified as relevant to the course. Therefore, student ratings of progress were dichotomized and binary logistic regression was conducted on the dummy variables. Descriptive statistics and point-biserial correlations were also conducted to test the hypotheses. Teaching methods that stimulated student interest were found to be among the strongest predictors of significant progress on the majority of learning objectives across all class sizes. For all class sizes, significant progress was correctly classified from a low of 76% of the time to a high of 90% of the time. The higher students rated the instructor in stimulating them to intellectual effort the more progress they reported on a majority of learning objectives across all class sizes. Higher instructor ratings on inspiring students to set and achieve challenging goals were also associated with significant student progress on learning objectives across all class sizes. Class size was not a major factor affecting the predictive strength of groups of teaching methods on student progress on learning objectives. However, it was a factor concerning the predictive strength of individual teaching methods. The larger the enrollment the greater was the predictive strength of key teaching methods. Implications of the study for faculty professional development and for future research are discussed.

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Dedication

This dissertation is dedicated to my wife, Amy, and my children, Isaac, Hope, Joy, Grace, Joshua, and Joseph. You have sacrificed much in order for this work to be completed. I look forward to making up for the time.

Chapter 1 - Statement of the Problem

American higher education in the 21st Century is held to increasing standards of accountability being caught between economic constraints on one side and increased scrutiny for benefits of the cost on the other (Massy, 2003). At the core of this transition is the question what - and to what degree - students learn as a result of their post-secondary education (Massy, 2003, p. 163)? When the Spellings Commission (U.S. Department of Education, 2006) stated that "student achievement is inextricably connected to institutional success" and that colleges and universities must become more transparent about student outcomes and "willingly share this information with students and families" (p.4), there was a renewed look at exploring the relationships between teaching methods and course learning objectives. In the most generic of terms, good teaching happens when students learn (McKeachie, 1997) and yet identifying and making specific connections between particular teaching methods and specific learning objectives has proven difficult. Enter the student rating of instruction.

There is nearly a century of studies that have used student ratings of instruction to ascertain connections between teaching and learning. In a meta-analysis of student ratings research, Cohen concluded that a majority of the research searches for statistically significant correlations between the variables, but not much research has been conducted beyond bivariate correlational studies (Cohen, 1981). Over time the sophistication of student ratings instruments increased concurrent with studies of teaching methods which correlate to student success (Feldman, 1989; Marsh, 2007). These advances lead to a clearer understanding of student success. When students indicate progress on learning objectives faculty have also selected as vital to their course, a more measurable connection between teaching and learning occurs. Therefore, student ratings instruments which directly measure teaching behaviors and student progress on relevant learning objectives produce a needed increase in clarity regarding the teaching and learning dynamic (Hoyt & Lee, 2002). While bivariate correlational studies on the relationship between teaching and learning behaviors provide valid and reliable measures, there remains ample room to encourage further study (Cashin, 1989; Centra, 1979; Marsh, 1982; McKeachie, 1997; Theall & Franklin, 1991). For example, do specific clusters of teaching methods have a stronger collective effect on learning objectives? How do individual teaching methods influence progress on learning objectives when the influence of other teaching methods is accounted? Are there certain teaching methods that influence a majority of learning objectives? And, to what degree do teaching methods influence progress on learning objectives? How does setting a minimum standard for student progress on learning objectives change the impact of teaching methods on learning objectives? In what ways does course size influence the strength of a teaching method to help students meet that minimum standard? This study examined these questions.

Significance of the Study

Higher education is significant to many stakeholders in American society and significant resources are invested in it. Legislators, parents, higher education administrators, faculty and students all want students to make desirable progress on learning objectives embedded in courses. Desirable progress, for the purpose of this study, means students made substantial or even exceptional progress on learning objectives. Student ratings can be a key source of data to understand which teaching methods will more likely lead to student progress. Also, when combined with appropriate feedback and consultation, student ratings results have been shown to assist instructors in improving their teaching effectiveness (Arreola, 2007; Cohen, 1981; McKeachie, 1997). The results of this study, therefore, provide implications for better preparing faculty to help students make substantial or exceptional progress in their courses. The study can also provide more specific direction for how institutions of higher education direct resources for faculty development such as those created and utilized by teaching and learning centers. By more precisely understanding how, and to what degree, specific teaching methods influence progress on learning objectives this study can translate into more efficient faculty preparation and, ultimately, to increasing the likelihood that students will make good progress on relevant learning objectives.

Purpose of the Study

Most faculty and institutions of higher education in America desire for students to succeed and, therefore, invest great resources into tools, such as student ratings of instruction, that can show ways for improving praxis. Although existing student ratings research shows teaching methods to be correlated with certain learning objectives, what has been left relatively unexplored is how teaching methods influence a set criterion of at least substantial progress on learning objectives. This study extends existing student ratings research by exploring more precisely how teaching methods, individually and collectively, influence a minimum standard of student achievement on learning objectives and how class size impacts this influence.

Research Questions

To answer the questions of this study archived student ratings of instruction (SRI) data from The IDEA Center in Manhattan, KS were used. The data includes teaching methods used by instructors and student progress on learning objectives key to the course. The IDEA Center is a nonprofit organization dedicated to helping postsecondary institutions improve learning, teaching and leadership performance. The questions of the study were:

Question 1a: How well do teaching methods predict substantial or exceptional progress on IDEA learning objectives the instructor identifies as relevant to the course?

Question 1b: Are these predictions moderated by class enrollment groupings?

Question 2a: Which teaching methods have the largest effect on whether students experience substantial or exceptional progress on each of the IDEA learning objectives?

Question 2b: Are these effects moderated by class enrollment groupings?

Delimitations of the Study

The primary constraints of this study are due to limitations within the IDEA system. Although there is a considerable history and track record for the valid and reliable use for the IDEA instruments (see Chapter 3 for further discussion), there are limitations to the use of student self-report data to examine the association between teaching methods and learning objectives.

First, the results of this study are only generalizable to the extent the sample represents the larger population. Although this study includes a very large sample size, there remain courses for which the results of this study should only be applied with caution. For example, by design courses with enrollments of fewer than 10 students were not be included in the data set due to the impact on statistical reliability. Even so, the large population, diversity in geography, and institution type present a compelling case for generalization to specific samples not represented in the data.

Second, there are known areas of bias, which may impact the accuracy of the data presented by students. One source of bias in student ratings is the Systematic Distortion Hypothesis (SDH) which suggests personality factors on a survey can be influenced by "what is thought to go with what rather than what actually goes with what" (Renaud & Murray, 2005). On student ratings of instruction, SDH implies students may mark instructors highly for being accessible outside of class simply because they feel good about their instructor and not because they actually contacted their instructor outside of class, i.e., students believe that liking an instructor and their availability outside of class should be correlated and therefore respond to the question about instructor availability outside of class based more on the degree to which they like instructors and less on instructors' actual availability outside of class. SDH is more likely to occur when raters do not know the ratee very well or lacks the opportunity to observe the person perform the trait being rated (Woehr, Day, Arthur, Jr., & Bedeian, 1995). In most cases, however, student raters have had ample opportunities to interact with the instructor and observe her or him in action. SDH and other sources of bias can be accounted for in the reliability and validity of the student ratings of instruction data, and this is further addressed in Chapters 2 and 3.

Third, a correlational research design was used in this study. Therefore, although teaching methods have an effect on student achievement of learning objectives, only associations between teaching methods and learning objectives are assessed in this study. Thus, the design of this study limits the extent that causal statements can be made about the effects of teaching methods on student progress ratings of learning objectives.

Definition of Terms

Learning objectives. Learning objectives are the knowledge, skills, and aptitudes designed as outcomes for a course (Bloom, 1956). For this study, learning objectives are most often the 12 items used in the IDEA SRI system which designate an outcome or outcomes designed within the course. Although more than 12 learning objectives exist in higher education these 12 have a strong theoretical foundation whose soundness will be described in the review of the literature.

Teaching effectiveness. For the purposes of this study, teaching effectiveness concerns the degree to which an instructor facilitates student progress on measures of achievement such as learning objectives. Other achievement measures unrelated to this study include graduation rates or a sufficiently high grade (Cohen, 1981).

Teaching methods. The methods used by an instructor to convey the content of a course (McKeachie, Pintrich, Lin, & Smith, 1986). Primarily all discussion of teaching methods in this study center around the specific 20 teaching methods outlined in the IDEA data. Although other behaviors could be included, the theoretical foundations for these specific behaviors is sound and will be described in later chapters.

Chapter 2 - Review of the Literature

The validity, reliability and usability of SRIs have been studied for over 90 years. Herman Remmers of Purdue University began publishing his research on the study of student ratings in the 1920's (Marsh, 1982). In addition to using SRI system data to examine the teaching and learning dynamic, these data were also used for personnel decisions, to understand how students determine which courses to enroll in, and curricular development. This chapter reviews research on the teaching and learning dynamic that used SRI system data. Discussed first is the topic of how student ratings instruments were developed. Within this discussion are included issues of validity, reliability, and areas of bias found in student ratings and their usefulness to examine the teaching and learning dynamic. Of particular interest to this conversation is how the research has succeeded or failed at using student ratings to clarify connections between teaching methods and student progress on learning objectives. The second topic explores the theoretical frameworks undergirding concepts of good teaching and how these theories influence student rating instruments. Within this discussion is also the subject of instruments which measure particular teaching methods and a designated set of learning objectives. The third and final topic explores in depth the IDEA Center instrument as a viable source of data for discerning a set of teaching methods which may predict progress on student learning objectives.

Development of Student Ratings of Instruction Instruments

Not long after the conclusion of World War I researchers examined student ratings for discernible links between what teachers were doing in the classroom and its impact on student achievement. The focus of the research looked for any particular benefits of lecture versus discussion or self-paced independent study versus classroom instruction on students' final exam scores (Dubin & Taveggia, 1968). The literature suggests correlations between student ratings and exam scores is likely due to variance found within the assessments and in how grades are administered as opposed to relationships with the student ratings. These findings have spurred further research into other areas of the student experience, one of which is the use of student ratings to discover more precise links between teaching and learning (Astin, 1993; Frick, Chadha, Watson, & Wang, 2010; McKeachie et al., 1986; Merrill, 2007; Seldin, 1995). Today's learning spaces are apt to be vastly different compared to the classrooms of the early 1900's, adding an increased level of sophistication to student ratings studies. Even so, some pieces of the larger puzzle regarding the teaching and learning dynamic have become more focused as a direct result of the increasing sophistication of SRI system instruments and the resulting analysis of the data. The limited variety of teaching methods described in the early years of research (lecture vs. discussion or face-to-face vs. independent study) has given way to a greater nuance of teaching methods described by familiar terms such as time on task, active learning, critical thinking, and problem based learning (Astin, 1993; Bain, 2004; Centra, 1979; Fink, 2003; Hatfield, 1995).

Teaching methods and learning objectives as measures in SRIs. Even though there is a greater nuance of teaching methods measured on SRI system instruments, they still tend to focus on the teaching methods applicable to the largest cross-sections of courses. The aggregate results of this information have given more specific insight into teaching and learning, but not many SRI system instruments are designed to explore the effectiveness of specific teaching and learning theories. One exception is the Teaching and Learning Quality instrument (TALQ) which has sub-scales specifically designed to measure the five First Principles of Instruction originally described by Merrill (Frick, Chadha, Watson, Zlatkovska, & Denver, 2010; Merrill, 2002). The organizing principle behind the First Principles is there are five foundational ideas inherent in many instructional design theories. The five principles are “learning is promoted when learners are engaged in solving real-world problems; learning is promoted when existing knowledge is activated as a foundation for new knowledge; learning is promoted when new knowledge is demonstrated to the learner; learning is promoted when new knowledge is applied by the learner; and learning is promoted when new knowledge is integrated in to the learner's world” (Merrill, 2002, p. 2). The TALQ seeks to explore if the presence of these five principles in a college course improve student mastery, as defined by the instructor, over the selected course objective. Although this approach appears promising, its generalizability to the larger context of higher education is inferior to the prominent SRI system instruments described in the following sections. Data provided by the TALQ has a much smaller sample size when compared to the data collected by the most widely used SRI system instruments. Even so, the initial findings of Frick, et al (2010) suggest further research should be conducted. The aim of this study is to use predominant SRI system data to discern clusters of teaching methods that predict progress on learning objectives.

There are three widely used SRI systems that explore specifically the connection between particular teaching methods and the resultant impact on student learning. These instruments are the Student Instructional Report (SIR) II (Centra, 1998), the Student’s Evaluation of Educational Quality (SEEQ) (Marsh, 1982), and the IDEA Center Student Ratings of Instruction, which is the focus of this study (Hoyt & Lee, 2002). Each of these instruments was designed via a process of faculty and student input combined with review of the current literature. Each of these SRI system instruments came into prominence during the 1970’s, an era when studies on the usefulness of student ratings of instruction were increasing in dramatic fashion (Arreola, 2007; Centra, 1979; Cohen, 1981; McKeachie, 1997).

Valid and reliable use of student ratings of instruction. Evidence exists supporting the validity and reliability of properly designed student ratings of instruction instruments (Cohen, 1981; Marsh, 2007). In repeated studies, the authors of SEEQ, SIR II and IDEA instruments make compelling cases that their careful and proper construction resulted in the instruments having evidence of acceptable validity and reliability (Centra, 1998; Hoyt & Lee, 2002; Marsh, 1982). Not all factors measured by student ratings instruments are within the control of an instructor, though. For example, an instructor can try to facilitate group interaction but it belongs to each group of students what quality that interaction will entail. Likewise, not all of these scales measure what would typically qualify as teaching methods per se. For example, effective use of course materials is included on these SRI system instruments, as it is certainly a component of a course that helps student learning, but this factor is not usually discussed when looking for direct linkages between teaching methods and student learning. Other common items across the instruments are global items asking students to give overall impressions of instruction and the course. In a seminal study Cohen (1981) conducted a meta-analysis of 41 studies that showed an average correlation of .43 between global ratings of instruction and student achievement. The global ratings of instruction used in the 41 studies were either a single question, such as “the instructor is an excellent teacher”, or an average of all items on the instrument related to instructor effectiveness. In his meta-analysis, Cohen also reviewed the correlation between global ratings of the course and student achievement and found an average correlation of .47. The global ratings of the course used in the 41 studies were also either a single item, such as “this is an excellent course”, or an average of related instrument items. Further, Cohen most often operationalized student achievement using a final exam grade (p. 293).

Are student ratings inherently biased? An additional concern addressed in the literature is whether student ratings are acceptable sources of information by which to judge the overall performance of an instructor. The key question regarding bias is whether variables that correlate with student ratings are also related to teaching effectiveness and student learning. For example, on specific items student ratings have been found to weakly correlate with class size. Ratings tend to be higher when students have a strong interest in or motivation to take the course (Cashin, 1995; Hardy, 2003; McKeachie, 1997). The most important student variables that may require control in student ratings are student motivation, expected grades, level of the course, academic field, and workload/difficulty (Cashin, 1995). What has not been sufficiently addressed in the literature is the underlying assumption that class size directly influences student learning. The assumption is students get more direct interaction with the instructor and with one another in small classes resulting in more learning than found in large classes. One of the aims of this study addresses some of the impact class size has on student ratings of progress on learning objectives. The IDEA student ratings control statistically for motivation, workload/difficulty, academic field (by reporting separate norms by discipline), as well as student work habits.

Concerning personnel issues, such as merit and tenure there are criticisms that student ratings of instruction are not appropriate (McKeachie, 1997; Theall & Franklin, 1991). Arreola (2007) argued that whereas students are very apt at describing what is occurring in the classroom, other sources of information, such as peer and self-evaluation, should be included. Even so, students are seen as very useful sources of data on how the teaching and learning dynamic can be improved to increase student success (Arreola, 2007; Cashin, 1989; Centra, 1979; Cohen, 1981; Frick et al., 2008; Hoyt & Lee, 2002; Kuh, Kinzie, Buckley, Bridges, & Hayek, 2006).

Another concern is that students are poor judges of what constitutes useful learning in a course because they lack experience that can only be gained after their course work is completed and they have applied their knowledge and skills in the work force. Several researchers performed follow up evaluations by administering the same SRI instrument to students one year after graduation so students had time to use their knowledge in the world of work and other areas. Marsh found in his study of 100 management school classes at California State University the correlation between individual student ratings collected at the end of semester and the same students completing the instrument again one year later was .83 (Marsh, 1982). In a similar study, Feldman (1989) found an average correlation of .69 between SRI ratings of students currently enrolled and alumni who re-took the SRI instrument after having already completed the course. Students, even up to one year after graduation, show markedly similar perceptions of their college classroom learning experiences.

Theoretical Frameworks for Student Rating Instruments

SRI system data studies include attempts to synthesize and find common areas across the majority of higher education in order to develop a common standard of good teaching. Even though research shows in general the usefulness of SRI systems for studying the connections between teaching and learning there is variability in instrument items. Feldman (1976) compiled a list of 21 common items students used to describe the superior college teacher which became one of the foundational documents for SRI systems such as SEEQ, SIR, and IDEA. Consideration of the factor structure underlying SRI system instruments is therefore important. Feldman (1976) discovered as many as 28 dimensions, Marsh (2007) reported at least nine underlying factors for the SEEQ, there are seven factors in the SIR II (Centra, 2003), and research supported the presence of five factors for the IDEA SIR (Hoyt & Lee, 2002). Cashin

(1995) argued wherease “we must distinguish among the various items and their dimensions to insure all of the appropriate dimensions are rated, averaging dissimilar items is not appropriate”. Al-Sulimoni (2001) detailed that the SEEQ, SIR and the IDEA instruments all had in common eight instructional and course related sub-scales. These are course organization, presentation skills, nature and value of the course materials, learning of the course materials, rapport, group interaction, and assessment and workload difficulty. Held by at least two of the three instruments were sub-scales for class management and instructor enthusiasm (Al-Suleimani, 2001). These SRI systems were based upon the research first published by Remmer in the late 1920’s. As presented in the research surrounding the SRI systems in the IDEA, SEEQ, and SIR II systems there is, with a few variations associated with course modality (i.e. online or face to face, and technologies used in the classroom), a general set of items which describe successful teaching from the 1920’s until present day (Centra, 1998; Cohen, 1981; Hoyt & Lee, 2002; Kuh et al., 2006; Marsh, 2007).

Interestingly these SRI system instruments were not created based on any single instructional design or learning theory. Developed concurrently with these SRI systems was a set of guiding principles for what makes for best instruction in the college undergraduate classroom. These principles became known as the Seven Best Practices of Instruction for Undergraduate Education (Chickering & Gamson, 1987). Though not intentional, the designers of these SRI systems and the designers of the Seven Best Practices used many of the same research to come to their conclusions (Centra, 1998) linking areas of teaching methodology and student success to an overall theory of student success in college.

Seven best practices for undergraduate education. The codification of best practices of undergraduate education began to happen when Arthur Chickering and Zelda Gamson, as members of the board of the American Association for Higher Education, embarked on a series of conferences on the subject of improving undergraduate education. The list was narrowed down to seven principles for best practice at The Johnson Foundation in Racine, Wisconsin in the summer of 1986 via discourse by many prominent researchers on the subject. A few of these individuals were K. Patricia Cross, Alexander Astin, C. Robert Pace, Russel Edgerton and Joseph Katz among others (Hatfield, 1995). From this group came the concept that there are six "powerful forces" of education which are:

- Activity
- Expectations
- Cooperation
- Interaction
- Diversity
- Responsibility (Chickering & Gamson, 1987)

These six forces became the foundation for seven best practices intended to be "guidelines for faculty members, students, and administrators -- with support from state agencies and trustees -- to improve teaching and learning". The seven practices are:

1. Encourages contacts between students and faculty.
2. Develops reciprocity and cooperation among students.
3. Uses active learning techniques.
4. Gives prompt feedback.
5. Emphasizes time on task.
6. Communicates high expectations.
7. Respects diverse talents and ways of learning (Chickering & Gamson, 1987).

According to the history of the seven best practices there was an immediate interest across higher education, which led to the creation of self-assessments for faculty and institutional inventories. The instrument for faculty inventory was divided into seven sections, one for each of the principles (Hatfield, 1995). This instrument was used not only to confirm the basic suppositions of the seven best practices but others began to adapt it for more specific uses. George Kuh used the best practices instrument as a first draft of an instrument which later became known as the National Survey of Student Engagement (NSSE), which is administered and utilized by a wide swath of institutions of higher education precisely because the seven best practices have been shown to address key areas necessary for college success (Chickering & Gamson, 1999; Hoyt & Lee, 2002; Kuh, Kinzie, Buckley, Bridges, & Hayek, 2007). Furthermore, the NSSE instrument is also used as a guide for understanding the five factors found within the IDEA SRI system (Hoyt & Lee, 2002). These factors are stimulating student interest, fostering student collaboration, establishing rapport, encouraging student involvement, and structuring the classroom.

Setting Apart IDEA for Study

The IDEA instrument's measure of student learning will be the central focus of this study. The IDEA Student Rating of Instruction instrument is designed to measure student perceptions of 20 teaching methods utilized by the course instructor. The instrument also measures student perception of progress on 12 learning objectives among other items. Faculty select the learning objectives they deem important to their course. It is the correlations between teaching methods and learning objectives within each course that provide insight into the larger questions regarding the connection between teaching and learning in higher education.

Another advantage to utilizing the IDEA Center data to understand the teaching and learning dynamic is the large sample size. There are nearly 600,000 classes in the IDEA research database from 2002-2009. This study examined approximately 330,000 of these classes (see following chapters for further clarification). While one must be cautious when considering the generalizability of these classes to all of higher education it is a large enough sample from across numerous institutions and institution types that findings are likely applicable to a greater number of institutions and instructors.

The IDEA system was not designed around a single learning theory or instructional design strategy but from the general understanding of what successful teaching looks like. Although not directly referenced in the literature concerning the creation of SRI system instruments there is enough overlap in content and the era in which both came into wider use (the mid 1980's) it is possible to make connections between the seven principles and the underlying factors found in SRI systems. Using the Seven Best Practices as a lens with which to view the IDEA SRI system further establishes why the data show connections between teaching methods and progress on learning objectives.

IDEA teaching methods (TM) and the seven best practices. Best Practice 1 is "Encourages contact between students and faculty." IDEA TM1, "Displayed personal interest in students and their learning." and TM20, "Encouraged student-faculty interaction outside of class," contain key ideas found within Best Practice 1. Several decades of research has consistently made the connection between student progress on learning objectives and interaction with faculty. This interaction includes the manner of interaction within the classroom (approachable, easy to talk to, interested in students views) as well as being available for students informally outside of the classroom (Cohen, 1981; Pascarella, 1980; Tinto, 1987; Wilson, Gaff, Dienst, Wood, & Barry, 1975).

Best Practice 2 is "Develops reciprocity and cooperation among students." IDEA TM5, "Formed 'teams' or 'discussion groups' to facilitate learning," TM16, "Asked students to share ideas and experiences with others whose backgrounds and viewpoints differ from their own," and TM18, “Asked students to help each other understand ideas or concepts,” each fit within Chickering and Gamson’s Best Practice 2. Whereas the instructional goals selected by the instructor of a course are a key variable in determining which particular TMs are the most effective, research has shown students working together in groups and even being the teachers of content is one of the most effective methods of teaching. Benefits from group work include increased productivity, stronger student relationships, and even enhanced self-esteem (Goldschmid & Goldschmid, 1976; McKeachie et al., 1986; Whitman, 1988).

Best Practice 3 is “Uses active learning techniques.” The parlance of the Seven Best Practices defines active learning to be “that something happen[ing] to stimulate students to think about *how* as well as *what* they are learning and to increasingly take responsibility for their own education” (Hatfield, 1995). With this definition in mind, several of the IDEA TMs can be applied. Those with the strongest logical link are TM8, “Stimulated students to intellectual effort beyond that required by most courses,” TM11, “Related courses to real life situations,” TM13, “Introduced stimulating ideas about the subject,” TM14, “Involved students in ‘hands on’ projects such as research, case studies, or ‘real life’ activities,” TM15, “Inspired students to set and achieve goals which really challenged them,” and TM19, “Gave projects, tests, or assignments that required original or creative thinking.” Active learning is fairly broadly defined, and Sorcinelli (Chickering & Gamson, 1991) acknowledges there is strong overlap between active learning and peer learning. There are several studies underscoring the importance of active learning and their connection to these particular IDEA SRI system TMs. Merrill classifies this as working on real-world problems (2002) in which the larger parts of a learned behavior or concept is broken into its component parts. These components are practiced and implemented in various modes, individually as well as in groups. When these components and subsequent whole tasks directly relate to real world activities, the retained knowledge is stronger and more comprehensive.

Best Practice 4 is “Gives prompt feedback.” The two IDEA TMs most logically linked with this best practice are TM7, “Explained the reasons for criticisms of students’ academic performance,” and TM17, “Provided timely and frequent feedback on tests, reports, projects, etc. to help students learn.” Timely feedback impacts success in the college classroom (Ambrose, 2010; Cross, 1987; Dunkin, 1986). Cross (1976) advocates feedback as one of five essential ingredients in moving instruction from teacher centered to student centered but it also is important to consider the type and quality of the feedback. The significant conclusion is “that immediate, corrective, and supportive feedback is central to learning” (Sorcinelli, 1991).

The fifth best practice is “Emphasizes time on task.” The creators of the seven best practices consider time on task to mean “allocating realistic amounts of time [for] effective learning for students and effective teaching for faculty” (Hatfield, 1995). Closely related is the idea of Academic Learning Time which also suggests it is not only the amount of time spent on task but also the level of engagement during that time on task which matters (Rangel & Berliner, 2007). From this perspective TM3, “Scheduled course work in ways which encouraged students to stay up-to-date in their work,’ and TM15, “Inspired students to set and achieve goals which really challenged them,” most logically tie to this best practice. Depending on how one understands the emphasis of time on task TM9, “Encouraged students to use multiple resources to improve understanding,” could also apply if the context is efficiency of student learning. Real world, authentic problem solving as practice work for students consistently shows improved learning and greater engagement between student, teacher and content (Ambrose, 2010; Kuh et al., 2007; Merrill, 2007; Rangel & Berliner, 2007). Merrill (2007) explains that time on task is represented by an approach which is designed from the outside, in. A task from the real world is demonstrated and broken into its component parts for students. The curriculum then assigns these component parts as the tasks of focus. Students are therefore challenged beyond the learning of concepts to also holistic application within the learning, which often requires an expanded range of resources being used to complete the task. Both the quantity and quality of the academic learning time are involved in this approach.

Best Practice 6 is, “Best practice communicates high expectations.” TM8, “Stimulated students to intellectual effort beyond that required by most courses,” and TM15, “Inspired students to set and achieve goals which really challenged them,” both support the context of Best Practice six. A common myth concerning student perceptions of work as reported on student rating instruments is students will prefer to take the path of least resistance and, therefore, courses with high expectations will be rated lower than courses which are seen as requiring little effort (Cashin, 1995) but the literature demonstrates this not to be true (Cashin, 1995; Centra, 2003; Cohen, 1981; Kuh et al., 2007; McKeachie et al., 1986; Sprinkle, 2008). Centra’s study of 50,000 classes using the SIR II instrument showed students rated courses they perceived as too difficult or too elementary lower than courses they perceived to have just the right amount of challenge (2003). Ken Bain (2004) found teachers shown to be consistently highly rated by peers, administrators and students also held a high standard for students as individuals. As Bain states, “the educators we studied invited people to pursue ambitious goals and promised to help them achieve, but they left learners in control of their own education” (p. 74). Moreover, students are more motivated to take a course when instructors have high achievement standards and expect students to take their share of responsibility for learning (Hornbeak, 2009). Although not necessarily attending to the affective aspect of how instructors perceive their students, the IDEA SRI instrument facilitates the measurement of student perception of best practice six.

The final best practice is "Respects diverse talents and ways of learning." Chickering and Gamson (1999) explain that this best practice underscores instruction that takes into account the learning style and learning pace of individual students. A full study on all the aspects of learning styles is beyond the scope of this study but, as Sorcinelli (1991) states, this best practice represents a philosophical frame by which instructors view their students and the differences they bring to the classroom. This sensitivity "likely facilitates student growth in every sphere – academic, social, personal and vocational" (1999, p. 21). A more recent study done by Bain (2004) corroborates the findings of the seven best practices. Among the many findings a general attitude in alignment with Best Practice 7 is "the best teachers tended to look for and appreciate the individual value of each student." In this sense nearly all of the 20 IDEA SRI system TMs fit this more global understanding of the final best practice. Likewise IDEA TM1, "Displayed personal interest in students and their learning," holds a similar global value as it provides information from a relational paradigm (as opposed to a strictly didactic or functional one). The first 6 best practices are essentially couched within Best Practice 7. Likewise, IDEA TM1 essentially describes the other 19 teaching methods.

IDEA learning objectives as success measures. The research has looked for ways to measure student learning as a result of instruction given over the course of a semester. Often the final grade of the course was the measure of student learning used, as in the studies included in Cohen's (1981) meta-analysis of student ratings. Several critics justifiably said that final grades are insufficient indicators of student learning to use when the purpose is to examine the effect of specific teaching methods, because of the subjectivity of instructors' assessment reflected in final grades, and variations in learning objectives for each course and the instructional methodology chosen to meet those goals (Bok, 2008; Centra, 1979; Frick et al., 2008; Marsh, 2007; Merrill, 2007). The IDEA system was built on the supposition “that effective teaching could be recognized by its effect on students; if instruction was effective, students learned. But the type of change would differ depending on the subject matter, the level at which it was taught, and the intentions of the instructor” (Hoyt & Cashin, 1977). In other words, upper division courses will have a different set of learning objectives than lower division courses. Likewise, humanities courses will have different learning objectives than STEM courses. Although it can be generally said that effective teaching results in student learning, quantifying student learning and how the learning takes place is more specific and nuanced.

To better quantify the teaching and learning dynamic in a student ratings instrument, the IDEA system asks students to rate their perception of progress on 12 specific learning objectives. For each course, instructors select from the 12 learning objectives those they consider to be “Essential” or “Important”. There is some legitimate debate on instructors being the ones to define what should result from a particular course as it regards what students gain, but, as Hoyt and Cashin state, “In the final analysis, the instructor must be responsible for selecting the objectives to be pursued, because only the instructor has an understanding of the diverse expectations of all who are legitimately concerned” (1977). The reference considers that other stakeholders are rightly concerned with student success in college, namely the public (in the case of public institutions in particular), but also governments and communities who are beneficiaries of a quality student entering the workforce. As stated in Chapter 1, many of these stakeholders make increasing demands for accountability in higher education for student learning (Bok, 2008; Massy, 2003). Whether through accreditation processes or institutional culture, instructors are expected to best describe what learning objectives apply to the course being surveyed by the IDEA SRI system.

Benjamin Bloom described a foundational understanding of learning in creating a taxonomy of several learning domains which are cognitive, affective, and psychomotor. Within these domains are hierarchies of learning, one building on the next (Bloom, 1956). In 2000 this taxonomy was revised to reflect a change from nouns to verbs (Anderson et al., 2000).

The work of Bloom is a common vocabulary for quantifying and understanding the learning process in education and is considered a good point from which to develop a standard set of learning objectives. However, Bloom's taxonomy was thought to be too general by the creators of the IDEA system to be converted into a specific set of learning objectives used on a SRI system. Instead the team creating the IDEA SRI instrument turned to the work of Deshpande and Webb (1968) who synthesized and made actionable the work of Bloom. The authors used factor analysis to show that a large number of learning objectives put together by faculty at the Georgia Institute of Technology could be reduced to a small set of general learning objectives. Some of these more general learning objectives were, "Learning fundamental principles"; "Understanding myself – my interests, talents, values, etc."; "Gaining factual knowledge (terminology, classifications, methods, trends)"; and "Learning to apply principles to solve practical problems". These learning objective items were used to inform a more specific set of learning objectives for the IDEA system, some of which persist to the current form of the IDEA SRI system instrument (Hoyt & Cashin, 1977).

The body of literature on teaching and learning by Bloom, Anderson, Krathwal, Desphande, and Webb (among others) established an understanding of what teaching behaviors constitute good teaching. The literature further describes learning objectives useful for measuring student success. The IDEA instrument measures all of these major concepts and has done so with high measures of validity and reliability over time (see discussion in Chapter 3). Furthermore, research based on the IDEA system data shows which of these teaching methods correlate highly with specified learning objectives as assigned by instructors of each course. Table 2.1, replicated from data produced by the IDEA Center ("IDEA Student Ratings of Instruction Relationship of Teaching Methods to Learning Objectives," 2006), presents the correlations between student ratings of instructors use of each of the 20 teaching methods and student ratings of their progress on the 12 learning objectives, separated by class size; student ratings of progress on specific learning objectives (LO) were only included if the instructor rated the specific learning objective as "essential" or "important" to the course on the Faculty Information Form. The teaching method items are described below Table 2.1.

This table shows how strongly instructors' use of each TM correlates with student progress on a given learning objective. Also evident is that, generally, the same set of TMs tends to correlate with progress on a specific learning objective regardless of class size. What is not evident is whether a specific set of TMs is most highly correlated with a given learning objective, and within that set of TMs, which have the greatest effect on student progress on a learning objective.

Table 2.1

IDEA Student Ratings of Instruction Relationship of Teaching Methods to Learning Objectives

	Relevant Teaching Methods by Class Size *Methods that are highly correlated with learning objectives (.60 or above); those in parenthesis are moderately correlated (.50-.59)*			
Learning Objective	**Small (<15)**	**Medium (15-34)**	**Large (35-49)**	**Very Large (50+)**
1. Gaining factual knowledge (terminology, classifications, methods, trends)	2, 3, 4, 6, 8, 10, 12, 13, 15	2, 4, 6, 8, 10, 12, 13, 15	2, 4, 6, 8, 10, 12, 13, 15	2, 4, 6, 8, 10, 12, 13, 15
2. Learning fundamental principles, generalizations, and theories	2, 4, 6, 8, 10, 12, 13, 15	2, 4, 6, 8, 10, 12, 13, 15	2, 4, 6, 8, 10, 12, 13, 15	2, 4, 6, 8, 10, 12, 13, 15
3. Learning to apply course material (to improve thinking, problem solving, and decisions)	1, 2, 3, 4, 6 ,8 ,10, 11, 13, 15	1, 2, 4, 6, 7, 8, 10, 11, 13, 15	2, 4, 6, 7, 8, 10, 13, 15	2, 4, 6, 7, 8, 11, 13, 15
4. Developing specific skills, competencies, and points of view needed by professionals in the field most closely related to this course	1, 2, 4, 6, 7, 8, 10, 13, 15	1, 2, 4, 6, 7, 8, 10, 11, 13, 15	2, 4, 6, 7, 8, 10, 13, 15	2, 4, 6, 7, 8, 13, 15, 18
5. Acquiring skills in working with others as a member of a team	5, 14, 15, 18 (2, 6, 7)	5, 14, 18, (2, 8, 15, 16, 19)	5, 14, 15, 18 (7, 8, 19)	5, 7, 14, 15, 18, 19 (2)
6. Developing creative capacities (writing, inventing, designing, performing in art, music, drama, etc.)	7, 15, 19 (1, 2, 8, 13, 14, 16, 18)	7, 15, 19 (2, 8, 13, 16, 18	2, 7, 13, 14, 15, 16, 18, 19	2, 5, 7, 13, 14, 15, 16, 18, 19
7. Gaining a broader understanding and appreciation of intellectual/cultural activity (music, science, literature, etc.)	(1, 2, 6, 7, 8, 13, 15, 19)	7, 8, 13, 19 (2, 6, 10, 15, 16)	7, 10, 13, 16, 19 (2, 4, 6, 8, 15)	(2, 4, 6, 7, 10, 13, 15, 16, 19)
8. Developing skill in expressing myself orally or in writing	7, 15, 16, 19 (2, 8, 13, 18)	7, 15, 16, 18, 19 (1, 2, 8, 13)	7, 8, 13, 15, 16, 18, 19 (2)	7, 15, 16, 19 (2, 8, 13)
9. Learning how to find and use resources for answering questions or solving problems	2, 7, 8, 9, 13, 14, 15, 18, 19	2, 7, 8, 9, 13, 14, 15, 18, 19, 20	2, 7, 8, 9, 14, 15, 18, 19, 20	2, 7, 8, 9, 14, 15, 16, 18, 19
10. Developing a clearer understanding of, and commitment to, personal values	1, 2, 4, 6, 8, 11, 13, 15, 16, 18	2, 4, 6, 8, 11, 13, 15, 16, 18	1, 2, 4, 6, 10, 11, 13, 15, 16	1, 2, 4, 6, 13, 15, 16
11. Learning to analyze and critically evaluate ideas, arguments, and points of view	2, 7, 8, 13, 15, 16, 18, 19	2, 7, 8, 13, 15, 16, 18, 19	2, 4, 7, 8, 13, 15, 16, 19	2, 4, 6, 7, 8, 13, 15, 16, 18, 19
12. Acquiring an interest in learning more by asking my own questions and seeking answers	1, 2, 4, 6, 7, 8, 10, 13, 15, 18	1, 2, 4, 6, 7, 8, 13, 15, 18	1, 2, 4, 6, 7, 8, 13, 15, 16, 18, 19	1, 2, 4, 7, 8, 13, 15, 18

TMs:

1. Displayed personal interest in students and their learning
2. Found ways to help students answer their own questions
3. Scheduled course work (class activities, tests, projects) in ways which encouraged students to stay up-to-date in their work
4. Demonstrated the importance and significance of the subject matter
5. Formed "teams" or "discussion groups" to facilitate learning
6. Made it clear how each topic fit into the course

Table 2.1 (cont.)

7. Explained the reasons for criticisms of students' academic performance
8. Stimulated students to intellectual effort beyond that required by most courses
9. Encouraged students to use multiple resources (e.g., data banks, library holdings, outside experts) to improve understanding
10. Explained course material clearly and concisely
11. Related course material to real life situations
12. Gave tests, projects, etc. that covered the most important points of the course
13. Introduced stimulating ideas about the subject
14. Involved students in "hands on" projects such as research, case studies, or "real life" activities
15. Inspired students to set and achieve goals which really challenged them
16. Asked students to share ideas and experiences with others whose backgrounds and viewpoints differ from their own
17. Provided timely and frequent feedback on tests, reports, projects, etc. to help students learn
18. Asked students to help each other understand ideas or concepts
19. Gave projects, tests, or assignments that required original or creative thinking
20. Encouraged student-faculty interaction outside of class (office visits, phone calls, emails, etc.)

What is known regarding the connection between teaching methods and learning objectives. Review of Table 2.1 shows that learning objective 1, "Gaining factual knowledge (terminology, classifications, methods, trends)" correlates highly (r=.60 or higher) with the same nine TMs across all course sizes. Therefore, instructors who find ways to help students answer their own questions, demonstrate the importance of the subject matter, make clear how topics fit into the course, stimulate students intellectually beyond what is required by most courses, explain material clearly and concisely, give assessments that cover the most important points of the course, introduce stimulating ideas about the subject, and inspire students to achieve challenging goals are more likely to have students who report they have made greater progress on this learning objective as presented by the IDEA SRI system. One interesting point to note is class sizes of 15 students or fewer have one additional TM that correlates highly with LO1 which is TM3, "Scheduled course work – class activities, tests, projects – in ways which encouraged students to stay up-to-date in their work". Further study of the IDEA data presented on this table as well as in the larger literature is required to show connections between class size and this particular TM.

By exploring the research done by the IDEA center on how the LOs correlate with TMs, a very interesting observation is made regarding TM17, “Provided timely feedback on tests, reports, projects, etc. to help students learn.” This TM does not show up on the chart at all. One possible reason is that TM17 correlates lower than r=.50, and the IDEA chart only shows correlations greater than .50 (2006). It is striking to note all of the other TMs correlate at least with one LO at r=.50 or better. All of these correlations are statistically significant given the very large sample size of the IDEA data, and an r=.50 indicates at least a medium effect (J. Cohen, 1988; Hoyt & Lee, 2002). Even so this finding is somewhat startling as it flies in the face of ample research to the contrary regarding the importance of timely feedback (Centra, 1979; Chickering & Gamson, 1999; Cohen, 1981; “Development and Adaptations of the Seven Principles for Good Practice in Undergraduate Education - Chickering - 2002 - New Directions for Teaching and Learning - Wiley Online Library,” n.d.; Fink, 2003; Kuh et al., 2006; McKeachie et al., 1986; Merrill, 2002; Theall & Franklin, 1991).

A closer look at the research provided by the IDEA Center in this chart also shows that TM9, “Encouraged students to use multiple resources to improve understanding” only correlates at r=.50 and above with LO9, “Learning how to find and use resources for answering questions or solving problems”. This raises the question of how strong are the correlations between TM9 and the other 11 LOs? Does this invalidate TM9 as useful information for understanding the teaching and learning relationship? Could there be large implications confirming or refuting the existing research on the topic?

Frick, et al. (2010) initiated a study that at least partially addressed this question. They used the TALQ, a SRI instrument created by the author and designed for the study (see discussion above), and analyzed the data using a statistical methodology developed by Frick (1990) called Analysis of Patterns Across Time (APT). They had 256 students complete the TALQ. Students were from twelve different courses taught by eight different instructors in business, philosophy, history, kinesiology, social work, informatics, nursing, and health, physical education and recreation, and they rated their time on task, their instructors' use of Merrill's First Principles of Instruction and their own perception of mastery of the course material as a result of the course (Frick, Chadha, Watson, & Wang, 2010; Merrill, 2002). Instructors were also asked to rate students on whether or not they had gained mastery of the subject material. Using APT, analysis was conducted to discern if the combination of time on task and First Principles of Instruction increased the predictive power of student mastery of course LO. The study concluded that a student was 5.2 times more likely to be rated as having mastery over the course material when academic learning time and First Principles of Instruction were both present. The results of this study are compelling by introducing student mastery as an additional criteria for measuring the effectiveness of teaching methods. This would provide needed insight into the use of student ratings as a means for understanding the impact of TMs on LOs. APT is not a widely accepted method of analysis and further research is needed to validate the findings.

What is still not known. Even though the study of SRI systems is voluminous and, as this literature review shows, there are several known factors regarding the connection between TMs and progress on LOs, as reported by students, there are still numerous areas yet to be studied. Because it is difficult to conduct a true experimental study on student learning, even if one could be ethically derived (Campbell & Stanley, 1963; Cohen, 1981), there remain vast areas of uncertainty regarding which conditions, methods, and contexts are needed to enhance learning and it will likely remain thus for the foreseeable future.

A key area not addressed in the literature is how studies present progress on learning objectives as on a continuum where the differences between no progress and moderate progress is essentially equal distances along the continuum. Practical experience suggests this not to be so. Likewise, there is not an equal distance on a continuum from moderate progress to exceptional progress on learning objectives. Additionally, more work remains to be done exploring the relationships among particular sets of TMs as predictors for progress on LOs. Having established connections between widely adopted teaching and learning theory, particular TMs should stand out as better suited for influencing progress on learning objectives, but the research has not soundly explored these possibilities. Benefits of this kind of research can address what Cohen (1990) stated as "a lack of research translating to improved practice." New faculty and teaching assistant training programming are direct beneficiaries of this research, leading to more precise tools in the hands of administrators and faculty developers (Fink, 2003; Seldin, 1995).

Chapter Summary

This review of the literature demonstrated that student ratings instruments are a valid source of data for research into the dynamics between teaching methods and progress on learning objectives. It also considered the influence of Chickering and Gamson's (1987) Seven Best Practices of Instruction and the work of others as theoretical frameworks for describing the teaching and learning dynamic as presented in the IDEA Center SRI system. The chapter described how the data from this instrument can be generalized to the larger American higher education landscape and how the IDEA SRI system has been used in the past to explore relationships between teaching methods and learning objectives. Finally, this chapter explored key areas where research is needed to increase the understanding of how, and under what conditions, TMs best predict progress on LOs.

Research Questions and Hypotheses

Thus, the following research questions and hypotheses were examined in this study:

Question 1a: How well do teaching methods predict substantial or exceptional progress on IDEA learning objectives the instructor identifies as relevant to the course?

Hypothesis 1a: Teaching methods will accurately and significantly predict whether students report substantial-exceptional progress on each of the 12 learning objectives.

Question 1b: Are these predictions moderated by course enrollment groupings?

Hypothesis 1b: This question is exploratory. Therefore, there are no specific hypotheses.

Question 2a: Which teaching methods have the largest effect on whether students experience substantial or exceptional progress on each of the IDEA learning objectives?

Hypothesis 2a: For all learning objectives, TM2 and TM15 will have the largest effect on progress on learning objectives. Additionally, TM13, TM4, TM6 and TM8 will have meaningful effects on progress on learning objectives.

Question 2b: Are these effects moderated by course enrollment groupings?

Hypothesis 2b: This question is exploratory. Therefore, there are no specific hypotheses. (It is important to note that some of the literature [Centra, 1979; Cohen, 1981; Feldman, 1976; McKeachie, 1997] suggest that class size moderates student ratings in general. However, specific teaching method-by-learning objective combinations that are likely to be moderated by class size have not been identified. Thus no specific hypotheses are provided for this question.)

Chapter 3 - Method

Introduction

This study extends existing student ratings research by exploring more precisely how teaching methods, individually and collectively, influence a minimum standard of student achievement on learning objectives and how class size impacts this influence. This chapter describes the data source, instrumentation, reliability and validity of the instruments used, and the statistical analysis, binary logistic regression.

Data Source

Archival data from 2002 to 2009 was obtained from The IDEA Center (www.theideacenter.org), a nonprofit organization devoted to helping faculty members solicit feedback and evaluate teaching as it relates to curricular goals and the measurement of learning. The IDEA Student Ratings of Instruction (SRI) system was developed in 1975 from a research grant obtained from the Kellogg Foundation. Prior to releasing the data to the researcher, The Center created an aggregate database of class means aligned with instructor information. All instructor-identifying information were removed. The archival data used for this study consists of aggregated class means and not individual student responses.

Several exclusion criteria were employed: novice users, classes with fewer than 10 respondents, and classes that used the IDEA Short Form. In addition, classes were randomly deleted until no institution contributed more than 5% of classes to the total database. More than 580,000 classes of university/college students were retained in the 2002 to 2009 database. The average enrollment in these classes is expected to be around 20 students but may range from 1 to 900 students in each class. Administration of the forms is up to faculty. The IDEA Center recommends the surveys be administered any time after the first half of the semester but not on the last day of class or on the day of the final exam. They are typically administered near the end of a course. Two response formats are available: paper and pencil and IDEA Online. Classes completing ratings online have four delivery options: Blackboard Building Block™, an email delivery system with a unique URL for each student, a unique URL posted on the course web page, or a combination of the above. From 2002-2009 the majority (77.2%) of classes used the paper-and-pencil version, although IDEA Online increased steadily across the years. No meaningful differences exist between paper and online response formats in student progress on relevant course objectives, global ratings of the course and instructor, and frequency of various teaching methods (Benton, Webster, Gross, & Pallett, 2010). Regarding student ratings in general, no meaningful differences are found between response formats in subscale means (Layne, DeCristoforo, & McGinty, 1999), the proportion of positive and negative written comments (Hardy, 2003), and the underlying factor structure (Layne et al., 1999). For the purposes of this study, there were three key response variables: First, faculty rated each learning objective (LO) for its relevance to their course; second, students reported their progress on each of the 12 LOs; third, student reported how frequently the instructor demonstrated each of the 20 teaching methods (TM).

Instrumentation

Learning objectives. The IDEA Student Rating of Instruction system assesses student progress on 12 LOs, which were developed from reviews of two taxonomies of educational objectives originally created by Bloom (1956) and later synthesized by Deshpande and Webb (1968). The taxonomies describe higher order learning and thinking as well as potential learning objectives such as, “Gaining factual knowledge (terminology, classifications, methods, trends).”

Instructors complete a *Faculty Information Form* (FIF) for each course in the IDEA SRI system. On the FIF, instructors rate each of the 12 LOs as either "Essential", "Important", or of "Minor or no importance," for the purpose of the course. Faculty are encouraged to select from 3 to 5 learning objectives as "Essential" or "Important." As a guide in selecting relevant objectives faculty are asked to answer the following questions: a)"Is it a significant part of the course?"; b) "Do you do something to help students to progress on the objective?"; and c) "Are student grades influenced by their progress on the objective?".

Instructors also complete additional information on the FIF. They indicate the time and days the class meets and the number of students in the course. Instructors also have the option of responding to several contextual questions about the course. First they may specify which of several teaching methods (e.g. lecture, discussion, seminar, etc.) were the primary and secondary approaches to instruction. Next they can indicate the course requirements with respect to the amount (none, some, or much) of writing, oral communication, computer applications, group work, mathematical/quantitative work, critical thinking, creative/artistic/design endeavor, reading, and memorization. Instructors can also rate the impact (positive, negative or neither positive nor negative) that each of several circumstances (e.g. physical facilities, previous experience teaching the course, desire to teach the course, etc.) had on the course. In addition they are asked to identify the primary type of student enrolled (e.g. first-year/sophomore, meeting general education requirements, upperclassman non-majors, graduate or professional students). Finally, instructors indicate if the course is team taught and if it is a distance learning course.

On the IDEA *Student Diagnostic Form* students indicate their progress on the same 12 LOs. Students use the following scale, 1) *No apparent progress*, 2) *Slight progress; I made small* *gains on this objective*, 3) *Moderate progress; I made some gains on this objective*, 4) *Substantial progress; I made large gains on this objective*, and, 5) *Exceptional progress; I made outstanding gains on this objective*. One of the research questions of this study, however, makes the case that progress on learning objectives is not evenly distributed on a continuum as this rating scale would suggest. A case could be made that, "No apparent progress," is not equal in distance from, "Slight progress; I made small gains on this objective." A logical separation of these progress ratings would be to separate out, "No apparent progress," from the other four items on the scale because they each represent at least some progress on the LO. A philosophical choice was made by the researcher to instead re-group LO results so that student responses 1-3 representing "no, slight, or moderate" progress on the LO equated "not enough" progress on a higher education LO. Explained in greater detail later in the chapter, these responses were coded 0 for the purposes of this study. Student responses of "substantial or exceptional" progress on LOs were considered "desired progress" for a higher education LO. These responses were coded 1 in the data. This distinction has not previously been analyzed on the IDEA SRI system data.

Reliability of learning objective items. The most recent reliability data for the IDEA forms was published by Hoyt and Lee (Hoyt & Lee, 2002) who used split-half reliability coefficients to evaluate the internal consistency of the LOs sorted by different class sizes. The authors examined the reliability of individual items and scale scores on student ratings completed in class sizes of 13 to 17 students. The results were taken as an estimate of the split-half reliability of classes averaging 7.5 respondents. The Spearman-Brown Prophecy formula was used to estimate class sizes averaging 12.5, 24.5, 42.5 and 60 respondents, which correspond to IDEA's class size ranges shown in the tables below (2002, p. 44). Table 3.1 presents the reliability estimates and standard errors of measurement for the learning objective items.

Reliability estimates range from acceptable to good for the smallest class sizes (i.e., between 10-14 students), and from good to excellent for classes with 15 or more students.

Table 3.1

Learning Objective Reliabilities: Split Half Reliabilities (Spearman-Brown Prophecy) and Standard Errors

	Reliability		Standard Error	
Class Size	Range	Average	Range	Average
10 – 14	.73 - .85	.78	.21 - .34	.27
15 – 34	.84 - .94	.87	.16 - .25	.20
35 – 49	.90 - .95	.92	.13 - .20	.16
50+	.93 - .97	.94	.11 - .17	.13

Note: Data summarized from IDEA Technical Report 12 Table 17 page 45.

Validity of learning objective items. In order to examine the extent to which the IDEA student ratings of progress on LOs can be trusted, Hoyt and Lee (2002) conducted several validity studies. First, in order to address the validity of the LOs they correlated the average of students' reported progress on each objective with the instructors' average ratings of the importance of those objectives (which was collected on the FIF). The authors made the following three assumptions: a) instruction is effective; b) instructors make meaningful judgments when they rate the importance of LOs; and c) students make conscientious ratings on these objectives. If these assumptions are true, then student progress on LOs should be significantly and highly correlated with the instructors' ratings. The results supported the assumptions; the highest correlations were found between the instructor's averaged ratings of LO importance for the course and the average rating of student progress on the same objectives. The average correlation for these matching objectives was .265. For LOs that were irrelevant to the course the average correlation between instructor ratings of importance and the average ratings of student progress was only .024. The authors point out this finding is consistent with reports dating back to 1973 (2002, p. 47).

Second, in order to evaluate the construct validity of the LOs, Pallett, Duchon, and Benton (2011) examined the correlation between students' self-ratings of progress on relevant course objectives and their performance on exams administered during a college course. Across three sections of the same course taught by a single instructor, students rated themselves on objectives identified by the instructor as either relevant or irrelevant to the course. Self-ratings on relevant objectives correlated significantly and positively with four out of five exams and the course total, whereas ratings on irrelevant objectives did not.

Another study exploring the validity of the learning objective items involved Contextual Question 3 of the FIF. This item focuses on the instructor's description of class emphases where they indicate whether the class required 1) *None*, 2) *Some*, or 3) *Much* of seven activities: writing, oral communication, computer applications, group work, mathematical/quantitative work, critical thinking, and creative/artistic/design endeavor. If the system is valid there should be a relationship between instructor reported emphases of course activities and student reports of progress on related objectives (2002, p.49). The authors conducted F tests ($p<.001$) which revealed the following: a) where writing was emphasized, students showed above average progress on LO8, "Developing skill in expressing in expressing myself orally or in writing;" b) where critical thinking was emphasized, students reported above average progress on LO11, "Learning to analyze and critically evaluate ideas, arguments, and points of view;" c) where "creative/artistic/design endeavor" was emphasized, students showed above average progress on LO6, "Developing creative capacities (writing, inventing, designing, performing in art, music, drama, etc.);" and d) lastly, when instructors emphasized "group work" student progress on LO5, “Acquiring skills in working with others as a member of a team,” was also above average. The authors’ conclusion was that the relationships between course activities and student ratings of progress on relevant LOs established criterion validity for both instructor and student ratings (p. 50).

Teaching methods. The IDEA SRI system also gathers information from students about instructor use of 20 teaching methods. On the IDEA *Student Diagnostic Form* students rate how frequently their instructor used each of 20 TMs using a scale of, 1) *hardly ever*, 2) *occasionally*, 3) *sometimes*, 4) *frequently*, and 5) *almost always*. Students are asked to compare the course with others they took at the institution with respect to the amount of reading, the amount of non-reading assignments, and the relative difficulty of the subject matter. They also indicate their desire to take the course, both from their instructor and regardless of who taught it, as well as their effort as a student in the course compared to other courses they have taken. Three summary questions assess students’ overall impressions: a) their attitude toward the field of study as a result of taking the course, b) their overall impressions of the instructor, and c) their overall rating of the course. Additional questions concern the instructor’s use of technology in the course, the student’s typical effort in their coursework, and the instructor’s assessment methods and standards for learning and achievement. Space is provided for open-ended written comments, but student responses are only shared with the instructor and are not placed into the IDEA Center database. The archival data used for this study consists of aggregated class means and not individual student responses.

Reliability of teaching method items. Table 3.2 was constructed from Hoyt and Lee’s report (2002). Reported in the table are the likely ranges of split-half reliability estimates and standard error of measures based on class size. There is a .68 probability the true mean falls within one standard error of the obtained mean. There is a .95 probability the reliability measure will fall within two standard errors of the obtained mean. As indicated in Table 3.2, when class sizes exceed n = 15 an individual item mean has a standard error of measurement equal to approximately to .2. Thus, the true score of an observed mean of 4.0 on an individual item has a 68% chance of being between 3.8 to 4.2, and a 95% chance of being between 3.6 to 4.4.

Table 3.2

Teaching Method Reliabilities[1]:Split Half Reliabilities (Spearman-Brown Prophecy) and Standard Errors

	Reliability		Standard Error	
Class Size	Range	Average	Range	Average
10 – 14	.72 - .90	.80	.22 - .33	.27
15 – 34	.84 - .95	.88	.17 - .24	.20
35 – 49	.90 - .97	.93	.13 - .19	.15
50+	.93 - .98	.95	.11 - .16	.13

[1]Experimental items not included. Note: Data summarized from IDEA Technical Report 12 Table 17 page 45.

The alpha for individual items fall above the .70 cut off accepted in social science research (Nunnally & Bernstein, 1994), providing evidence of high internal consistency.

Validity of teaching method items. Hoyt and Lee (2002) indicate there are five factors, or scales, underlying the IDEA TMs. They reported evidence that supports the validity of each scale. The focus of this study, however, is the individual TM items and clusters of TMs based upon strength of correlation to LOs. Although validity of the five TM factors could also suggest validity of the individual TMs, other studies of individual TMs can be used to establish validity. One such study posited that if student ratings are valid then there should be a degree of correspondence between their ratings of progress and their perceptions of how frequently the instructor employed teaching methods highly correlated with the specific learning objective (Hoyt & Lee, 2002). For example, the teaching method most closely related to student ratings of progress on LO9, “Learning to find and use resources for answering questions or solving problems”, was most closely related to TM9, “Encouraged students to use multiple resources to improve understanding.” Similarly, the TM most highly correlated with progress on LO5, “Acquiring skills in working with others as a member of a team,” was TM5, “Formed teams of ‘discussion groups’ to facilitate learning.”

Furthermore, these relationships varied depending on the size of the class. For example the correlation between LO6, “Developing creative capacities (writing, inventing, designing, performing in art, music, drama, etc.),” and TM5, “Formed teams of ‘discussion groups’ to facilitate learning,” was higher in large classes (50 or more students) than it was in smaller classes. This makes sense in that teams and groups would be typical teaching methods for courses where performing arts, music and drama were important or essential learning objectives. This finding shows that students are capable of making differential judgments.

According to Hoyt and Lee (p. 48) another indication of differential judgments on the part of students, and thereby further evidence of validity, involves the TMs that are most highly correlated with student ratings of progress. For each LO, the list of highly correlated TMs was relatively distinctive. When considering the TMs most highly correlated with a given LO there were only 50% of the TM items shared for any two sets of LOs. The authors contend that without differential judgments on the part of students distinctive patterns like this would not exist.

Validity of the IDEA system overall. Not many studies explore the validity of the component parts of the IDEA SRI system (i.e., student ratings of progress on LOs, student ratings of TMs) apart from the entirety of the instruments and the IDEA rating system generally. One study does explore the contextual questions given to faculty regarding the impact of certain circumstances on student learning reported on the FIF. If expected relationships exist between faculty reported circumstances impacting learning and corresponding impacts on student ratings of progress, these relationships “would constitute evidence for the validity of the system since the instructors and students each made their ratings without knowledge of each other’s views” (Hoyt & Lee, 2002, p. 48).

For example, Contextual Question 4 on the FIF asks faculty to rate the impact on the course of factors such as previous experience in teaching the course, desire to teach the course, student preparation for the course, and student enthusiasm toward the course. Ratings responses are 1) *Positive*, 2) *In Between*, or 3) *Negative*. Hoyt and Lee (2002) correlated responses to Question 4 with student-rating items regarding overall student attitude toward the subject and two overall ratings regarding the instructor and the course (“Overall, I rate this instructor an excellent teacher” and “Overall, I rate this course as excellent.”). They reported that,

> “in every instance the expected differences were found. In classes where the circumstance was expected to have a positive influence on student learning the global [student] ratings were significantly higher than in those where the expected impact was negative. Classes with ‘in between’ faculty ratings invariably had ‘in between’ student ratings on these four measures” (p.49).

Finally, the validity of the IDEA instrument also corroborates evidence presented in meta-analyses of validity studies conducted on student ratings of instruction generally. An area of SRI requiring control is for courses that prepare students for a profession, as opposed to general education courses, are rated more highly by students on items such as, “I had a strong desire to take this course,” and, “I really wanted to take this course regardless of who was teaching it," (Cashin, 1995; Cohen, 1981; Marsh, 2007). The IDEA SRI system used this information to adjust student ratings on these items to "make the playing field level" for all courses. If these adjustments are successful then they should be positive in direction for those teaching general and liberal education courses whereas negative in direction for those teaching courses related to a student's major. The authors then applied the adjustment to student ratings of progress on LOs. All *F* tests (p<.0001) conducted showed the results to be in line with expectations. The authors concluded this provides evidence of validity in the IDEA SRI system (Hoyt & Lee, 2002, p. 52).

Statistical Analyses

Binomial logistic regression was the statistical analysis deemed desirable for the focus of this study. "In logistic regression we predict the *probability* of Y occurring given the known values of X" (Field, 2005). One of the advantages of logistic regression is the ability to classify criterion variables based on information contained in the independent variables (Johnson, 1998). The aim of this study was to explore more precisely how the 20 TMs, individually and collectively, predict and classify substantial or exceptional progress on the 12 LOs and how class size impacts these classifications. As explained earlier, the criterion variable for each LO was converted to a binomial expression.

Because stepwise entry of variables into a regression equation can be influenced by random variation in the data and the sample used, which are threats to generalizability (Field, 2005; Menard, 1995), forced entry was utilized for the regression models. The result of a binary logistic regression equation provides a probability value between 0 and 1. "A value close to 0 means that Y is very unlikely to have occurred, and a value close to 1 means that Y is very likely to have occurred" (Field, 2005, p. 221). Estimation is done using maximum likelihood techniques to maximize how likely it is to "obtain the observed values of Y given the values of the independent variables and parameters" (Menard, 1995, p. 13). As a result, an iterative process can be employed to find the best fit of possible models until any changes are negligible or, in other words, the solution has converged (Orme, 2009).

In keeping with the larger body of student evaluation research, TMs were entered into the logistic regression model as a continuous variable (Arreola, 2007; Cashin, 1995; Centra, 1998; J. Cohen, 1988; P. Cohen, 1990; Hoyt & Lee, 2002; Marsh, 2007; Renaud & Murray, 2005). Student ratings of learning objective progress 1-3 were coded 0 and labeled as not enough progress. Student ratings of learning objective progress 4 or 5 were coded 1 and labeled desired progress.

For each of the 12 LOs analyses was only performed on classes in which the instructor selected the objective as "Important" or "Essential" on the IDEA FIF. Courses with fewer than 10 responses were also excluded from the data to better protect for statistical validity of the class mean (Hoyt & Lee, 2002). Due to these and other limiting factors explained at the start of this chapter the beginning sample for this study was just under 330,000 classes.

Testing the 20 TMs as predictive clusters. The research questions were, "How well do teaching methods predict substantial or exceptional progress on IDEA learning objectives the instructor identifies as relevant to the course?" and "Are these predictions moderated by class enrollment groupings"? To answer these questions, first point-biserial correlations were run between all 20 TMs with each of the 12 LOs, separated by class enrollment groups established by existing IDEA research. The six most highly correlated TMs, separated by class enrollment groups and for each of the 12 LOs, were selected as predictor variables for the logistic regression models. Additionally, any TM correlations that were within r=.01 of the lowest of the top six correlations scores were also included in the model. In many cases this resulted in a different set of TMs comprising predictors for the 12 LO models for each class enrollment group.

In logistic regression the log-likelihood function, which is based on summing the probabilities between the predicted and observed outcomes, is used to explain the amount of unexplained variance after the logistic model has been fitted. Chi-square test of goodness of fit is used to compare the fitness of one model of the iteration to other iterations in the modeling process (Field, 2005; Leech, 2008). A finding of non-significance for this test corresponds to the researcher concluding the model adequately fits the data. Alternately, statistical packages also provide the Omnibus model test of coefficients which tests if the model with the predictors is significantly different from the model with only the intercept. Conversely a significant result on this test implies an overall goodness of fit for the model (Field, 2005; Garson, 2011). The chi-square goodness of fit test and the overall percent correct classification were used to answer how well each set of teaching methods predicted progress for each learning objective by course enrollment groups.

Testing the 20 TMs individually. The final questions of this study are, “Which teaching methods have the largest effect on whether students experience substantial or exceptional progress on each of the IDEA learning objectives?”, and, “Are these predictions moderated by course enrollment groups?” For all variables significant at the $\alpha = .001$, level the values of the Exp(B) statistic were used to determine which individual TMs were the best predictors of progress on each of the 12 LOs separated by class enrollment groups. Exp(B) is an odds ratio. It states the odds for success over the odds for failure. For this study it meant the odds the TM predicted desired progress on the LO over the odds for the TM predicting not enough progress on the LO.

Addressing assumptions of logistic regression. Although some of this section has been addressed in the preceding paragraphs it bears pointing out how this study addressed assumptions of logistic regression. Burns (2008) highlights the assumptions that must be met in order to correctly run logistic regression analysis (see also Field, 2005; Johnson, 1998; and Menard, 1995).

- The dependent variable must be a dichotomy (2 categories).
- These dichotomous categories (groups) must be mutually exclusive and exhaustive; a case can only be in one group and every case must be a member of one of the groups.
- Larger samples are needed because maximum likelihood coefficients are large sample estimates. A minimum of 50 cases per predictor is recommended.

All of these assumptions were met within the parameters of this study. It is also worthwhile to note that logistic regression does not assume a linear relationship between the criterion and predictor variables, and the predictor variables need not be interval, nor normally distributed, nor of equal variance within each group (Burns, 2008) These assumptions of the data, therefore, do not need to be tested in this study.

Chapter 4 - Results

Results of the analyses that investigated the strength of teaching methods as predictors of progress on learning objectives are covered in this chapter. The following results are presented: a) descriptive statistics for each of the 12 learning objectives and 20 teaching methods separated by class enrollment groupings; b) correlations between teaching methods and learning objectives separated by class enrollment groupings; and c) binary logistic regressions, run separately by class enrollment groupings, with teaching methods serving as predictor variables and learning objectives serving as criterion variables. The correlations were used to identify which TMs to include in the regression models predicting progress on a specific LO, and to examine if this differed by class size grouping. The binary logistic regressions were used to examine how well TMs predicted progress on LOs (question 1a), if the power of TMs to predict making progress on LOs differed by class size (question 2a), which TMs had the largest effect on making progress on LOs (question 2a), and if the effect of individual TMs on making progress on LOs was moderated by class size (question 2b).

Descriptive Statistics by Enrollment Groups

The overall sample size included 331,766 classes. Sample size by class enrollments was: a) 43,659 (13%) for the Small group (class enrollments between 10-14 students; the IDEA data excludes enrollments of less than 10 students); b) 238,088 (72%) for the Medium group (class enrollments between 15 – 34 students); c) 32,710 (10%) for the Large group (class enrollments between 35-49 students); and d) 12,258 (4%) for the Very Large group (class enrollments of 50 or more students).

Tables 4.1, 4.3, 4.5, and 4.7 present means and standard deviations for each of the 20 IDEA system teaching methods (TM) organized by the 12 learning objectives (LO) and sorted by the 4 class enrollment groupings. Again, student ratings of progress on specific LOs are only included in the database if the faculty member rated that LO as “Important” or “Essential” for the course. For example, the mean score of TM1 with 15 or less students was 4.53 on a scale of 1-5. Tables 4.2, 4.4, 4.6, and 4.8 present the number of classes where students rated “Desired Progress” or “Not Enough Progress” was made on a given LO sorted by class enrollment groupings. For example, for the 30,794 classes with enrollments of 15 or fewer students, the students in 7,118 classes (23.1%) reported “Not Enough Progress” on LO1, whereas students in 23,676 classes (76.9%) indicated they made “Desired Progress” on LO1. Refer to Appendix A for the full text of the 20 TM items and the 12 LO items.

Table 4.1

Means and Standard Deviations of Teaching Methods (TM) by Learning Objective (LO) for Small Class Enrollment Group (between 10-14 students enrolled)

	LO1		LO2		LO3		LO4		LO5		LO6	
	M	S.D.	M	S.D.	M	S.D.	M	S.D.	M	S.D.	M	S.D.
TM1	4.53	.44	4.53	.44	4.54	.44	4.55	.43	4.56	.43	4.56	.42
TM2	4.32	.49	4.32	.49	4.34	.49	4.35	.48	4.36	.49	4.34	.48
TM3	4.38	.47	4.38	.47	4.38	.47	4.39	.47	4.38	.49	4.38	.47
TM4	4.50	.43	4.50	.43	4.50	.44	4.52	.43	4.51	.44	4.49	.43
TM5	3.83	.89	3.84	.89	3.90	.87	3.92	.86	4.26	.68	3.88	.82
TM6	4.40	.49	4.39	.48	4.39	.49	4.41	.48	4.41	.49	4.38	.48
TM7	4.10	.56	4.10	.56	4.12	.56	4.15	.56	4.16	.55	4.22	.53
TM8	4.16	.55	4.16	.55	4.18	.55	4.18	.55	4.18	.57	4.17	.55
TM9	4.07	.63	4.07	.63	4.10	.62	4.12	.62	4.16	.60	4.11	.61
TM10	4.30	.59	4.29	.59	4.29	.59	4.30	.59	4.29	.60	4.29	.57
TM11	4.40	.54	4.41	.54	4.42	.54	4.44	.52	4.47	.51	4.34	.54
TM12	4.42	.48	4.41	.48	4.40	.49	4.40	.49	4.37	.52	4.34	.51
TM13	4.27	.55	4.27	.55	4.27	.55	4.29	.54	4.31	.55	4.31	.53
TM14	4.13	.72	4.13	.72	4.18	.69	4.25	.65	4.35	.58	4.25	.61
TM15	4.10	.59	4.10	.59	4.13	.58	4.17	.57	4.19	.57	4.22	.55
TM16	3.98	.74	4.00	.74	4.04	.73	4.06	.71	4.17	.65	4.09	.65
TM17	4.30	.58	4.30	.59	4.30	.59	4.30	.59	4.29	.60	4.27	.59
TM18	4.09	.59	4.10	.59	4.13	.58	4.15	.58	4.24	.53	4.14	.57
TM19	4.17	.61	4.18	.60	4.22	.59	4.24	.59	4.27	.57	4.38	.52
TM20	4.17	.60	4.16	.59	4.18	.59	4.20	.59	4.21	.59	4.16	.60

Table 4.1 (cont.)

Means and Standard Deviations of Teaching Methods (TM) by Learning Objective (LO) for Small Class Enrollment Group (between 10-14 students enrolled)

	LO7		LO8		LO9		LO10		LO11		LO12	
	M	S.D.	M	S.D.	M	S.D.	M	S.D.	M	S.D.	M	S.D.
TM1	4.55	.43	4.55	.43	4.54	.44	4.59	.41	4.54	.44	4.55	.43
TM2	4.33	.48	4.35	.48	4.33	.49	4.39	.48	4.34	.49	4.34	.49
TM3	4.36	.47	4.39	.46	4.37	.49	4.39	.48	4.37	.48	4.37	.48
TM4	4.48	.43	4.50	.43	4.49	.44	4.55	.41	4.49	.44	4.50	.43
TM5	3.85	.86	4.03	.79	3.94	.84	4.07	.79	3.94	.84	3.90	.85
TM6	4.39	.48	4.40	.48	4.38	.50	4.45	.46	4.39	.49	4.40	.49
TM7	4.16	.54	4.16	.54	4.12	.56	4.16	.54	4.13	.55	4.12	.56
TM8	4.17	.55	4.20	.54	4.18	.56	4.21	.56	4.20	.55	4.17	.56
TM9	4.07	.64	4.18	.59	4.22	.58	4.17	.60	4.17	.60	4.13	.62
TM10	4.30	.57	4.30	.57	4.29	.60	4.34	.56	4.29	.58	4.31	.58
TM11	4.31	.57	4.41	.53	4.42	.53	4.52	.48	4.41	.54	4.42	.53
TM12	4.34	.51	4.37	.49	4.38	.50	4.38	.50	4.36	.49	4.38	.50
TM13	4.32	.52	4.30	.53	4.28	.55	4.38	.51	4.31	.54	4.31	.54
TM14	4.06	.72	4.17	.67	4.23	.65	4.26	.64	4.15	.69	4.17	.69
TM15	4.12	.59	4.14	.58	4.14	.58	4.20	.57	4.13	.58	4.14	.59
TM16	4.08	.68	4.17	.64	4.10	.68	4.28	.61	4.15	.66	4.10	.69
TM17	4.27	.59	4.30	.59	4.28	.60	4.31	.59	4.28	.60	4.29	.59
TM18	4.11	.59	4.16	.56	4.14	.58	4.22	.56	4.14	.58	4.14	.59
TM19	4.27	.58	4.30	.53	4.25	.57	4.31	.55	4.29	.54	4.24	.58
TM20	4.15	.60	4.21	.58	4.19	.60	4.21	.59	4.19	.58	4.17	.60

Table 4.2

Frequency Count of " Not Enough Progress" or" Desired Progress" for all 12 Learning Objectives (LO) for Small Class Enrollment Group (between 10-14 students enrolled)

	LO1		LO2		LO3		LO4	
	Freq.	%	Freq.	%	Freq.	%	Freq.	%
Not Enough Progress	7118	23.1%	7881	27.0%	7577	24.1%	5766	22.1%
Desired Progress	23676	76.9%	21308	73.0%	23876	75.9%	20311	77.9%
Total	30794	100.0%	29189	100.0%	31453	100.0%	26077	100.0%

	LO5		LO6		LO7		LO8	
	Freq.	%	Freq.	%	Freq.	%	Freq.	%
Not Enough Progress	4556	35.1%	3636	34.2%	3822	40.8%	7705	42.8%
Desired Progress	8434	64.9%	7005	65.8%	5548	59.2%	10278	57.2%
Total	12990	100.0%	10641	100.0%	9370	100.0%	17983	100.0%

	LO9		LO10		LO11		LO12	
	Freq.	%	Freq.	%	Freq.	%	Freq.	%
Not Enough Progress	6841	43.6%	3510	40.1%	6790	38.5%	5902	38.6%
Desired Progress	8849	56.4%	5244	59.9%	10858	61.5%	9392	61.4%
Total	15690	100.0%	8754	100.0%	17648	100.0%	15294	100.0%

Table 4.3

Means and Standard Deviations of Teaching Methods (TM) by Learning Objective (LO) for Medium Class Enrollment Group (15-34 students enrolled)

	LO1		LO2		LO3		LO4		LO5		LO6	
	M	S.D.	M	S.D.	M	S.D.	M	S.D.	M	S.D.	M	S.D.
TM1	4.42	.46	4.42	.46	4.43	.46	4.45	.46	4.45	.46	4.46	.45
TM2	4.21	.49	4.22	.50	4.23	.49	4.24	.50	4.24	.50	4.24	.48
TM3	4.31	.45	4.31	.45	4.32	.45	4.33	.46	4.32	.47	4.33	.45
TM4	4.41	.44	4.41	.44	4.41	.44	4.43	.44	4.41	.45	4.40	.44
TM5	3.65	.94	3.67	.94	3.75	.92	3.78	.90	4.20	.68	3.82	.85
TM6	4.31	.48	4.31	.48	4.30	.49	4.33	.49	4.32	.50	4.30	.48
TM7	3.97	.54	3.97	.55	3.99	.55	4.03	.55	4.04	.54	4.11	.53
TM8	4.03	.54	4.03	.54	4.04	.54	4.06	.55	4.05	.55	4.05	.54
TM9	3.94	.63	3.94	.63	3.98	.62	4.01	.62	4.07	.58	4.07	.58
TM10	4.24	.58	4.23	.58	4.23	.58	4.24	.59	4.22	.60	4.25	.57
TM11	4.31	.55	4.32	.55	4.32	.55	4.36	.53	4.36	.52	4.27	.54
TM12	4.39	.45	4.38	.45	4.37	.46	4.37	.47	4.33	.50	4.30	.48
TM13	4.16	.55	4.16	.56	4.15	.56	4.18	.55	4.19	.55	4.21	.53
TM14	3.89	.76	3.89	.76	3.95	.74	4.07	.69	4.19	.60	4.09	.62
TM15	3.93	.59	3.93	.59	3.96	.59	4.02	.58	4.04	.57	4.07	.56
TM16	3.81	.75	3.83	.75	3.87	.74	3.90	.72	4.03	.66	4.01	.64
TM17	4.25	.55	4.24	.56	4.24	.56	4.25	.57	4.23	.57	4.21	.56
TM18	3.93	.60	3.94	.60	3.97	.59	4.01	.58	4.11	.53	4.03	.56
TM19	4.02	.61	4.03	.61	4.08	.60	4.12	.59	4.17	.56	4.29	.51
TM20	4.05	.58	4.05	.58	4.07	.58	4.09	.58	4.09	.58	4.05	.59

Table 4.3 (cont.)

Means and Standard Deviations of Teaching Methods (TM) by Learning Objective (LO) for Medium Class Enrollment Group (15-34 students enrolled)

	LO7		LO8		LO9		LO10		LO11		LO12	
	M	S.D.	M	S.D.	M	S.D.	M	S.D.	M	S.D.	M	S.D.
TM1	4.43	.45	4.44	.45	4.43	.46	4.49	.43	4.43	.45	4.44	.45
TM2	4.22	.49	4.23	.48	4.22	.50	4.27	.48	4.23	.49	4.24	.49
TM3	4.29	.46	4.32	.45	4.31	.46	4.32	.46	4.30	.46	4.31	.46
TM4	4.39	.43	4.40	.43	4.39	.45	4.46	.42	4.40	.44	4.42	.44
TM5	3.72	.90	3.92	.83	3.81	.87	3.91	.85	3.81	.88	3.76	.90
TM6	4.30	.48	4.31	.48	4.29	.50	4.36	.47	4.30	.48	4.32	.49
TM7	4.02	.54	4.05	.52	4.01	.54	4.05	.53	4.01	.53	4.01	.54
TM8	4.03	.54	4.06	.53	4.04	.54	4.07	.54	4.06	.53	4.05	.54
TM9	3.98	.62	4.11	.57	4.13	.57	4.05	.59	4.06	.60	4.01	.61
TM10	4.25	.56	4.25	.56	4.22	.59	4.28	.55	4.24	.56	4.25	.57
TM11	4.23	.54	4.32	.52	4.31	.54	4.44	.49	4.32	.53	4.34	.54
TM12	4.31	.48	4.32	.47	4.33	.48	4.34	.48	4.32	.47	4.35	.48
TM13	4.21	.53	4.19	.53	4.16	.55	4.27	.52	4.20	.54	4.20	.55
TM14	3.86	.73	3.98	.67	4.03	.67	4.03	.69	3.92	.71	3.95	.73
TM15	3.94	.59	3.98	.56	3.98	.58	4.03	.57	3.96	.57	3.98	.59
TM16	3.95	.68	4.05	.63	3.96	.68	4.15	.62	4.02	.66	3.97	.70
TM17	4.20	.57	4.23	.56	4.22	.57	4.24	.56	4.22	.57	4.23	.56
TM18	3.96	.59	4.01	.56	3.99	.58	4.06	.57	3.98	.58	3.99	.59
TM19	4.14	.58	4.20	.52	4.14	.56	4.18	.55	4.16	.55	4.11	.58
TM20	4.02	.59	4.08	.57	4.07	.58	4.08	.58	4.06	.57	4.06	.59

Table 4.4

Frequency Count of " Not Enough Progress" or" Desired Progress" for all 12 Learning Objectives (LO) for Medium Class Enrollment Group (15-34 students enrolled)

	LO1		LO2		LO3		LO4	
	Freq.	%	Freq.	%	Freq.	%	Freq.	%
Not Enough Progress	51872	30.5%	56723	35.3%	56396	33.7%	36098	31.4%
Desired Progress	118431	69.5%	104142	64.7%	110987	66.3%	78932	68.6%
Total	170303	100.0%	160865	100.0%	167383	100.0%	115030	100.0%

	LO5		LO6		LO7		LO8	
	Freq.	%	Freq.	%	Freq.	%	Freq.	%
Not Enough Progress	26944	41.8%	21062	43.5%	26951	50.8%	49549	50.1%
Desired Progress	37512	58.2%	27316	56.5%	26051	49.2%	49267	49.9%
Total	64456	100.0%	48378	100.0%	53002	100.0%	98816	100.0%

	LO9		LO10		LO11		LO12	
	Freq.	%	Freq.	%	Freq.	%	Freq.	%
Not Enough Progress	44173	52.7%	22806	48.8%	47442	46.1%	39865	49.7%
Desired Progress	39607	47.3%	23889	51.2%	55530	53.9%	40310	50.3%
Total	83780	100.0%	46695	100.0%	102972	100.0%	80175	100.0%

Table 4.5

Means and Standard Deviations of Teaching Methods (TM) by Learning Objective (LO) for Large Class Enrollment Group (35-49 students enrolled)

	LO1		LO2		LO3		LO4		LO5		LO6	
	M	S.D.	M	S.D.	M	S.D.	M	S.D.	M	S.D.	M	S.D.
TM1	4.31	.48	4.30	.48	4.31	.48	4.34	.48	4.34	.49	4.33	.49
TM2	4.09	.50	4.09	.50	4.11	.50	4.13	.51	4.12	.52	4.10	.51
TM3	4.20	.45	4.20	.45	4.21	.46	4.24	.45	4.23	.45	4.18	.47
TM4	4.34	.44	4.34	.43	4.34	.45	4.36	.45	4.33	.46	4.34	.45
TM5	3.38	.98	3.39	.98	3.46	.98	3.55	.96	4.11	.73	3.57	.97
TM6	4.25	.47	4.24	.47	4.24	.49	4.26	.48	4.25	.50	4.24	.48
TM7	3.80	.52	3.80	.52	3.82	.53	3.86	.54	3.87	.54	3.88	.54
TM8	3.91	.52	3.91	.52	3.92	.53	3.96	.54	3.92	.55	3.91	.55
TM9	3.74	.61	3.73	.62	3.76	.62	3.82	.63	3.88	.61	3.87	.61
TM10	4.17	.58	4.16	.58	4.15	.59	4.16	.60	4.11	.63	4.16	.59
TM11	4.30	.54	4.31	.53	4.32	.54	4.33	.53	4.33	.53	4.29	.54
TM12	4.36	.42	4.36	.42	4.35	.43	4.34	.45	4.29	.48	4.27	.48
TM13	4.09	.55	4.09	.55	4.08	.56	4.09	.56	4.10	.56	4.15	.54
TM14	3.60	.79	3.60	.80	3.66	.79	3.78	.77	4.03	.63	3.82	.75
TM15	3.73	.58	3.73	.58	3.76	.59	3.83	.59	3.85	.59	3.83	.61
TM16	3.64	.75	3.64	.76	3.67	.77	3.70	.77	3.85	.70	3.84	.70
TM17	4.18	.53	4.18	.54	4.18	.55	4.19	.55	4.15	.57	4.09	.57
TM18	3.74	.59	3.75	.59	3.78	.59	3.84	.59	3.98	.53	3.83	.61
TM19	3.81	.60	3.80	.60	3.84	.60	3.88	.60	3.98	.57	4.02	.57
TM20	3.98	.55	3.98	.55	4.00	.56	4.03	.56	4.02	.57	3.97	.57

Table 4.5 (cont.)

Means and Standard Deviations of Teaching Methods (TM) by Learning Objective (LO) for Large Class Enrollment Group (35-49 students enrolled)

	LO7		LO8		LO9		LO10		LO11		LO12	
	M	S.D.	M	S.D.	M	S.D.	M	S.D.	M	S.D.	M	S.D.
TM1	4.29	.48	4.31	.48	4.31	.48	4.31	.48	4.31	.48	4.32	.48
TM2	4.06	.51	4.09	.50	4.09	.50	4.09	.50	4.09	.50	4.11	.51
TM3	4.15	.47	4.20	.45	4.20	.45	4.20	.45	4.20	.45	4.18	.47
TM4	4.31	.44	4.34	.43	4.34	.43	4.34	.43	4.34	.43	4.35	.45
TM5	3.33	.98	3.42	.98	3.42	.98	3.42	.98	3.42	.98	3.46	.97
TM6	4.23	.48	4.25	.47	4.24	.47	4.25	.47	4.25	.47	4.25	.48
TM7	3.80	.53	3.81	.52	3.81	.52	3.81	.52	3.81	.52	3.82	.53
TM8	3.86	.54	3.91	.52	3.91	.52	3.91	.52	3.91	.52	3.92	.53
TM9	3.74	.63	3.75	.62	3.75	.62	3.75	.62	3.75	.62	3.78	.62
TM10	4.16	.59	4.16	.58	4.16	.58	4.16	.58	4.16	.58	4.17	.59
TM11	4.21	.54	4.30	.53	4.30	.53	4.30	.53	4.30	.53	4.32	.54
TM12	4.29	.45	4.35	.43	4.35	.43	4.35	.43	4.35	.43	4.33	.44
TM13	4.13	.54	4.09	.55	4.09	.55	4.09	.55	4.09	.55	4.13	.55
TM14	3.55	.78	3.62	.79	3.62	.79	3.62	.79	3.62	.79	3.65	.78
TM15	3.68	.60	3.74	.58	3.74	.58	3.74	.58	3.74	.58	3.75	.59
TM16	3.71	.73	3.67	.75	3.67	.75	3.67	.75	3.67	.75	3.78	.73
TM17	4.12	.55	4.17	.54	4.17	.54	4.17	.54	4.17	.54	4.16	.55
TM18	3.72	.60	3.76	.59	3.76	.59	3.76	.59	3.76	.59	3.79	.59
TM19	3.85	.61	3.83	.60	3.82	.60	3.82	.60	3.83	.60	3.87	.59
TM20	3.90	.57	3.98	.55	3.98	.55	3.98	.55	3.98	.55	3.96	.57

Table 4.6

Frequency Count of " Not Enough Progress" or" Desired Progress" for all 12 Learning Objectives (LO) for Large Class Enrollment Group (35-49 students enrolled)

	LO1		LO2		LO3		LO4	
	Freq.	%	Freq.	%	Freq.	%	Freq.	%
Not Enough Progress	9732	35.2%	10241	39.7%	10320	44.2%	5807	43.1%
Desired Progress	17949	64.8%	15555	60.3%	13021	55.8%	7671	56.9%
Total	27681	100.0%	25796	100.0%	23341	100.0%	13478	100.0%

	LO5		LO6		LO7		LO8	
	Freq.	%	Freq.	%	Freq.	%	Freq.	%
Not Enough Progress	3760	49.9%	2285	68.2%	4452	63.8%	24757	83.6%
Desired Progress	3768	50.1%	1064	31.8%	2531	36.2%	4859	16.4%
Total	7528	100.0%	3349	100.0%	6983	100.0%	29616	100.0%

	LO9		LO10		LO11		LO12	
	Freq.	%	Freq.	%	Freq.	%	Freq.	%
Not Enough Progress	22327	75.7%	22024	75.1%	20724	69.3%	6983	63.8%
Desired Progress	7175	24.3%	7307	24.9%	9200	30.7%	3961	36.2%
Total	29502	100.0%	29331	100.0%	29924	100.0%	10944	100.0%

Table 4.7

Means and Standard Deviations of Teaching Methods (TM) by Learning Objective (LO) for Very Large Class Enrollment Group (more than 50 students enrolled)

	LO1		LO2		LO3		LO4		LO5		LO6	
	M	S.D.	M	S.D.	M	S.D.	M	S.D.	M	S.D.	M	S.D.
TM1	4.19	.50	4.19	.51	4.21	.51	4.24	.51	4.25	.52	4.21	.53
TM2	3.97	.52	3.98	.52	4.00	.53	4.03	.53	4.03	.54	3.99	.53
TM3	4.08	.47	4.08	.48	4.11	.47	4.13	.48	4.13	.47	4.07	.47
TM4	4.28	.44	4.28	.45	4.28	.46	4.30	.46	4.27	.48	4.26	.48
TM5	3.08	.95	3.09	.96	3.20	.97	3.30	.97	3.91	.81	3.36	.98
TM6	4.18	.48	4.18	.48	4.18	.49	4.20	.50	4.18	.51	4.15	.50
TM7	3.66	.53	3.66	.54	3.69	.55	3.75	.56	3.78	.57	3.76	.57
TM8	3.83	.54	3.84	.54	3.87	.55	3.90	.57	3.87	.57	3.82	.56
TM9	3.64	.60	3.63	.60	3.68	.62	3.74	.63	3.82	.60	3.74	.61
TM10	4.11	.59	4.10	.59	4.09	.61	4.10	.61	4.05	.64	4.08	.60
TM11	4.25	.54	4.26	.53	4.27	.54	4.28	.54	4.27	.54	4.17	.56
TM12	4.29	.43	4.29	.43	4.28	.45	4.26	.47	4.20	.51	4.13	.55
TM13	4.03	.55	4.02	.56	4.02	.57	4.03	.57	4.03	.57	4.04	.56
TM14	3.33	.80	3.33	.81	3.42	.83	3.58	.82	3.86	.70	3.62	.75
TM15	3.61	.59	3.61	.60	3.66	.61	3.74	.62	3.78	.61	3.73	.62
TM16	3.45	.78	3.44	.79	3.48	.80	3.53	.80	3.73	.74	3.63	.76
TM17	4.08	.54	4.08	.55	4.08	.55	4.08	.57	4.03	.58	3.95	.59
TM18	3.59	.60	3.60	.60	3.65	.61	3.71	.62	3.88	.57	3.69	.63
TM19	3.59	.62	3.59	.62	3.64	.63	3.70	.63	3.85	.59	3.82	.60
TM20	3.91	.54	3.91	.55	3.94	.55	3.98	.55	3.96	.56	3.89	.56

Table 4.7 (cont.)

Means and Standard Deviations of Teaching Methods (TM) by Learning Objective (LO) for Very Large Class Enrollment Group (more than 50 students enrolled)

	LO7		LO8		LO9		LO10		LO11		LO12	
	M	S.D.	M	S.D.	M	S.D.	M	S.D.	M	S.D.	M	S.D.
TM1	4.15	.52	4.22	.52	4.20	.53	4.27	.49	4.22	.50	4.22	.51
TM2	3.91	.53	4.00	.53	3.99	.55	4.04	.52	4.01	.52	4.00	.53
TM3	4.00	.49	4.10	.47	4.10	.48	4.10	.48	4.08	.48	4.07	.47
TM4	4.23	.45	4.28	.47	4.26	.48	4.35	.44	4.30	.44	4.29	.46
TM5	3.01	.95	3.44	.96	3.29	.98	3.33	.98	3.21	.99	3.17	.97
TM6	4.13	.49	4.18	.49	4.16	.51	4.24	.47	4.20	.48	4.19	.49
TM7	3.62	.55	3.74	.55	3.70	.56	3.74	.54	3.71	.54	3.69	.54
TM8	3.76	.54	3.84	.56	3.85	.57	3.85	.55	3.87	.54	3.85	.55
TM9	3.61	.59	3.81	.59	3.81	.61	3.74	.59	3.71	.60	3.70	.60
TM10	4.08	.59	4.09	.60	4.06	.62	4.15	.58	4.12	.59	4.11	.60
TM11	4.10	.57	4.25	.54	4.25	.55	4.37	.49	4.29	.52	4.27	.54
TM12	4.19	.49	4.23	.48	4.24	.47	4.25	.48	4.27	.44	4.26	.46
TM13	4.02	.54	4.06	.55	4.01	.58	4.13	.52	4.09	.53	4.06	.56
TM14	3.26	.79	3.64	.74	3.57	.80	3.55	.77	3.42	.81	3.42	.80
TM15	3.54	.60	3.70	.60	3.69	.62	3.72	.59	3.64	.59	3.64	.60
TM16	3.44	.76	3.71	.72	3.55	.78	3.80	.69	3.64	.75	3.59	.77
TM17	3.99	.55	4.00	.59	4.03	.58	4.05	.56	4.06	.55	4.05	.55
TM18	3.53	.62	3.70	.61	3.67	.62	3.71	.61	3.65	.61	3.64	.61
TM19	3.59	.63	3.85	.58	3.73	.62	3.76	.61	3.70	.62	3.66	.62
TM20	3.82	.56	3.91	.57	3.92	.57	3.91	.56	3.90	.55	3.91	.56

Table 4.8

Frequency Count of "Not Enough Progress" or "Desired Progress" for all 12 Learning Objectives (LO) for Very Large Class Enrollment Group (50 or more students enrolled)

	LO1		LO2		LO3		LO4	
	Freq.	%	Freq.	%	Freq.	%	Freq.	%
Not Enough Progress	5682	38.0%	6184	44.3%	5958	50.2%	3217	47.8%
Desired Progress	9262	62.0%	7784	55.7%	5917	49.8%	3517	52.2%
Total	14944	100.0%	13968	100.0%	11875	100.0%	6734	100.0%

	LO5		LO6		LO7		LO8	
	Freq.	%	Freq.	%	Freq.	%	Freq.	%
Not Enough Progress	1782	56.0%	1211	74.8%	2755	71.6%	2936	82.4%
Desired Progress	1400	44.0%	407	25.2%	1092	28.4%	625	17.6%
Total	3182	100.0%	1618	100.0%	3847	100.0%	3561	100.0%

	LO9		LO10		LO11		LO12	
	Freq.	%	Freq.	%	Freq.	%	Freq.	%
Not Enough Progress	3260	73.5%	1804	66.3%	4512	67.6%	3832	72.6%
Desired Progress	1175	26.5%	915	33.7%	2163	32.4%	1445	27.4%
Total	4435	100.0%	2719	100.0%	6675	100.0%	5277	100.0%

Reviewing Tables 4.1- 4.8 a number of general observations can be made. Regarding student ratings of the teaching methods there is, generally speaking, a slight skew to the results as represented by class size as well as for the individual teaching methods. For example, the lowest average mean teaching method score for all class sizes was 3.01 for TM5 in Very Large classes where the instructor rated LO7 as "Important" or "Essential". TM5, "Formed 'teams' or 'discussion groups' to facilitate learning," was consistently the lowest rated teaching method for each of the class enrollment groups particularly so for LO1, "Gaining factual knowledge (terminology, classifications, methods, trends)," and LO7, "Gaining a broader understanding and appreciation of intellectual/cultural activity (music, science, literature, etc.)." The overall highest rated class average in the data set was 4.59 for TM1 in Small classes where instructors rated LO10 as "Important" or "Essential". TM1, "Displayed a personal interest in students and their learning," was also rated highly for LO10, "Developing a clearer understanding of, and commitment to, personal values," across all class sizes where instructors rated LO10 as "Important" "Essential" although the mean score decreased with the increase in enrollment group size.

There were a few notable observations regarding the frequencies for student progress on the LO items. Generally speaking there were higher percentages of classes indicating they made desired progress on a given learning objective in the Small and Medium class enrollment groups. This fact is more pronounced in LO1 – LO6 (see Table 4.2 and Table 4.4). Likewise, in the Large and Very Large class enrollment groups, students indicated that they were more likely to have not made enough progress on each of the LO items. This is most pronounced in LO8, "Developing myself orally or in writing", for classes of 35 or more students. These classes fell into the "Not Enough Progress" group approximately 83% of the time (see Table 4.6 and Table 4.8).

A final note can be made regarding the sample size for each of these groups. Generally speaking, faculty in all four class size groups selected LO1, LO2 and LO3 much more frequently than the other LO items (instructors are not limited to the number of learning objectives they select for a given class, but are encouraged to be true to the class and select 3 to 5 objectives). An exception is in the Large class enrollment group where LO8, LO9, LO10, and LO11 were selected slightly more often than the first three LO items. It is interesting to note, though, that for each of these four LO items in the Large class enrollment group students in 75% of classes reported they did not make enough progress.

Summary of descriptive statistics. The information in Tables 4.9 – 4.12 confirm and replicate what was found by Hoyt and Lee (2002). Regarding LO1 – LO4 being selected as "Important" or "Essential" by faculty more often than any of the other 12 LOs, Hoyt and Lee state, "these (learning objectives) represent the acquisition and application of basic cognitive background, often as a part of professional preparation." The authors categorized LO8 and LO11 as representing "academic skills" and LO9 and LO12 as representing "life-long learning". The least selected objectives by faculty were LO6, LO7, and LO10, which Hoyt and Lee describe as learning objectives concerned with values development. The authors conclude "American higher education is often portrayed as pragmatic and utilitarian; these results are consistent with that stereotype" (p. 3).

Review of Research Questions and Primary Analyses

The four research questions and related hypotheses were:

Question 1a: How well do teaching methods predict substantial or exceptional progress on IDEA learning objectives the instructor identifies as relevant to the course?

Hypothesis 1a: Teaching methods will accurately and significantly predict whether students report substantial-exceptional progress on each of the 12 learning objectives.

Question 1b: Are these predictions moderated by class enrollment groupings?

Hypothesis 1b: This question is exploratory. Therefore, there are no specific hypotheses.

Question 2a: Which teaching methods have the largest effect on whether students experience substantial or exceptional progress on each of the IDEA learning objectives?

Hypothesis 2a: For all learning objectives, TM2 and TM15 will have the largest effect on progress on learning objectives. Additionally, TM13, TM4, TM6 and TM8 will have meaningful effects on progress on learning objectives.

Question 2b: Are these predictions moderated by class enrollment groupings?

Hypothesis 2b: This question is exploratory. Therefore, there are no specific hypotheses. (It is important to note that some of the literature [Centra, 1979; Cohen, 1981; Feldman, 1976; McKeachie, 1997] suggest that class size moderates student ratings in general. However, specific teaching method by learning objective combinations that are likely to be moderated by class size have not been identified. Thus no specific hypotheses are provided for this question.)

To test the hypotheses two main analyses were conducted: a) point-biserial correlations were run for all 20 TM items by the 12 LO items separated into the 4 class enrollment groupings (960 correlations); and b) binomial logistic regressions were conducted for each of the 12 LO items separated by class enrollment groupings (48 regressions). The point-biserial correlations were conducted to identify the six most highly correlated TMs for each LO by class enrollment grouping. The six most highly correlated TMs were then used as predictor variables in the logistic regression models. (However, correlations that fell within r=.01 of the correlation coefficients of the six most highly correlated TMs were also included as variables in the regression for the corresponding LO.)

Correlations of teaching methods and learning objectives by enrollment groups. Tables 4.9- 4.12 present correlations between the 20 TM scores and the student ratings of their progress on each of the 12 LO items separated by the 4 class enrollment groups. Point-biserial correlation coefficients were calculated because TMs were continuous variables and LOs were dichotomous variables. Also, due to calculating 960 correlation coefficients a conservative alpha was used (α=.001) to identify statistically significant correlations.

Table 4.9

Point-Biserial Correlations Between Teaching Methods (TM) and Learning Objectives (LO) for Small Class Enrollment Group (between 10-14 students enrolled)

	LO1	LO2	LO3	LO4	LO5	LO6	LO7	LO8	LO9	LO10	LO11	LO12
TM1	.537	.534	.580	.565	.403	.451	.448	.444	.463	.504	.488	.530
TM2	.572	.579	.622	.598	.462	.475	.472	.496	.539	.567	.558	.604
TM3	.529	.527	.559	.547	.401	.437	.417	.454	.487	.482	.481	.511
TM4	.597	.590	.635	.622	.427	.428	.445	.437	.489	.534	.514	.556
TM5	.254	.289	.361	.340	.571	.283	.273	.369	.371	.412	.384	.395
TM6	.608	.606	.630	.622	.445	.446	.470	.450	.496	.530	.521	.556
TM7	.517	.524	.561	.566	.449	.539	.494	.520	.526	.506	.535	.551
TM8	.590	.597	.597	.582	.470	.479	.470	.515	.584	.562	.594	.620
TM9	.414	.415	.463	.449	.412	.328	.316	.444	.615	.461	.486	.508
TM10	.593	.586	.607	.596	.419	.449	.469	.469	.497	.520	.513	.552
TM11	.495	.499	.575	.552	.404	.311	.306	.372	.438	.517	.456	.508
TM12	.551	.539	.535	.523	.349	.334	.340	.378	.438	.426	.422	.460
TM13	.589	.597	.634	.619	.460	.506	.515	.491	.533	.594	.585	.618
TM14	.366	.377	.484	.503	.520	.439	.314	.354	.489	.444	.401	.467
TM15	.551	.561	.618	.618	.519	.565	.495	.531	.596	.582	.572	.628
TM16	.378	.409	.483	.461	.432	.413	.414	.511	.502	.582	.563	.559
TM17	.479	.477	.479	.472	.350	.362	.359	.412	.433	.424	.419	.454
TM18	.452	.478	.539	.521	.533	.458	.440	.499	.527	.569	.545	.584
TM19	.418	.442	.517	.502	.439	.558	.447	.547	.527	.514	.552	.546
TM20	.482	.494	.507	.499	.431	.407	.413	.463	.515	.502	.489	.508
N=	30,794	29,189	31,453	26,077	12,990	10,641	9,370	17,983	15,690	8,754	17,648	15,294

Note: All correlations significant at α=.001. Darker shaded cells are 6 most highly correlated TMs with specific LO. Lighter shaded cells denote additional TMs within r=.01 of the correlation coefficient of the 6th most highly correlated TM.

The strongest correlation was between TM13 and LO3 (r=.634), while the weakest correlation was between TM5 and LO1 (r=.254). Table 4.6 shows that for small enrollment classes TM2, TM8, TM13, and TM15 were most highly correlated with at least 11 of the LO items. TM2 was most highly correlated with all 12 LO items; for LO8 the correlation did not fall within the top six correlations (as denoted by lighter shading in the table). Similarly, TM13 was most highly correlated with all 12 LO items, considering the values for LO5 and LO8 did not fall within the top six correlations. TM4, TM6, TM10, and TM18 were most highly correlated with half of the 12 LO items and four of these high correlations fell slightly outside the six most highly correlated TM items. Of note is that TM1, TM3, TM11, TM12, TM17, and TM20 never made the list of most highly correlated teaching methods for any learning objective in the Small class enrollment group. TM5, TM9, and TM14 only made the most highly correlated teaching methods one time each.

Table 4.10

Point-Biserial Correlations Between Teaching Methods (TM) and Learning Objectives (LO) for Medium Class Enrollment Group (15-34 students enrolled)

	LO1	LO2	LO3	LO4	LO5	LO6	LO7	LO8	LO9	LO10	LO11	LO12
TM1	.558	.557	.595	.590	.440	.487	.459	.461	.475	.514	.511	.537
TM2	.592	.602	.635	.626	.490	.509	.486	.495	.537	.569	.574	.605
TM3	.546	.544	.573	.569	.435	.479	.430	.466	.492	.487	.492	.515
TM4	.619	.612	.643	.641	.449	.454	.464	.434	.483	.542	.521	.555
TM5	.240	.259	.334	.341	.593	.319	.264	.364	.363	.375	.351	.366
TM6	.630	.620	.642	.644	.472	.465	.487	.439	.492	.542	.529	.557
TM7	.544	.550	.593	.604	.485	.569	.514	.546	.544	.530	.558	.572
TM8	.616	.626	.632	.625	.499	.518	.508	.518	.583	.585	.616	.641
TM9	.424	.424	.479	.489	.426	.400	.368	.482	.606	.463	.482	.511
TM10	.611	.602	.614	.612	.429	.474	.477	.465	.489	.521	.521	.543
TM11	.515	.520	.577	.572	.429	.338	.335	.360	.422	.528	.463	.501
TM12	.564	.558	.548	.535	.385	.354	.371	.354	.430	.437	.431	.468
TM13	.616	.616	.643	.642	.478	.519	.541	.475	.524	.591	.586	.612
TM14	.373	.379	.484	.518	.570	.471	.349	.388	.496	.455	.410	.468
TM15	.572	.584	.647	.651	.542	.586	.513	.544	.598	.603	.585	.638
TM16	.402	.424	.497	.499	.461	.461	.452	.517	.501	.572	.571	.555
TM17	.499	.496	.505	.499	.380	.407	.380	.414	.436	.443	.429	.468
TM18	.470	.491	.558	.555	.566	.498	.453	.500	.529	.564	.545	.589
TM19	.435	.452	.532	.534	.478	.591	.483	.581	.541	.515	.565	.549
TM20	.513	.518	.535	.537	.458	.442	.433	.468	.519	.514	.499	.529
N=	170,302	160,863	167,379	115,026	64,456	48,378	53,002	98,816	83,780	46,695	102,969	80,175

Note: All correlations significant at α=.001. Darker shaded cells are 6 most highly correlated TMs with specific LO. Lighter shaded cells denote additional TMs within r=.01 of the correlation coefficient of the 6th most highly correlated TM.

Of note in Table 4.10 is that the sample size for LO6 and LO10 was less than half of the sample size for LO1, LO2, LO3 and LO4. This suggests that for this class enrollment group instructors do not consider LO6 and LO10 as important or essential nearly as often as they do

LO1 – LO4. The strongest correlation in Table 4.10 was between TM15 and LO4 (*r*=.651) whereas the weakest correlation was once again between TM5 and LO1 (*r*=.240). In this enrollment group TM8 was again highly correlated with all 12 LO items. For this enrollment group all correlations were found in the top six for each LO. TM2 and TM15 were also in the top six most highly correlated variables with all 12 LO items except for the correlation between TM2 and LO8 which fell just outside the top six. TM15 fell outside the top six most highly correlated variables twice. For 9 of the 12 LO items TM13 was highly correlated and found in the top six. TM6 and TM7 were in the top six for 5 of the 12 LO items. Just as in the Small class enrollment group TM1, TM3, TM11, TM12, TM17, and TM20 never made the most highly correlated teaching methods for classes of 15-34 students. And again TM5, TM9, and TM14 only made the most highly correlated TM items one time for any of the 12 LO items.

Table 4.11

Point-Biserial Correlations Between Teaching Methods (TM) and Learning Objectives (LO) for Large Class Enrollment Group (enrollment of 35-49 students)

	LO1	LO2	LO3	LO4	LO5	LO6	LO7	LO8	LO9	LO10	LO11	LO12
TM1	.584	.583	.601	.603	.458	.436	.423	.343	.406	.435	.397	.526
TM2	.615	.626	.652	.653	.510	.467	.439	.390	.468	.476	.464	.588
TM3	.552	.555	.573	.584	.460	.413	.398	.346	.424	.384	.333	.485
TM4	.638	.628	.643	.650	.464	.404	.419	.340	.413	.453	.423	.533
TM5	.210	.238	.325	.341	.561	.396	.217	.343	.357	.354	.235	.346
TM6	.650	.637	.642	.656	.473	.408	.442	.348	.417	.450	.424	.536
TM7	.591	.597	.631	.650	.537	.555	.501	.453	.517	.500	.450	.590
TM8	.641	.646	.661	.669	.529	.499	.461	.428	.515	.490	.502	.629
TM9	.455	.440	.520	.557	.513	.401	.397	.445	.580	.467	.394	.526
TM10	.640	.628	.612	.611	.430	.387	.447	.325	.390	.410	.403	.510
TM11	.520	.530	.568	.587	.432	.296	.249	.295	.353	.420	.383	.466
TM12	.593	.591	.561	.550	.367	.205	.320	.267	.347	.336	.352	.437
TM13	.630	.624	.638	.653	.491	.457	.485	.395	.446	.502	.492	.580
TM14	.351	.356	.462	.495	.593	.462	.315	.396	.482	.421	.283	.449
TM15	.599	.608	.673	**.692**	.588	.577	.477	.469	.568	.547	.456	.636
TM16	.404	.418	.496	.528	.508	.449	.451	.449	.457	.549	.475	.553
TM17	.518	.518	.503	.511	.384	.334	.335	.273	.346	.328	.310	.419
TM18	.478	.502	.573	.586	.587	.533	.417	.443	.506	.506	.416	.584
TM19	.454	.469	.554	.566	.565	.491	.470	.496	.522	.505	.459	.562
TM20	.551	.556	.573	.591	.488	.449	.399	.363	.453	.411	.372	.529
N=	27,680	25,794	23,339	13,476	7,527	3,349	6,982	29,614	29,500	29,329	29,922	10,943

Note: All correlations significant at α=.001. Darker shaded cells are 6 most highly correlated TMs with specific LO. Lighter shaded cells denote additional TMs within r=.01 of the correlation coefficient of the 6^{th} most highly correlated TM.

The strongest correlation in Table 4.11 was between TM15 and LO4 (r=.692), whereas the weakest correlation was between TM12 and LO6 (r=.205). In the Large class enrollment group TM15 was most highly correlated with the greatest number of learning objectives (10 times in the top six and one time within r=.01 of the top six). TM7, TM8 and TM13 were most highly correlated in the top six for eight of the LO items with each having an additional correlation fall just below the top six. TM19 was in the top six highly correlated teaching methods seven times – a considerable jump when compared to the Small and Medium enrollment groups. Just as in the previous two enrollment groups TM1, TM3, TM11, TM12, TM17, and TM20 never made the most highly correlated teaching methods.

Table 4.12

Point-Biserial Correlations Between Teaching Methods (TM) and Learning Objectives (LO) for Very Large Class Enrollment Group (enrollment of 50 or more students)

	LO1	LO2	LO3	LO4	LO5	LO6	LO7	LO8	LO9	LO10	LO11	LO12
TM1	.606	.600	.602	.599	.475	.445	.399	.375	.452	.538	.498	.495
TM2	.636	.639	.655	.656	.525	.437	.407	.423	.520	.567	.566	.563
TM3	.558	.551	.557	.571	.477	.300	.346	.404	.470	.481	.467	.464
TM4	.657	.635	.634	.638	.478	.389	.389	.360	.462	.534	.508	.496
TM5	.241	.276	.353	.398	.545	.373	.236	.293	.406	.362	.394	.381
TM6	.670	.648	.640	.644	.482	.353	.402	.368	.465	.532	.514	.506
TM7	.606	.617	.648	.664	.588	.540	.485	.471	.565	.569	.583	.571
TM8	.659	.662	.667	.673	.544	.420	.407	.455	.565	.573	.593	.582
TM9	.491	.482	.551	.579	.510	.254	.340	.411	.594	.464	.495	.502
TM10	.650	.628	.604	.599	.442	.361	.406	.358	.432	.490	.469	.467
TM11	.553	.553	.577	.571	.426	.242	.199	.311	.405	.464	.454	.436
TM12	.617	.591	.544	.510	.320	.001	.210	.297	.386	.391	.414	.388
TM13	.656	.642	.640	.642	.500	.420	.441	.411	.491	.559	.558	.534
TM14	.376	.393	.496	.528	.584	.413	.300	.377	.514	.432	.453	.460
TM15	.622	.632	.685	.701	.621	.552	.452	.492	.606	.620	.595	.619
TM16	.423	.442	.527	.530	.537	.424	.417	.431	.504	.522	.563	.524
TM17	.551	.538	.519	.522	.392	.273	.307	.348	.415	.429	.415	.417
TM18	.508	.532	.588	.614	.619	.514	.407	.459	.551	.566	.570	.581
TM19	.465	.492	.563	.576	.564	.355	.414	.487	.556	.517	.562	.531
TM20	.574	.580	.587	.593	.497	.419	.363	.398	.504	.524	.489	.507
N=	14,930	13,954	11,859	6,726	3,180	1,618	3,847	3,559	4,433	2,716	6,664	5,276

Note: All correlations significant at α=.001. Darker shaded cells are 6 most highly correlated TMs with specific LO. Lighter shaded cells denote additional TMs within r=.01 of the correlation coefficient of the 6th most highly correlated TM.

The strongest correlation in Table 4.12 was between TM15 and LO4 (r=.701). The weakest correlation was between TM12 and LO6 (r=.001), but this value was the only correlation of all those run which was not statistically significant (p=.49). The weakest, statistically significant, correlation in Table 4.12 was therefore between TM12 and LO7 (*r*=.210). In the Very Large enrollment group for 11 of the 12 LO items TM15 was among the top six most highly correlated teaching methods. TM7 was in the top six correlations for 10 out of 12 LOs. TM8 was in the top six correlations for 9 out of 12 LOs and was within *r*=.01 of the top six correlations for the remaining three LOs. TM1 and TM20 were in the highest correlations group for the first time in this enrollment group size. TM1 was in the top six with LO6 and another two times just outside the top six. TM20 was just outside the top six for LO6. Just as in the other three class enrollment groupings TM3, TM11, TM12, and TM17 did not make the list of most highly correlated teaching methods in the Very Large enrollment group.

Summary of point-biserial correlations. TM15 was the most highly correlated teaching method with the greatest number of learning objectives across all class sizes. TM2, TM8 and TM13 were consistently among the most highly correlated teaching methods with the greatest number of learning objectives in all four class enrollment groupings. TM1, TM3, TM11, TM12, TM17, and TM20 (with the two exceptions noted above) were never highly correlated with any learning objective for any of the class enrollment groupings.

Binary logistic regressions: general. Binary logistic regressions were run for all 12 LOs separately by the four class size groupings, which resulted in 48 logistic regressions. For each logistic regression, one of the LOs served as the criterion variable, and the six TMs that were the most highly correlated teaching methods with that specific LO served as the predictor variables. The TMs with correlation coefficients within *r*=.01 of the sixth most highly correlated TM (i.e., those correlation coefficients highlighted in light grey in Tables 4.9 – 4.12) were also included as predictor variables. TMs were entered by forced block entry method. The results of the 48 binary logistic regressions are presented in Tables 4.13- 4.16.

Table 4.13

Binary Logistic Regressions for Small Class Enrollment Group (between 10-14 students enrolled)

LO1

	B	S.E.	Sig.	Exp(B)
TM2	-.124	.077	.106	.884
TM4	.932	.093	.000	2.540
TM6	1.258	.089	.000	3.520
TM8	1.812	.058	.000	6.122
TM10	.870	.062	.000	2.386
TM13	.060	.072	.404	1.062
Nagelkerke R^2	.561			
Overall % Correct	86.8%			
Chi-Squared	14278.391			

LO2

	B	S.E.	Sig.	Exp(B)
TM2	.138	.078	.077	1.147
TM4	.638	.094	.000	1.893
TM6	1.238	.092	.000	3.449
TM8	1.784	.063	.000	5.952
TM9	.725	.062	.000	2.066
TM13	.333	.074	.000	1.395
TM15	.025	.060	.672	1.026
Nagelkerke R^2	.562			
Overall % Correct	85.2%			
Chi-Squared	14268.586			

LO3

	B	S.E.	Sig.	Exp(B)
TM2	.682	.081	.000	1.977
TM4	1.529	.097	.000	4.612
TM6	.845	.090	.000	2.328
TM8	.657	.064	.000	1.929
TM10	.333	.063	.000	1.395
TM13	.418	.076	.000	1.519
TM15	1.173	.064	.000	3.231
Nagelkerke R^2	.616			
Overall % Correct	87.6%			
Chi-Squared	16697.921			

LO4

	B	S.E.	Sig.	Exp(B)
TM2	.128	.089	.148	1.137
TM4	1.432	.107	.000	4.187
TM6	1.170	.101	.000	3.221
TM10	.338	.070	.000	1.402
TM13	.359	.085	.000	1.432
TM15	1.865	.067	.000	6.455
Nagelkerke R^2	.597			
Overall % Correct	88.1%			
Chi-Squared	12863.168			

LO5

	B	S.E.	Sig.	Exp(B)
TM2	-.283	.111	.011	.753
TM5	1.758	.056	.000	5.799
TM8	.196	.090	.029	1.217
TM13	-.418	.101	.000	.658
TM14	.926	.068	.000	2.525
TM15	1.282	.103	.000	3.605
TM18	.760	.091	.000	2.137
Nagelkerke R^2	.540			
Overall % Correct	81.7%			
Chi-Squared	6470.760			

LO6

	B	S.E.	Sig.	Exp(B)
TM2	-.481	.120	.000	.618
TM7	1.374	.090	.000	3.950
TM8	-.585	.099	.000	.557
TM13	.110	.110	.316	1.117
TM15	1.866	.107	.000	6.462
TM19	1.992	.081	.000	7.333
Nagelkerke R^2	.517			
Overall % Correct	81.6%			
Chi-Squared	4980.721			

LO7

	B	S.E.	Sig.	Exp(B)
TM2	-.230	.119	.053	.794
TM6	.015	.125	.902	1.016
TM7	.972	.086	.000	2.642
TM8	.236	.089	.008	1.267
TM10	.433	.096	.000	1.542
TM13	1.371	.114	.000	3.940
TM15	.580	.089	.000	1.786
Nagelkerke R^2	.409			
Overall % Correct	75.8%			
Chi-Squared	3389.057			

LO8

	B	S.E.	Sig.	Exp(B)
TM2	.108	.094	.247	1.114
TM7	.974	.066	.000	2.647
TM8	.907	.078	.000	2.477
TM13	-.510	.081	.000	.600
TM15	.188	.079	.017	1.207
TM16	.906	.056	.000	2.474
TM18	.051	.068	.450	1.053
TM19	1.514	.069	.000	4.543
Nagelkerke R^2	.491			
Overall % Correct	78.6			
Chi-Squared	8196.675			

LO9

	B	S.E.	Sig.	Exp(B)
TM2	.676	.107	.000	1.966
TM7	.022	.076	.768	1.023
TM8	.857	.094	.000	2.356
TM9	2.542	.071	.000	12.707
TM13	-.208	.092	.024	.812
TM15	1.113	.098	.000	3.043
TM18	.382	.071	.000	1.466
TM19	.030	.072	.679	1.030
Nagelkerke R^2	.607			
Overall % Correct	82.2%			
Chi-Squared	9448.595			

Table 4.13 (cont.)

Binary Logistic Regressions for Small Class Enrollment Group (between 10-14 students enrolled)

LO10

	B	S.E.	Sig.	Exp(B)
TM2	.193	.150	.200	1.213
TM4	.560	.155	.000	1.751
TM8	.518	.109	.000	1.679
TM13	1.106	.150	.000	3.021
TM15	.881	.113	.000	2.412
TM16	1.517	.091	.000	4.558
TM18	.406	.109	.000	1.501
Nagelkerke R^2	.576			
Overall % Correct	81.9%			
Chi-Squared	4863.324			

LO11

	B	S.E.	Sig.	Exp(B)
TM2	.160	.097	.098	1.173
TM8	1.999	.086	.000	7.383
TM13	.764	.086	.000	2.147
TM15	-.089	.081	.273	.915
TM16	1.108	.058	.000	3.029
TM18	.166	.072	.021	1.181
TM19	.732	.068	.000	2.078
Nagelkerke R^2	.571			
Overall % Correct	82.4%			
Chi-Squared	9616.830			

LO12

	B	S.E.	Sig.	Exp(B)
TM2	.722	.117	.000	2.059
TM4	.050	.133	.710	1.051
TM6	-.381	.130	.003	.683
TM7	-.214	.079	.006	.807
TM8	1.378	.089	.000	3.966
TM10	.545	.091	.000	1.725
TM13	.982	.112	.000	2.669
TM15	1.157	.092	.000	3.179
TM16	.527	.058	.000	1.693
TM18	.676	.079	.000	1.966
Nagelkerke R^2	.622			
Overall % Correct	84.0%			
Chi-Squared	9364.825			

Table 4.14

Binomial Logistic Regression for Medium Class Enrollment Group (15-34 students enrolled)

LO1

	B	S.E.	Sig.	Exp(B)
TM2	-.233	.034	.000	.792
TM4	.899	.043	.000	2.458
TM6	1.498	.042	.000	4.471
TM8	2.062	.030	.000	7.865
TM10	.987	.028	.000	2.683
TM13	.281	.032	.000	1.325
TM15	-.159	.027	.000	.853
Nagelkerke R^2	.594			
Overall % Correct	84.7%			
Chi-Squared	92933.611			

LO2

	B	S.E.	Sig.	Exp(B)
TM2	.194	.035	.000	1.214
TM4	.836	.043	.000	2.307
TM6	1.151	.043	.000	3.162
TM8	2.142	.030	.000	8.514
TM10	.897	.029	.000	2.451
TM13	.352	.032	.000	1.422
TM15	-.092	.027	.001	.912
Nagelkerke R^2	.598			
Overall % Correct	83.4%			
Chi-Squared	91794.864			

LO3

	B	S.E.	Sig.	Exp(B)
TM2	.696	.036	.000	2.005
TM4	1.419	.044	.000	4.135
TM6	1.083	.043	.000	2.952
TM8	.872	.030	.000	2.392
TM10	.447	.029	.000	1.564
TM13	.232	.033	.000	1.261
TM15	1.478	.028	.000	4.386
Nagelkerke R^2	.647			
Overall % Correct	85.3%			
Chi-Squared	105162.022			

LO4

	B	S.E.	Sig.	Exp(B)
TM2	.285	.042	.000	1.329
TM4	1.327	.055	.000	3.771
TM6	1.656	.050	.000	5.237
TM8	.643	.037	.000	1.903
TM13	.245	.041	.000	1.278
TM15	1.846	.036	.000	6.337
Nagelkerke R^2	.638			
Overall % Correct	85.8%			
Chi-Squared	69677.772			

LO5

	B	S.E.	Sig.	Exp(B)
TM2	-.222	.051	.000	.801
TM5	2.193	.029	.000	8.966
TM8	.313	.047	.000	1.367
TM14	1.255	.032	.000	3.506
TM15	1.054	.051	.000	2.868
TM18	.705	.047	.000	2.024
Nagelkerke R^2	.616			
Overall % Correct	83.0%			
Chi-Squared	39420.496			

LO6

	B	S.E.	Sig.	Exp(B)
TM2	-.270	.062	.000	.764
TM7	1.549	.048	.000	4.706
TM8	-.582	.055	.000	.559
TM13	-.082	.055	.138	.921
TM15	1.821	.055	.000	6.175
TM19	2.631	.045	.000	13.890
Nagelkerke R^2	.569			
Overall % Correct	81.1%			
Chi-Squared	26730.685			

LO7

	B	S.E.	Sig.	Exp(B)
TM2	-.500	.056	.000	.607
TM6	.162	.061	.008	1.176
TM7	.928	.043	.000	2.529
TM8	.306	.046	.000	1.358
TM10	.382	.049	.000	1.465
TM13	1.957	.057	.000	7.078
TM15	.127	.043	.003	1.135
TM19	.764	.033	.000	2.148
Nagelkerke R^2	.469			
Overall % Correct	76.9%			
Chi-Squared	22988.633			

LO8

	B	S.E.	Sig.	Exp(B)
TM2	-.327	.042	.000	.721
TM7	1.369	.034	.000	3.930
TM8	.514	.038	.000	1.673
TM15	.148	.038	.000	1.160
TM16	.779	.026	.000	2.179
TM18	-.116	.031	.000	.890
TM19	2.529	.035	.000	12.541
Nagelkerke R^2	.540			
Overall % Correct	79.4%			
Chi-Squared	51336.045			

LO9

	B	S.E.	Sig.	Exp(B)
TM2	.572	.048	.000	1.772
TM7	.019	.038	.626	1.019
TM8	1.069	.045	.000	2.913
TM9	2.866	.034	.000	17.573
TM15	1.069	.047	.000	2.912
TM18	.391	.033	.000	1.478
TM19	.184	.035	.000	1.203
Nagelkerke R^2	.631			
Overall % Correct	83.0%			
Chi-Squared	53598.974			

Table 4.14 (cont.)

Binomial Logistic Regression for Medium Class Enrollment Group (15-34 students enrolled)

LO10

	B	S.E.	Sig.	Exp(B)
TM2	.210	.069	.002	1.234
TM8	.704	.054	.000	2.021
TM13	1.700	.063	.000	5.472
TM15	1.362	.051	.000	3.903
TM16	1.474	.042	.000	4.365
TM18	.133	.050	.007	1.142
Nagelkerke R^2	.604			
Overall % Correct	81.9%			
Chi-Squared	28166.411			

LO11

	B	S.E.	Sig.	Exp(B)
TM2	.431	.044	.000	1.539
TM7	.353	.034	.000	1.423
TM8	2.559	.042	.000	12.924
TM13	.637	.038	.000	1.891
TM15	-.544	.038	.000	.581
TM16	1.200	.024	.000	3.319
TM19	1.008	.031	.000	2.739
Nagelkerke R^2	.608			
Overall % Correct	82.1%			
Chi-Squared	62476.366			

LO12

	B	S.E.	Sig.	Exp(B)
TM2	1.011	.054	.000	2.748
TM7	-.229	.040	.000	.796
TM8	2.008	.046	.000	7.448
TM13	1.501	.045	.000	4.487
TM15	1.209	.044	.000	3.351
TM18	1.016	.034	.000	2.762
Nagelkerke R^2	.659			
Overall % Correct	83.9%			
Chi-Squared	54635.605			

Table 4.15

Binomial Logistic Regression for Large Class Enrollment Group (35-49 students enrolled)

LO1

	B	S.E.	Sig.	Exp(B)
TM2	-.694	.090	.000	.500
TM4	.711	.127	.000	2.037
TM6	1.658	.132	.000	5.248
TM8	2.747	.076	.000	15.598
TM10	1.826	.082	.000	6.207
TM13	-.240	.087	.006	.787
Nagelkerke R^2	.640			
Overall % Correct	84.8%			
Chi-Squared	17315.601			

LO2

	B	S.E.	Sig.	Exp(B)
TM2	.115	.097	.236	1.122
TM4	.783	.130	.000	2.189
TM6	1.191	.136	.000	3.290
TM8	2.814	.089	.000	16.677
TM10	1.606	.084	.000	4.984
TM13	-.140	.089	.115	.869
TM15	-.133	.075	.076	.875
Nagelkerke R^2	.641			
Overall % Correct	84.0%			
Chi-Squared	16575.560			

LO3

	B	S.E.	Sig.	Exp(B)
TM2	1.158	.105	.000	3.184
TM4	1.780	.150	.000	5.927
TM6	1.509	.143	.000	4.524
TM7	.019	.092	.834	1.019
TM8	1.517	.093	.000	4.559
TM13	-.329	.099	.001	.720
TM15	1.593	.089	.000	4.919
Nagelkerke R^2	.686			
Overall % Correct	85.2%			
Chi-Squared	16743.542			

LO4

	B	S.E.	Sig.	Exp(B)
TM2	.235	.145	.106	1.264
TM4	1.530	.204	.000	4.618
TM6	2.093	.196	.000	8.106
TM7	.372	.122	.002	1.450
TM8	1.230	.123	.000	3.423
TM13	-.484	.138	.000	.616
TM15	2.183	.129	.000	8.875
Nagelkerke R^2	.697			
Overall % Correct	85.6%			
Chi-Squared	9866.538			

LO5

	B	S.E.	Sig.	Exp(B)
TM5	2.205	.094	.000	9.074
TM7	.068	.152	.656	1.070
TM8	.218	.162	.177	1.244
TM14	1.206	.111	.000	3.339
TM15	1.954	.188	.000	7.059
TM18	.433	.153	.005	1.542
TM19	-.401	.127	.002	.670
Nagelkerke R^2	.647			
Overall % Correct	84.0%			
Chi-Squared	4994.723			

LO6

	B	S.E.	Sig.	Exp(B)
TM2	-1.921	.314	.000	.146
TM7	2.227	.248	.000	9.276
TM8	-.915	.274	.001	.400
TM13	.200	.273	.464	1.221
TM14	-.318	.150	.033	.727
TM15	2.846	.285	.000	17.212
TM18	.900	.202	.000	2.459
TM19	1.665	.199	.000	5.288
Nagelkerke R^2	.571			
Overall % Correct	83.8%			
Chi-Squared	1750.943			

LO7

	B	S.E.	Sig.	Exp(B)
TM7	1.368	.141	.000	3.929
TM8	-.128	.148	.390	.880
TM10	.816	.139	.000	2.261
TM13	1.197	.180	.000	3.311
TM15	-.367	.137	.007	.693
TM16	.317	.077	.000	1.373
TM19	.825	.095	.000	2.282
Nagelkerke R^2	.438			
Overall % Correct	77.0%			
Chi-Squared	2691.528			

LO8

	B	S.E.	Sig.	Exp(B)
TM7	1.221	.107	.000	3.389
TM9	.717	.077	.000	2.049
TM15	.661	.111	.000	1.938
TM16	1.353	.076	.000	3.871
TM18	-.520	.097	.000	.595
TM19	3.485	.108	.000	32.628
Nagelkerke R^2	.603			
Overall % Correct	90.0%			
Chi-Squared	13036.537			

LO9

	B	S.E.	Sig.	Exp(B)
TM7	.351	.098	.000	1.421
TM8	.921	.106	.000	2.513
TM9	3.727	.082	.000	41.534
TM15	1.884	.117	.000	6.581
TM18	.377	.078	.000	1.458
TM19	.378	.078	.000	1.460
Nagelkerke R^2	.681			
Overall % Correct	89.0%			
Chi-Squared	18000.437			

Table 4.15 (cont.)

Binomial Logistic Regression for Large Class Enrollment Group (35-49 students enrolled)

LO10					LO11					LO12				
	B	S.E.	Sig.	Exp(B)		B	S.E.	Sig.	Exp(B)		B	S.E.	Sig.	Exp(B)
TM7	-.062	.095	.512	.940	**TM2**	.518	.092	.000	1.679	**TM2**	.808	.184	.000	2.244
TM8	.356	.104	.001	1.427	**TM7**	-.244	.077	.001	.784	**TM7**	-.059	.140	.673	.943
TM13	1.786	.105	.000	5.964	**TM8**	3.365	.092	.000	28.920	**TM8**	2.507	.159	.000	12.263
TM15	1.998	.102	.000	7.374	**TM13**	1.398	.083	.000	4.049	**TM13**	2.180	.151	.000	8.850
TM16	2.422	.067	.000	11.274	**TM15**	-1.990	.083	.000	.137	**TM15**	1.238	.144	.000	3.447
TM18	-.318	.082	.000	.728	**TM16**	1.145	.043	.000	3.141	**TM18**	1.118	.109	.000	3.058
TM19	.235	.070	.001	1.265	**TM19**	.599	.055	.000	1.820					
Nagelkerke R^2	.631				Nagelkerke R^2	.504				Nagelkerke R^2	.693			
Overall % Correct	87.6%				Overall % Correct	81.7%				Overall % Correct	86.7%			
Chi-Squared	16275.550				Chi-Squared	13219.079				Chi-Squared	7719.357			

Table 4.16

Binomial Logistic Regressions for Very Large Class Enrollment Group (50 or more students enrolled)

LO1

	B	S.E.	Sig.	Exp(B)
TM2	-.966	.132	.000	.381
TM4	.069	.201	.731	1.072
TM6	2.542	.218	.000	12.705
TM8	3.227	.114	.000	25.209
TM10	1.825	.124	.000	6.202
TM13	-.125	.136	.357	.882
Nagelkerke R^2	.676			
Overall % Correct	85.7%			
Chi-Squared	10267.485			

LO2

	B	S.E.	Sig.	
TM2	-.223	.143	.119	.800
TM4	-.405	.209	.053	.667
TM6	1.877	.226	.000	6.535
TM8	3.246	.134	.000	25.699
TM10	1.853	.132	.000	6.376
TM13	.126	.141	.372	1.134
TM15	.028	.116	.806	1.029
Nagelkerke R^2	.670			
Overall % Correct	84.9%			
Chi-Squared	9690.449			

LO3

	B	S.E.	Sig.	Exp(B)
TM2	.716	.166	.000	2.046
TM4	1.025	.243	.000	2.787
TM6	2.309	.233	.000	10.065
TM7	.019	.141	.892	1.019
TM8	1.411	.140	.000	4.102
TM13	-.324	.159	.042	.723
TM15	2.109	.145	.000	8.243
Nagelkerke R^2	.697			
Overall % Correct	85.8%			
Chi-Squared	8780.440			

LO4

	B	S.E.	Sig.	Exp(B)
TM2	-.087	.223	.698	.917
TM4	1.092	.325	.001	2.979
TM6	2.315	.308	.000	10.124
TM7	.477	.186	.010	1.612
TM8	1.372	.173	.000	3.943
TM13	-.959	.220	.000	.383
TM15	2.637	.195	.000	13.976
Nagelkerke R^2	.701			
Overall % Correct	86.1%			
Chi-Squared	5011.264			

LO5

	B	S.E.	Sig.	Exp(B)
TM5	1.931	.145	.000	6.895
TM7	.153	.267	.567	1.166
TM14	.830	.175	.000	2.293
TM15	2.911	.292	.000	18.380
TM16	-.426	.155	.006	.653
TM18	.650	.254	.010	1.915
TM19	-.382	.217	.078	.683
Nagelkerke R^2	.665			
Overall % Correct	85.7%			
Chi-Squared	2182.854			

LO6

	B	S.E.	Sig.	Exp(B)
TM1	1.577	.547	.004	4.842
TM2	-2.543	.627	.000	.079
TM7	2.864	.425	.000	17.535
TM8	-2.497	.418	.000	.082
TM13	.894	.452	.048	2.445
TM14	-.057	.190	.763	.944
TM15	3.671	.466	.000	39.289
TM16	.316	.260	.223	1.372
TM18	.926	.387	.017	2.525
TM20	-1.274	.325	.000	.280
Nagelkerke R^2	.573			
Overall % Correct	85.8%			
Chi-Squared	793.219			

LO7

	B	S.E.	Sig.	Exp(B)
TM1	.290	.282	.303	1.337
TM2	-1.956	.336	.000	.141
TM6	-1.794	.353	.000	.166
TM7	2.392	.229	.000	10.931
TM8	-.530	.238	.026	.588
TM10	1.951	.276	.000	7.035
TM13	2.173	.319	.000	8.787
TM15	.092	.240	.703	1.096
TM16	.402	.123	.001	1.494
TM18	-.062	.187	.741	.940
TM19	.569	.124	.000	1.766
Nagelkerke R^2	.432			
Overall % Correct	79.2%			
Chi-Squared	1377.243			

LO8

	B	S.E.	Sig.	Exp(B)
TM1	-1.886	.350	.000	.152
TM7	1.659	.323	.000	5.251
TM8	.873	.342	.011	2.394
TM15	1.210	.357	.001	3.352
TM16	1.190	.226	.000	3.288
TM18	-.562	.281	.045	.570
TM19	3.605	.293	.000	36.765
Nagelkerke R^2	.586			
Overall % Correct	89.0%			
Chi-Squared	1556.780			

LO9

	B	S.E.	Sig.	Exp(B)
TM7	.111	.261	.672	1.117
TM8	1.207	.271	.000	3.343
TM9	4.255	.244	.000	70.450
TM15	2.002	.332	.000	7.406
TM18	.107	.199	.592	1.113
TM19	.415	.206	.045	1.514
Nagelkerke R^2	.714			
Overall % Correct	89.6%			
Chi-Squared	2977.494			

Table 4.16 (cont.)

Binomial Logistic Regressions for Very Large Class Enrollment Group (50 or more students enrolled)

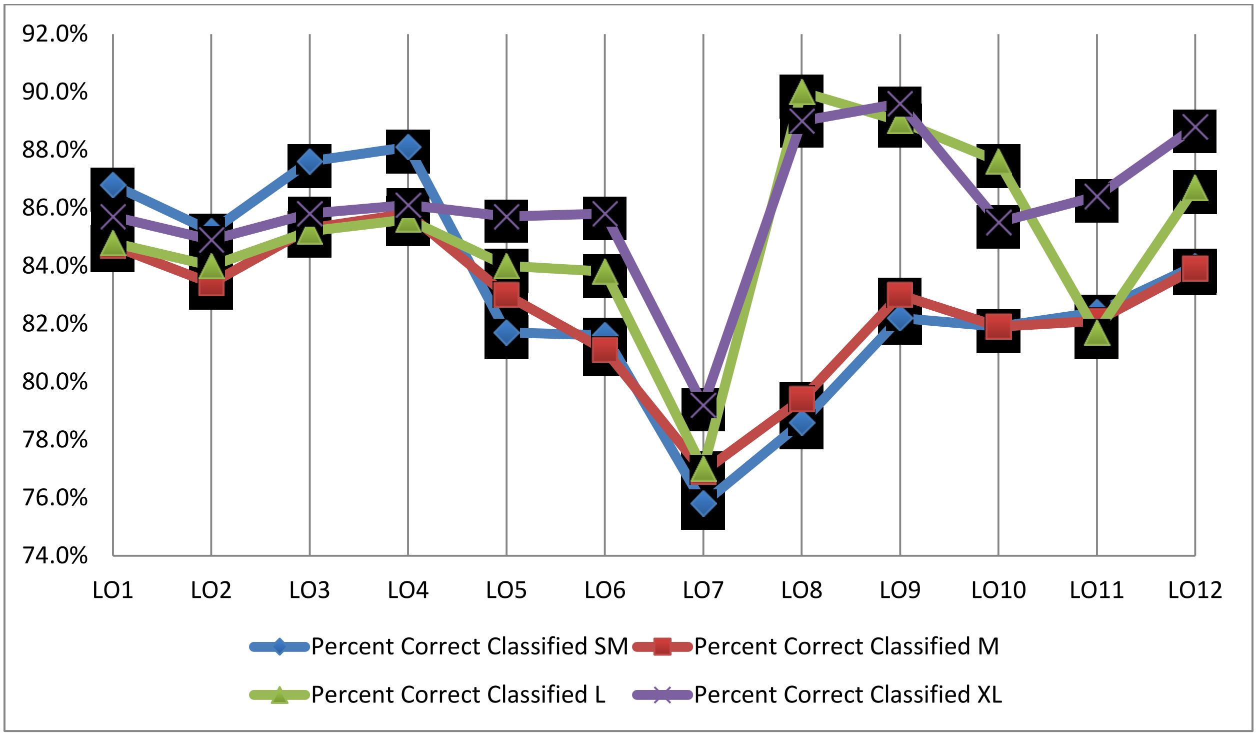
LO10				
	B	S.E.	Sig.	
TM2	.316	.412	.443	1.371
TM7	-.113	.286	.693	.893
TM8	-.727	.310	.019	.483
TM13	3.901	.366	.000	49.435
TM15	2.633	.293	.000	13.909
TM18	.636	.218	.004	1.889
Nagelkerke R^2	.634			
Overall % Correct	85.5%			
Chi-Squared	1660.448			

LO11				
	B	S.E.	Sig.	Exp(B)
TM2	-.374	.268	.163	.688
TM7	.537	.208	.010	1.711
TM8	3.620	.243	.000	37.320
TM13	1.851	.234	.000	6.365
TM15	-1.056	.226	.000	.348
TM16	1.647	.119	.000	5.190
TM18	-.202	.166	.224	.817
TM19	1.150	.129	.000	3.158
Nagelkerke R^2	.672			
Overall % Correct	86.4%			
Chi-Squared	4368.304			

LO12				
	B	S.E.	Sig.	Exp(B)
TM2	.985	.338	.004	2.677
TM7	-.360	.251	.151	.698
TM8	2.333	.279	.000	10.308
TM13	1.505	.289	.000	4.506
TM15	1.869	.271	.000	6.484
TM16	1.066	.143	.000	2.904
TM18	.658	.206	.001	1.931
TM19	.258	.157	.100	1.295
Nagelkerke R^2	.705			
Overall % Correct	88.8%			
Chi-Squared	3522.056			

Figure 4.1

Patterns of Percent Correct Classification by Class Enrollment Groups



Results of binary logistic regressions: overall model fit. Two indices of overall model fit, the overall percent correctly classified and the Nagelkerke R2, were used to evaluate how well TMs predicted progress on each of the LOs, and if the predictive power differed by class enrollment groupings.

All of the regressions in Tables 4.13- 4.16 had chi-square distributions that far exceeded the 31.264 critical value ($p < .001$) for 11 degrees of freedom, which indicates that all of the regression models were significant. Most of the regressions had fewer degrees of freedom and, as a result, a lower critical cut rate value. For the Small class enrollment group (Table 4.13), the chi-square distribution values ranged from $X^2 = 3389.057$ ($p < .001$, df = 7) for LO7 to $X^2 = 16{,}697.921$ ($p < .000$, df = 7) for LO3. The chi-square distribution values for the Medium class enrollment group (Table 4.14) ranged from $X^2 = 22988.633$ ($p < .001$, df = 8) for LO7 to $X^2 = 105162.022$ ($p < .001$, df = 7) for LO3. For the Large class enrollment group (Table 4.15) the chi-square distribution values ranged from $X^2 = 1750.943$ ($p < .001$, df = 8) for LO6 to $X^2 = 18000.437$ ($p < .001$, df = 6) for LO9. The chi-square distribution values for the Very Large class enrollment group (Table 4.16) ranged from $X^2 = 793.219$ ($p < .001$, df = 10) for LO6 to $X^2 = 10267.485$ ($p < .001$, df = 6) for LO1.

The overall percent correctly classified value indicates the effect size of the model, and is better to use than the Nagelkerke R^2 to compare models and determine which model has the best power to predict desired progress on a given learning objective. The overall percent correctly classified value presents how well the model as a whole correctly classified both desired progress and not enough progress on the given LO. The logistic regression models for each of the class enrollment groups correctly classified progress on the specific learning objective with a minimum of 75.8% accuracy. The highest level of accuracy for all models across all enrollment groups was 90.0% for the Large class enrollment group for LO8 (see Table 4.15). Most models fell within the 80% - 89% range. To summarize, the results confirm hypothesis 1a, because the predictive models that include the most highly correlated teaching methods split by class enrollment groups accurately and significantly predicted whether students experienced substantial or exceptional progress or insufficient progress on each of the 12 learning objectives.

The Nagelkerke pseudo-R^2 statistic approximates the R^2 statistic used in linear regression. Although this statistic suggests the relative strength of an individual model, it is not sufficient for comparing one model against others. However, it is a useful statistic to evaluate individual models. As Tables 4.13 – 4.16 show, for all four class enrollment groups the sets of teaching methods predict progress on specific learning objectives at least at the moderate level. The smallest pseudo R^2 was .409 (LO7 for the Small class enrollment group) with the largest being .714 (LO9 for the Very Large class enrollment group). Thus, results confirmed hypothesis 1a that TMs significantly and meaningfully predicted progress on the LOs.

To examine if the predictive models differed by class enrollment groupings two comparisons were made. First, the TM items included in each binomial logistic regression model were examined. Second, the overall percentage of cases correctly classified within each of the models was reviewed. Figure 4.1 also shows how the class enrollment groupings influenced the predictive strength of the LO models.

For LO1, all four class enrollment groups contained the same TMs in the models with the exception of the Medium class enrollment group which also included TM15. The highest percentage of correct classification was for the Small class enrollment group model (86.8% correct classification) with the lowest being the Medium class enrollment group (84.7%). The

2.1% difference in correct classification indicates there was no meaningful difference across the 4 class enrollment groupings in the predictive power of the TMs to predict LO1.

For LO2, all four class enrollment groups contained the same TMs in the models with the exception of the Small class enrollment group where TM9 took the place of TM10. The highest percentage of correct classification was for the Small class enrollment group model (85.2% correct classification) with the lowest being the Medium group (83.4%). The 1.8% difference in correct classification indicates there was no meaningful difference across the 4 class enrollment groupings in the predictive power of the TMs to predict LO2.

For LO3 both the Large and Very Large class enrollment groups had identical TMs in the models. The difference was that both the Small and Medium class enrollment groups contained TM8 instead of TM7. The highest percentage of correct classification was for the Small class enrollment group model (87.6% correct classification) with the lowest being the Large group (85.2%). The 2.4% difference in correct classification indicates there was no meaningful difference across the 4 class enrollment groupings in the predictive power of the TMs to predict LO3.

For LO4 the Large and Very Large class enrollment groups had identical TMs in the models. The Small and Medium enrollment groups both lacked TM7. Additionally, the Small group had TM8, whereas the Medium group had TM10. All four enrollment groups contained TM2, TM4, TM6, TM13 and TM15. The highest percentage of correct classification was for the Very Large class enrollment group model (88.1% correct classification) with the lowest being the Large group (85.6%). The 2.5% difference in correct classification indicates there was no meaningful difference across the four class enrollment groupings in the predictive power of the TMs to predict LO4.

It is worth noting that the models for LO1, LO2, LO3, and LO4 contain essentially the same set of teaching methods. For these four learning objectives across the four class enrollment groups there were very minor differences between the classification percentages. The greatest variation between the class enrollment groupings and these learning objectives was found in the sample size of each group.

For LO5 none of the four class enrollment groups contained the exact same set of predictors. All four groups contained TM5, TM14, TM15, and TM18 and each carried significant and meaningful effect on the respective model. TMs in discrepancy among the enrollment groups for LO5 were TM2, TM13, TM16, and TM19. Generally speaking these TMs were not significant and/or did not have meaningful impact on the model. The highest percentage of correct classification was for the Very Large class enrollment group model (85.7% correct classification) with the lowest being the Small group (81.7%). The 4% difference in correct classification indicates there was no meaningful difference across the four class enrollment groupings in the predictive power of the TMs to predict LO5.

For LO6 the Small and Medium class enrollment groups held identical TM models. The Large enrollment group added three more TMs whereas the Very Large enrollment group had an additional four TMs. It is interesting to note that TM13 was not significant across any of the models for LO6. TM1, TM14, TM16, TM18, and TM20 were not equally present in the models for LO6. Generally speaking these TMs were not significant and/or did not have meaningful impact on the model. The highest percentage of correct classification was for the Very Large class enrollment group model (85.8% correct classification) with the lowest being the Medium group (81.1%). The 4.7% difference in correct classification indicates there was no meaningful difference across the four class enrollment groupings in the predictive power of the TMs to predict LO6.

For LO7 none of the four class enrollment groups contained the exact same regression model but TM7, TM8, TM10, TM13 and TM15 were common across all four enrollment groups. TM1, TM2, TM6, TM16, TM18 and TM19 were not equally present in the models for LO7. Generally speaking these TMs were not significant and/or did not have meaningful impact on the model. The highest percentage of correct classification was for the Very Large class enrollment group model (79.2% correct classification) with the lowest being the Small group (75.8%). The 3.4% difference in correct classification indicates there was no meaningful difference across the four class enrollment groupings in the predictive power of the TMs to predict LO7. It is worth noting that, in general terms, LO7 had the lowest percent of correct classifications across all class sizes for all regression models.

For LO8 none of the four class enrollment groups contained the exact same regression model but TM7, TM15, TM16, TM18, and TM19 were common across all the groups. Only the Large enrollment group did not contain TM8. TM1, TM2, TM8, TM9, and TM13 were not equally present in the models for LO8. Generally speaking these TMs were not significant and/or did not have meaningful impact on the model. The highest percentage of correct classification was for the Large class enrollment group model (90% correct classification) with the lowest being the Small group (78.6%). The TMs in all four class enrollment models for LO8 had the highest percent correct classification across all regressions in the study. The 11.4% difference in correct classification indicates a meaningful difference across the 4 class enrollment groupings in the predictive power of the TMs to predict LO8.

For LO9 the Very Large and Large class enrollment groups contained the exact same TMs in the models. TM7, TM8, TM9, TM15, TM18 and TM19 were common across all four enrollment groups. TM2 was significant and moderately meaningful in only the Small and Medium class enrollment groups. The highest percentage of correct classification was for the Very Large class enrollment group model (89.6% correct classification) with the lowest being the Small group (82.2%). Additionally, the classification for the Large class enrollment group correctly classified cases at 89.0%. The 7.0% difference in correct classification indicates there was no meaningful difference across the four class enrollment groupings in the predictive power of the TMs to predict LO9.

For LO10 none of the four class enrollment groups contained the exact same TMs in the model but TM8, TM13, TM15, and TM18 were common across all of the enrollment groups. TM16 did not appear in the Very Large enrollment group but was significant and meaningful in the other three groups. TM2, TM4, TM7, and TM19 were not equally present in the models for LO10. Generally speaking these TMs were not significant and/or did not have meaningful impact on the model. The highest percentage of correct classification was for the Large class enrollment group model (87.6% correct classification) with the lowest being both the Small and Medium groups (81.9% each). The 5.7% difference in correct classification indicates there was no meaningful difference across the four class enrollment groupings in the predictive power of the TMs to predict LO9.

For LO11 the TMs in the models were the same across all four enrollment groups with the exception of TM7 and TM18. Generally speaking these TMs were not significant and/or did not have meaningful impact on the model. The highest percentage of correct classification was for the Very Large class enrollment group model (86.4% correct classification) with the lowest being the Large group (81.7%). The 4.7% difference in correct classification indicates there was no meaningful difference across the four class enrollment groupings in the predictive power of the TMs to predict LO11.

For LO12 none of the four class enrollment groups contained the exact same regression model but TM2, TM7, TM8, TM15, and TM18 were common across all the groups. TM10 was included in the model for the Small enrollment group, TM13was included in the model for the Large enrollment group, and TM19 was included in the model for the Very Large enrollment group. TM4, TM6, and TM16 were not equally present in the models for LO12. Generally speaking these TMs were not significant and/or did not have meaningful impact on the model. The highest percentage of correct classification was for the Very Large class enrollment group model (88.8% correct classification) with the lowest being the Medium group (83.9%). It is worth noting the Small class enrollment group was only 0.1% away from being the lowest (84.0%). The 4.9% difference in correct classification indicates there was no meaningful difference across the four class enrollment groupings in the predictive power of the TMs to predict LO12.

In relation to hypothesis 1b, the results demonstrated that, in general, there were not meaningful differences across class enrollment groupings a) for the TMs used to model LOs, and b) the power of the sets of TMs to predict progress on the LOs. For example, several models contained the same TM items across all four class enrollment groupings for a specific LO. For those models that were not identical there were typically at least four TM items common across all four class enrollment groupings. Further, in only 1 out of 48 models was there a meaningful difference in the percent of correct classification. Within each LO, the difference across class size groupings differed by approximately 2% - 5% with the exception of LO8 where there was a difference of 11.4%. The percent correct classifications for all analyses ranged from 76% to 90%. The Very Large class enrollment group held the highest correct percent classification for 6 of the 12 LOs and never held the lowest overall percent classification for any LO. The Medium class enrollment group held the lowest percent of correct classifications for 5 of the 12 LOs and never held the highest overall percent classification for any of the 12 LOs.

Table 4.17

Teaching Methods (TM) Most Likely to Predict Desired Progress by Class Enrollment Groupings

Learning Objective	Small	Medium	Large	Very Large
1. Gaining factual knowledge (terminology, classifications, methods, trends)	4*, 6*, 8**, 10*	4*, 6**, 8**, 10*	4*, 6**, 8****, 10**	6****, 8****, 10**
2. Learning fundamental principles, generalizations, and theories	6*, 8**, 9*,	4*, 6*, 8***, 10*	4*, 6*, 8****, 10**	6**, 8****, 10**
3. Learning to apply course material (to improve thinking, problem solving, and decisions)	4**, 6*, 15*	2*, 4**, 6*, 8*, 15**	2*, 4**, 8**, 15**	2*, 4*, 6****, 8**, 15***
4. Developing specific skills, competencies, and points of view needed by professionals in the field most closely related to this course	4**, 6*, 15**	4*, 6**, 15**	4**, 6***, 8**, 15***	4*, 6****, 8*, 15****
5. Acquiring skills in working with others as a member of a team	5**, 14*, 15*, 18*	5***, 14*, 15*, 18*	5***, 14*, 15**	5**, 14*, 15****
6. Developing creative capacities (writing, inventing, designing, performing in art, music, drama, etc.)	7*, 15**, 19**	7**, 15**, 19****	7***, 15****, 18*, 19**	7****, 13*, 15*****, 18*
7. Gaining a broader understanding and appreciation of intellectual/cultural activity (music, science, literature, etc.)	7*, 13*	7*, 13**, 19*	7*, 10*, 13*, 19*	7****, 10**, 13***
8. Developing skill in expressing myself orally or in writing	7*, 8*, 16*, 19**	7*, 16**, 19****	7*, 9*, 16*, 19*****	7**, 8*, 15*, 16*, 19*****
9. Learning how to find and use resources for answering questions or solving problems	8*, 9****, 15*	8*, 9****, 15*	8*, 9*****, 15**	8*, 9*****, 15**,
10. Developing a clearer understanding of, and commitment to, personal values	13*, 15*, 16**	8*, 13**, 15*, 16**	13**, 15**, 16****	13*****, 15****
11. Learning to analyze and critically evaluate ideas, arguments, and points of view	8**, 13*, 16*, 19*	8****, 16*, 19*	8****, 13**, 16*,	8*****, 13**, 16**, 19*
12. Acquiring an interest in learning more by asking my own questions and seeking answers	8*, 13*, 15*	2*, 8**, 13**, 15*, 18*	2*, 8****, 13***, 15*, 18*	8****, 13**, 15**, 16*

* The TM is at least 2 times more likely to predict desired progress on the LO.

** The TM is at least 4 times more likely to predict desired progress on the LO.

*** The TM is at least 8 times more likely to predict desired progress on the LO.

**** The TM is over 10 times more likely to predict desired progress on the LO.

*****The TM is over 30 times more likely to predict desired progress on the LO.

Results of logistic regressions: predictive power of individual TMs. Exp(B) was used to evaluate the predictive power of the individual TMs included in each logistic regression model. By comparing the Exp(B) value for the TMs in the models it can be determined which of the 20 TMs in the IDEA system have the greatest ability to predict desired progress on the LOs. It should also be noted that because numerous analyses were conducted a conservative alpha level was set ($\alpha = .001$). The Exp(B) value is the increase in the odds of the outcome occurring for every one unit increase in one of the predictor variables while the influence of the other predictor variables in the model are controlled. For example, scores for the TMs range from 1-5, so an increase from 2) *Occasionally*, to 3) *Sometimes*, is an increase of one unit. The value of Exp(B) for TM8 for the regression model for LO1 for the Very Large class enrollment group is 25.209 (see Table 4.16). This means that for every one unit increase in TM8, "Stimulated students to intellectual effort beyond that required by most courses", classes are 25 times more likely to report making desired progress on LO1, "Gaining factual knowledge". Similarly, in the Small group classes are six times more likely, in the Medium group they are nearly eight times more likely, and in the Large group they are over 15 times more likely to indicate desired progress on LO1 (see Tables 4.13 – 4.15). Further, see Table 4.17, which summarizes the TMs with the largest effect on specific LOs for the different class enrollment groupings.

For LO1 the TM with the largest effect for predicting desired progress was TM8 for the Very Large class enrollment group, Exp(B) = 25.209, $p < .001$. TM8 is 25 times more likely to predict desired progress on LO1 in Very Large classes. For the other three class enrollment groups TM8 was also the TM with the largest effect for predicting desired progress on LO1. Small class enrollment, Exp(B) = 6.122, $p < .001$ (six times more likely to predict desired progress); Medium class enrollment, Exp(B) = 7.865, $p < .001$ (almost eight times more likely to predict desired progress); Large class enrollment, Exp(B) = 15.598, $p < .001$ (15 and a half times more likely to predict desired progress). Other TMs that held strong predictive power for this LO were TM6 which was the second largest for all four class enrollment groups except for the Large group where it came in third behind TM10 in that class enrollment group. TM6, TM10, and TM4 were all at least twice as likely to predict desired progress for LO1. Generally speaking, the Very Large class enrollment group had individual TMs with the strongest ability to predict desired progress on LO1.

For LO2 the TM with the largest effect for predicting desired progress was TM8 for the Very Large class enrollment group, Exp(B) = 25.699, $p < .001$. TM8 is over 25 times more likely to predict desired progress on LO2 in Very Large classes. For the other three class enrollment groups TM8 was also the TM with the largest effect for predicting desired progress on LO2; Small class enrollment, Exp(B) = 5.952, $p < .001$ (just under six times more likely); Medium class enrollment, Exp(B) = 8.514, $p < .001$ (eight and a half times more likely); and Large class enrollment, Exp(B) = 16.677, $p < .001$ (almost 17 times more likely). TM6 was the second largest predictor in LO2 for all four class enrollment groups except for the Large group where it came in third behind TM10 in that class enrollment group. TM9, Exp(B) = 2.066, $p < .001$, was only present in the Small enrollment group but like TM6, TM10, and TM4 also was at least twice as likely to predict desired progress. Generally speaking, the Very Large class enrollment group had individual TMs with the strongest ability to predict desired progress on LO2.

For LO3 there were three different TMs across the four class enrollment groupings that had the largest effect. For the Very Large class enrollment group TM6 had the largest effect, Exp(B) = 10.065, $p < .001$ (10 times more likely to predict desired progress); for the Small class enrollment group TM4 was the largest, Exp(B) = 5.952, $p < .001$ (just under six times more likely); for the Medium class enrollment group TM15 was the largest, Exp(B) = 4.386, $p < .001$ (just above four times more likely); and for the Large class enrollment group TM4 was again the largest, Exp(B) = 5.927, $p < .001$ (nearly six times more likely to predict desired progress). TM4, TM6, TM15 were among the top most influential TMs across all four class enrollment groups with the exception of the Very Large group where TM8, Exp(B) = 4.102, $p < .001$, exceeded TM4. Generally speaking, the Very Large class enrollment group had individual TMs with the strongest ability to predict desired progress on LO3.

For LO4 the TM with the largest effect for predicting desired progress was TM15 for the Very Large class enrollment group, Exp(B) = 13.976, $p < .001$ (nearly 14 times more likely to predict desired progress). For the other three class enrollment groups TM15 was also the TM with the largest effect for predicting desired progress on LO4: Small class enrollment, Exp(B) = 6.455, $p < .001$ (almost 6 and a half times more likely); Medium class enrollment, Exp(B) = 6.337, $p < .001$ (over 6 times more likely); and Large class enrollment, Exp(B) = 8.875, $p < .001$ (nearly 9 times more likely). TM4, TM6, TM15 were among the top most influential TMs across all four class enrollment groups with the exception of the Very Large group where TM8, Exp(B) = 3.943, $p < .001$, exceeded TM4. Generally speaking, the Very Large class enrollment group had individual TMs with the strongest ability to predict desired progress on LO4.

For LO5 there were two TMs across all four class enrollment groupings with the largest effect for predicting desired progress. TM15 in the Very Large group had the overall largest effect, Exp(B) = 18.380, p < .001 (18 times more likely to predict desired progress). For the other three groups TM5 had the largest effect for predicting desired progress on LO5: Small class enrollment, Exp(B) = 5.799, p < .001 (nearly six times more likely); Medium class enrollment, Exp(B) = 8.966, $p < .001$ (almost nine times more likely); and Large class enrollment, Exp(B) = 9.074, $p < .001$ (also nine times more likely). TM14, TM15, and TM18 also had meaningful effects across the four class enrollment groups, and all were at least two times more likely to predict desired progress on LO5. While the Very Large class enrollment group contained the TMs with the largest effects on making progress on LO5, the Medium class enrollment group had the largest number of TMs that were at least twice as likely to predict desired progress.

For LO6 there were two TMs across all four class enrollment groupings with the largest effect for predicting desired progress. TM15 in the Very Large group had the largest effect on this LO, Exp(B) = 39.289, $p < .001$ (39 times more likely to predict desired progress). In two more of the class enrollment groups, TM15 was also the TM with the largest effect for predicting desired progress on LO6: Small class enrollment, Exp(B) = 6.462, $p < .001$(almost six and a half times more likely); and Large class enrollment, Exp(B) = 17.212, $p < .001$ (17 times more likely). For the Medium class enrollment group TM19 had the largest effect, Exp(B) = 13.890, $p < .001$ (nearly 14 times more likely). TM7, TM15 and TM19 were each at least four times more likely to predict desired progress across all four class enrollment groups with the exception of the Very Large group where TM19 was not one of the TMs correlated highly enough to be entered into the model. Generally speaking, the Very Large class enrollment group had individual TMs with the strongest ability to predict desired progress on LO6.

For LO7 there were two TMs across all four class enrollment groupings with the largest effect for predicting desired progress. TM7 in the Very Large group had the overall largest effect, Exp(B) = 10.931, $p < .001$ (nearly 11 times more likely to predict desired progress). TM7 was also the TM with the largest effect for predicting desired progress on LO7 in the Large class enrollment, Exp(B) = 3.929, $p < .001$ (nearly four times more likely). It is worth noting that in this same class enrollment group that the effect of TM13 was very close, Exp(B) = 3.311 ($p < .001$) (3 times more likely). TM13 was the TM with the largest effect for the Small class enrollment group, Exp(B) = 3.940, $p < .001$ (almost four times more likely) and the Medium class enrollment group, Exp(B) = 7.078, $p < .001$ (seven times more likely). TM7 and TM13 were among the best at predicting desired progress for all four enrollment groups. Additionally, TM19 was a strong predictor for the Medium and Large groups being at least twice as likely to predict progress. TM10 was a strong predictor in the Very Large group, Exp(B) = 7.035, $p < .001$ (seven times more likely). Generally speaking, the Very Large class enrollment group had individual TMs with the strongest ability to predict desired progress on LO7.

For LO8 the TM with the largest effect for predicting desired progress was TM19 for the Very Large class enrollment group, Exp(B) = 36.765, $p < .001$ (over 36 times more likely to predict desired progress). For the other three class enrollment groups TM19 was also the TM with the largest effect for predicting desired progress on LO8; Small class enrollment, Exp(B) = 4.543, $p < .001$ (four and a half times more likely); Medium class enrollment, Exp(B) = 12.541, $p < .001$ (12 and a half times more likely); Large class enrollment, Exp(B) = 32.628, $p < .001$ (over 32 times more likely). TM7 and TM16 were also influential across all four class enrollment groups being at least twice as likely to predict desired progress. TM8 was influential in the Small group, Exp(B) = 2.477, $p < .001$ (two and a half times more likely), and TM15 in the Very Large group, Exp(B) = 3.352, $p < .001$ (3 times more likely), was also a strong factor. Generally speaking, the Very Large class enrollment group had individual TMs with the strongest ability to predict desired progress on LO8.

For LO9 the TM with the largest effect for predicting desired progress was TM9 for the Very Large class enrollment group, Exp(B) = 70.450, $p < .001$ (over 70 times more likely to predict desired progress). For the other three class enrollment groups TM9 was also the TM with the largest effect for predicting desired progress on LO9: Small class enrollment, Exp(B) = 12.707, $p < .001$ (almost 13 times more likely); Medium class enrollment, Exp(B) = 17.573, $p < .001$ (17 and a half times more likely); and Large class enrollment, Exp(B) = 41.534, $p < .001$ (41 and a half times more likely). TM8 and TM15 were among the top three TMs predicting desired progress on LO9 for all four enrollment groups. Generally speaking, the Very Large class enrollment group had individual TMs with the strongest ability to predict desired progress on LO9.

For LO10 there were two TMs across all four class enrollment groupings with the largest effect for predicting desired progress. TM13 in the Very Large group was the overall largest effect, Exp(B) = 49.435, $p < .001$ (49 times more likely to predict desired progress). TM13 was also the TM with the largest effect for predicting desired progress on LO10 in the Medium class enrollment, Exp(B) = 7.078, $p < .001$ (seven times more likely). TM16 was the TM with the largest effect for the Small class enrollment group, Exp(B) = 4.558, $p < .001$ (four and a half times more likely) and the Large class enrollment group, Exp(B) = 11.274, $p < .001$ (11 times more likely). TM15 joined TM13 and TM16 across the four enrollment groups as a meaningful TM predicting desired progress. While the Very Large group had the single largest predictor the Medium class enrollment group had the largest number of TMs that were at least twice as likely to predict desired progress.

For LO11the TM with the largest effect for predicting desired progress was TM8 for the Very Large class enrollment group, Exp(B) = 49.435, $p < .001$ (over 49 times more likely to predict desired progress). For the other three class enrollment groups TM8 was also the TM with the largest effect for predicting desired progress on LO11: Small class enrollment, Exp(B) =

7.383, $p < .001$ (seven times more likely); Medium class enrollment, Exp(B) = 12.924, $p < .001$ (nearly 13 times more likely); and Large class enrollment, Exp(B) = 28.920, $p < .001$ (nearly 29 times more likely). TM13 and TM16 were meaningful predictors of desired progress across the four enrollment groups for LO11 with the exception of the Medium group where TM13 was surpassed by TM19, Exp(B) = 2.739, $p <.001$ (nearly three times more likely to predict desired progress). Generally speaking, the Very Large class enrollment group had individual TMs with the strongest ability to predict desired progress on LO11.

For LO12 the TM with the largest effect for predicting desired progress was TM8 for the Large class enrollment group, Exp(B) = 12.263, $p < .001$ (12 times more likely to predict desired progress). For the other three class enrollment groups TM8 was also the TM with the largest effect for predicting desired progress on LO12: Small class enrollment, Exp(B) = 3.966, $p < .001$ (almost four times more likely); Medium class enrollment, Exp(B) = 7.448, $p < .001$ (over seven times more likely); and Very Large class enrollment, Exp(B) = 10.308, $p < .001$ (over 10 times more likely). TM13, TM15 and TM18 were strong predictors of desired progress in the Medium and the Large class enrollment groups. TM16 was a strong predictor in the Very Large group, Exp(B) = 2.904, $p <.001$ (almost three times more likely). For the Small group TM2 was a strong predictor, Exp(B) = 2.059, $p < .001$ (twice as likely), as well as for the Medium class enrollment group where TM2, Exp(B) = 2.749, $p < .001$, was nearly three times as likely to predict desired progress on LO12. TM8 and TM15 were among the top three TMs predicting desired progress on LO9 for all four enrollment groups. Generally speaking, the Large class enrollment group had individual TMs with the strongest ability to predict desired progress on LO12.

Summary of predictive power of individual TMs. Table 4.17 summarizes, by LO and class enrollment groupings, which TMs had the greatest probability for predicting desired progress on specific LOs. For all 12 of the learning objectives across all four class enrollment groupings (a total of 48 regression models), TM8 had the largest effect in 16 of those occurrences (33.3% of the total). TM15 was next with nine occurrences (19% of the total). TM13 appeared 4 times (8%), TM4 appeared twice (4%), TM6 and TM19 each appeared once (2%). Several teaching methods not considered in hypothesis 2a also had the largest predictive effect across the 48 regression models. TM19 appeared 5 times (10% of the total), TM9 appeared four times (8%), TM5 appeared three times (6%), and TM16 and TM7 each appeared twice (4% each). Additionally, it was common to find each of these TMs which were not considered in hypothesis 2a among the top 3 highest predictors for desired progress on a LO across the enrollment groupings.

For over half of the LOs, TM15 was among the top three predictor variables across the enrollment groupings. Further, for all LOs, with the exception of LO12, the TM with the largest effect was found in the Very Large class enrollment group. The TM with the largest effect for LO12 was found in the Large class enrollment group.

These findings partially confirm hypothesis 2a in that TM15 was found to consistently have the largest effect on predicting progress for the LOs. Additionally, TM4, TM6, TM8, and TM13 also were found to be among those TMs with the strongest effect on predicting progress on the learning objectives. What was not predicted in hypothesis 2a was that TM8 was more often a better predictor than TM15. TM2 was prominent in hypothesis 2a because it was highly correlated with many of the LOs (see Tables 4.9- 4.12 as well as Table 2.1). However, in the regression analyses TM2 was never a TM that had the largest effect in any of the 12 LOs. Furthermore, TM2 had a negative beta coefficient in the Small class group for LO6; in the Medium class group for LO5-LO8; in the Large class group for LO1 and LO6; and in the Very

Large class group for LO1, LO6 and LO7 even though TM2 had a positive correlation coefficient with each of these LOs.

A potential reason that this occurred is because of a suppressor effect. A suppressor effect occurs when one predictor variable can be said to be explaining the error variance in another predictor variable. "By correlating with the error in another predictor, the suppressor variable helps purify that predictor and thereby enhances its predictive power" (Pedhazur, 1982). If one thinks of the relationship between two independent variables (points A and B) and a dependent variable (point C) as points on a triangle then a suppressor effect is akin to attempting to study the change in relationship between the variables but having the entire shape of the triangle shift when any one of the points is adjusted. A change in value of one of the variables adjusts the relationship between all three of them. For the data in this analysis it is possible part of the information that TM2 provides to help predict the relationship with a given LO is also contained within the LO, the other TMs and/or the relationship between the TMs. When looking at other TMs within the regression models there are some possible patterns to explore. For those instances where negative beta coefficients were obtained, an examination of the correlation coefficients between TMs and LOs provides information about the relationship between the LOs and TMs, although it does not take into account the influence of the other TMs in the regression on the LO, which is a benefit of using the beta coefficents and Exp(B) from the logistic regression analyses.

Because all of the TMs are positively and significantly correlated with the LOs (see Tables 4.9- 4.12) any significant but negative beta coefficients found in the regression analysis are likely suppressor effects. Across the 48 LO models there are 346 individual TM beta coefficients. TM1, TM2, TM6, TM7, TM8, TM13, TM15, TM18, and TM20 each were significant but had negative beta coefficients with the LO at least once (a total of 29 occurrences or 8% of the total analyses). TM2 occurred the most often with 11 occurrences. Next was TM15 with 5 occurrences. The remaining occurrences were split between TM13 (4 occurrences) and TM18 (3 occurrences) with the other TMs having two or fewer occurrences where the coefficients were significant and negative.

An examination of the 29 negative beta coefficients, which are likely suppressor effects, by class enrollment groupings reveals that the Medium class enrollment group is represented most often (10 occurrences), followed by the Very Large group (9 occurrences), with the Large group next (7 occurrences), and the Small group with the fewest occurrences at three. Additionally, looking at the 29 potential suppressor effects by LOs, LO6 appears the most (6 occurrences), LO8 was next (5 occurrences), and, with four occurrences each, LO1 and LO11 are last among the list of LOs with potential suppressor effects.

Further, TM2 was involved in over one third of the potential occurrences of suppressor effects. A potential explanation for this is that TM2 measures how often students observed that instructors "found ways to help students answer their own questions", which is conceptually associated with TM15, "Inspires students to set and achieve goals which really challenged them". TM15 was involved in a large number of the potential occurrences of suppressor effects. For example, if a class indicates that an instructor "almost always" helped students answer their own questions (TM2) it seems logical that students would also be more likely to also report that the instructor "almost always" inspired students to set and achieve challenging goals (TM15). There is a logic in assuming such an instructor would also be one who "displayed a personal interest in students and their learning" (TM1).

Chapter 5 - Discussion, Implications, and Recommendations

Purpose of the Study

The purpose of this study was to discover which of 20 teaching methods (TM) were the strongest predictors for student progress on the 12 IDEA learning objectives (LO), and to explore if these predictions were modified by class size. A unique element of this study was to go beyond the traditional bivariate correlational analyses and employ binary logistic regression to discover the unique predictive effects of individual TMs on specific LOs while controlling for the influence of other TMs. TMs were studied as clusters of teaching styles as well as individually. The study explored if any of these predictions (by clusters of TMs or by individual TMs) were modified by class size groupings.

Overview of the Methods

Archival data were obtained from The IDEA Center (www.theideacenter.org), a nonprofit organization that has as part of its mission supporting the improvement of learning and teaching through the use of its diagnostic student ratings instrument. An aggregate database of more than 580,000 classes of university/college students was retained in the 2002 to 2009 database. Several exclusion criteria were employed: novice users, classes with fewer than 10 respondents, and classes that used the IDEA Short Form. In addition, classes were randomly deleted until no institution contributed more than 5% of classes to the total database. The remaining 331,766 aggregated class statistics aligned with instructor information were the focus of this study.

The analyses consisted of: a) descriptive statistics for each of the 12 learning objectives and 20 teaching methods found in the IDEA system separated by class enrollment groupings; b) correlations between teaching methods and learning objectives separated by class enrollment groupings; and c) binary logistic regressions, run separately by class enrollment groupings, with teaching methods serving as predictor variables and learning objectives serving as criterion variables. All analyses were performed using PASW 18.0 statistical software.

Summary of Results

The study found that clusters of TM models were able to correctly predict desired progress for all 12 LOs across the four class size groupings. The percent correct classifications for all analyses ranged from 76% to 90%. However the class size differences in percent correct classification when compared by LO were not enough to make meaningful distinctions among the models. One exception was LO8 which had an 11.4% difference for the percent correct classifications across the four class size groups.

When considered individually TM8 and TM15 were discovered to consistently have the greatest odds of predicting desired progress for a majority of the LOs. Along with TM8 and TM15 -TM6, TM7, TM13, and TM19 were variables typically among the top three in each model to have the greatest odds of predicting success with any given LO across all class size groupings.

Although class size did not make a meaningful difference for the TM models, there was a consistent pattern for the strength of the odds ratios of the individual TMs across the four class-size groupings. For all LOs the Very Large class size group (more than 50 students) held the largest beta coefficient with the exception of LO12 which had its largest beta coefficient in the Large class enrollment group (between 35 and 49 students). For example, TM8 was the strongest predictor of desired progress on LO1 for all four class enrollment groups, but as the class enrollment group size increased so did the odds ratio for TM8. This TM was associated with the following increase in odds of desired progress on LO1: six times more likely for Small class enrollment; eight times more likely for Medium class enrollment; 15.5 times more likely for Large class enrollment; and over 25 times more likely for the Very Large class enrollment group.

LO12 was the only LO where the Very Large class enrollment group did not contain the highest relative beta coefficient. In this case the Large class enrollment group had the greatest beta coefficients. For example, TM8 was also the greatest single predictor of desired progress for all four class enrollment groups for LO12: four times more likely for Small class enrollment; seven times more likely for Medium class enrollment; over 10 times more likely for the Very Large class enrollment; and over 12 times more likely for the Large class enrollment group. In the following section findings for the research questions are discussed along with implications for further research and practice.

Discussion of the Research Questions: Overall Model Fit

Question 1a: How well do teaching methods predict substantial or exceptional progress on IDEA learning objectives the instructor identifies as relevant to the course? And Question 1b: Are these predictions moderated by class enrollment groupings?

Generally speaking each of the TM models of the study across the four class enrollment groupings were shown to be strong predictors of substantial or exceptional progress on the given LO. Drawing on the work of Hoyt and Lee (2002), who used factor analysis to discover teaching method subscales among the 20 TM items, an interesting understanding of this study comes to light. Consider the subscale “Stimulating Student Interest” which consists of TM4, “Demonstrated the importance and significance of the subject matter”; TM8, “Stimulated students to intellectual effort beyond that required by most courses”; TM13, “Introduced stimulating ideas about the subject”; and TM15, “Inspired students to set and achieve goals which really challenged them". The Stimulating Student Interest subscale was very prominent across all models in this study. At least three items from this subscale are found in 22 of the 48 regressions conducted. Furthermore, all four TM items from the Stimulating Student Interest (SSI) subscale are significant and among the top five variables (in terms of predictive strength) for five LOs across all class enrollment groupings. For example, this subscale was prominent across the four class enrollment groups for LO3, "Learning to apply course material (to improve thinking, problem solving, and decisions)"; and LO4, "Developing specific skills, competencies, and points of view needed by professionals in the field most closely related to this course". As mentioned in Chapter 4, these LOs are also among the most frequently selected as important or essential to the course by faculty across the entire IDEA system.

The literature suggests why this might be the case. Hoyt and Lee (2002) argue the prevalence of LO3 and LO4 reflect the more utilitarian view of American higher education. It is also reasonable to suggest teaching methods that demonstrate the significance of the subject matter, stimulate students to intellectual effort, introduce stimulating ideas, and inspire students to set and achieve challenging goals (teaching methods measured by the SSI subscale) are all inherent aspects typical of higher education. What might be understood by the predictive strength of the subscale and the commonality among American higher education?

One suggestion comes from the current literature reflecting cognitive learning theory. Methods which help students activate prior knowledge, goal directed learning, and build assessment around practical, real world tasks designed to build mastery (among other practices) are associated with improvement on measures of student engagement and assessment (Ambrose, 2010; Deslauriers, Schelew, & Wieman, 2011). Althought not directly measured by the TM items on the IDEA system, all of the items in the Stimulating Student Interest subscale cover very similar aspects. The other four TM subscales discovered by Hoyt and Lee (2002) each contain concepts found in cognitive learning theory but not to the extent of the Stimulating Student Interest subscale. Furthermore, none of the other subscales is wholly represented in the TM models resulting from this study.

Another possibility exists which might explain the prevalence of the Stimulating Student Interest TM subscale. Addressed as a possible delimitation in the first chapter of this study was Systematic Distortion Hypothesis (SDH). SDH, as applied to SRIs generally and the IDEA SRI system specifically, posits that student ratings of TMs is influenced when survey respondents assign “what is thought to go with what rather than what actually goes with what” (Renaud & Murray, 2005). The SSI subscale’s prominence, particularly with LO3 and LO4, in this study could imply students bring with them to class a utilitarian view of higher education, as suggested by Hoyt and Lee (2002). If so, students who indicate progress in the utilitarian aspects of higher education such as learning to apply course material and develop specific skills needed by professionals in the field (LO3 and LO4) are more likely to favorably rate instructors on TMs highly correlated to the LOs. Therefore ratings of the TMs go beyond instructor behavior and could be influenced by SDH, but, again, SDH is less likely when raters know the ratee well and have ample opportunities to observe the rated behavior. The converse could also be true for students who do not feel they made progress on these LOs rating instructors negatively on the associated TMs.

Discussion of the Research Questions: Predictive Power of Individual TMs

Question 2a: Which teaching methods have the largest effect on whether students experience substantial or exceptional progress on each of the IDEA learning objectives? And Question 2b: Are these predictions moderated by class enrollment groupings?

Two of the 20 TMs were repeatedly among the top three in predicting student progress on the LOs across the four class enrollment groupings: TM8, “Stimulated students to intellectual effort beyond that required by most courses” and TM15, “Inspired students to set an achieve goals which really challenged them”. Additionally, if these two TMs were not the highest predictor in a given model they were then among the top three best predictors. Other TMs which were within the top three best predictors were TM6, “Made it clear how each topic fit in the course”; TM7, “Explained the reasons for criticisms of students’ academic performance”; TM13, “Introduced stimulating ideas about the subject”; and TM19, “Gave projects, tests, or assignments that required original or creative thinking”. These findings might extend the work of Chickering and Gamson (1999), among others, whose seven best practices of undergraduate education are not expressed in rank order of effectiveness. Although all of the 20 TM items can be linked back to the work of Chickering and Gamson (see Chapter 2) the individual TMs in this study found to be of greatest predictive strength were associated with “Communicating high expectations” and “Using active learning techniques.”

Another foundational theory to the IDEA system is the work of Bloom and those who have extended his work (Anderson et al., 2000; Bloom, 1956). The taxonomy Bloom created has had broad adoption and numerous implementations across American education but was deemed too general by the creators of the IDEA SRI system to make an actionable list of LOs. Therefore they used the work of Deshpande and Webb (1968) to synthesize Bloom’s taxonomy leading to an iterative process resulting in the 12 LOs currently in the SRI system. Further exploration of the TMs found to consistently be in the top three of this study could lead to better ways to implement in the classroom the highest levels of Bloom’s taxonomy such as analysis, evaluation, and creating providing another means to improve the usefulness of SRI systems.

At the same time there were some findings from this study that seem to contradict current literature on how students learn best, namely the finding that hands-on and real life activities directly enhance students' learning (Ambrose, 2010; Merrill, 2002). TM14, "Involved students in 'hands-on' projects such as research, case studies, or 'real life' activities," would appear to be a decent surrogate for explicating how students come to indicate they are making progress on LOs, particularly those LOs which also appear to be linked to the same sorts of hands on, real world tasks. But the findings of this study suggest this is not the case. Two LOs which would seem to be logical fits for these principles of hands-on learning, and therefore TM14, are LO3, "Learning to apply course material," and LO4, "Developing specific skills, competencies, and points of view needed by professionals in the field most closely related to the course." But TM14 did not have a high enough correlation with either LO at any class enrollment level to be included in the analyses. The only LO where TM14 was significantly able to predict desired progress was LO5, "Acquiring skills in working with others as a member of a team." Without further study it is difficult to make an accurate assessment of this finding. A possible conclusion is that the common practice of faculty involved in the study was to only assign hands-on, real world tasks within a group context, and therefore students were connecting their progress on the LO with the group work as opposed to the improved skills and other learning. One other possible explanation, which was noted in Chapter 4, is that another variable, or multiple variables, are suppressing the true impact of TM14 upon the LOs.

An additional result of the study addressing Questions 2a and 2b was the finding that as class enrollment groupings increased so did the relative value of the odds ratios for all TMs within the LO models. Regarding the ability of a TM to predict desired progress on the LO, bigger was better, but this seems to also go against common research and practice regarding controlling for course means because student ratings in larger classes are generally rated lower than smaller classes (Cohen, 1981; Hoyt & Lee, 2002; Marsh, 2007) . Reviewing the class means for all 20 TM items across class enrollment groupings for this study confirmed that as class enrollment increased mean scores decreased. It should also be noted that sample size was likely not an explanation for the increase in predictive power as the Very Large class group was the smallest subsection of the dataset, whereas the Medium class enrollment group was the largest. But the pattern of increase for the odds ratios was very much from smallest to the largest class enrollments.

One possible suggestion for why the odds ratio of successfully predicting desired progress on the LO would increase in spite of an opposite direction of class means is that the smallest of improvements in teaching methods nets a greater return for progress on the LO. In other words, it appears that as enrollment increases a little improvement in TMs goes a long way toward increasing progress on the relevant LO.

Implications for Future Research

The following recommendations are made for future research:

1. A study should be conducted which replicates the methods here but on a student rating system other than the IDEA system. Although the question items may not be identical from one SRI system to another the underlying principles are universal enough that a valid and reliable instrument with sufficient overlap between instruments would extend and clarify the findings of this study. The work of Al-Suleimani, (2001) includes a comparison of prominent student evaluation systems that could be used to find instrument questions comparable to this study.

2. A follow-up study should be conducted on the same archival set of IDEA data to more specifically study the individual TM items suspected to be involved in suppressor effects, namely TM2. A study of this type would be useful to the growing understanding of the connections between teaching and learning.
3. Another study that extends the scope of this study, which would include other variables from the IDEA data archives, would be beneficial. Potential areas to explore are the modifying effects of institution type, academic discipline, online course delivery, team teaching, student type (first year, upper level, students in the major, etc.), student motivation, faculty motivation, student perception of effort required by the instructor, faculty reports of approach to coursework (i.e. lecture, discussion, field experience, mutli-media, etc.), and faculty reports regarding level of course requirements such as writing, group work, and critical thinking just to name some of the new areas of potential for which this study can serve as the foundation.
4. A study that, as much as is reasonably possible, follows experimental design to test out the findings of this study on future courses would validate and extend the work of this study.

Recommendations for Practice

Individual higher education faculty and American institutions of higher education can make maximum use of these findings in some of the following ways: First, a thoughtful discussion should ensue prioritizing learning objectives for individual instructors, particular programs, academic departments, college divisions and institutional initiatives. Having a strong sense of which learning objectives are a priority in a given time and context will enable the findings of this study to be maximized. For example, a private, liberal arts college with average class size in the 15-34 enrollment group may hold LO10, “Developing a clearer understanding of, and commitment to, personal values”, as a primary learning objective for all courses at their institution. Based on the findings of this study an institution such as this would do well to place significant resources in training faculty to improve in their ability to introduce stimulating ideas on the subject of study (TM13). Doing so could result in students being more likely to report at least substantial progress on LO10 as a result of their course work.

Second, the findings of this study should help institutions stretch the impact of their faculty development resources by focusing on TMs shown to have very good odds at predicting desired progress on the majority of LOs. This study found TM8 and TM15 to have the greatest odds of predicting desired progress for the largest cross section of all 12 LOs across all class enrollment groupings. Instruction where students observe these teaching methods frequently should result in a meaningful increase in students indicating they made progress on many LOs. This method is general in its approach but is also reasonably able to be applied quickly across an entire institution.

Third, because this study suggests that as class size increases so does the predictive power of certain TMs, higher education institutions should add to existing faculty training key concepts of how to “scale up” highly effective TMs for larger class enrollments. By helping instructors with class sizes of 35 or more students intentionally focus on improving in such areas as stimulating students to intellectual effort a meaningful increase in students reporting desired progress on learning objectives might result.

Fourth, institutions might improve student progress on learning objectives by providing learning communities for faculty with the 12 LOs serving as topical foci. These cohorts could explore ways to become more effective at TMs shown in this study to be best predictors for student progress.

Fifth, individual instructors may make good use of this study to do their own self-study to improve on TMs most likely to predict student progress on the LOs relevant to their courses. Furthermore, the findings of this study could serve as a foundation for individual instructors to enhance their scholarly agendas by systematically testing this research in their own teaching contexts. This would also increase the body of knowledge in the area of the Scholarship of Teaching and Learning (SoTL).

Conclusion

Making connections between specific teaching methods and student learning is inherently difficult, but student reports on observed teaching methods and self-perception of progress on learning objectives, while not as precise as one would like, make for an excellent foundation from which meaningful improvement can be made for American higher education. By studying how student perceptions of instructors' use of teaching methods is associated with student progress on learning objectives, instructors are given the opportunity to better serve their students and, ultimately, the communities where students apply their learning. Furthermore, predictive models of progress on learning objectives can assist faculty to become more successful teachers at a time when evidence of student learning is increasingly scrutinized.

This study found that for most learning objectives in most courses there are a number of teaching methods that are associated with increased odds that a student will report at least substantial progress on the learning objectives faculty members selected as of core importance to the course. As faculty in institutions of higher learning improve in teaching methods such as stimulating students to intellectual effort, inspiring students to achieve goals which challenge them, demonstrating the importance of the subject, and introducing stimulating ideas about the subject there are greater odds of students improving on core learning objectives central to most institutions of higher learning.

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