THE EFFECT OF MOTIVATION AND LEARNING ANXIETY ON ACHIEVEMENT BY MODELING PROBLEM SOLVING SKILLS AND USING OPEN EDUCATIONAL RESOURCES

by

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(Under the Direction of ROBERT MARIBE BRANCH)

ABSTRACT

Personalization in education has played an important role in supporting learning as well as instruction and has been conceptually classified into personalized learning and instruction. Personalized learning refers to student unique ways of learning determined by their individual needs (Carolan & Guinn, 2007; Carroll, 1975; Johnson, Adams, & Cummins, 2012; Keefe & Jenkins, 2008; Miller, 2010). Teachers implement personalized instruction by contextualizing teaching practices to accommodate student needs. However, teachers may hesitate to implement personalized instruction, due to three constrains: 1) time, 2) continuous support, and 3) the required knowledge for personalized instruction (Lin & Kim, 2013). Modeling (Bandura, 1986; Schunk, 2008) determines the development of social learning environment involving the factors of people, behaviors, and environments, and thus formed a theoretical framework of this study. A peer modeling process perceived as the environmental factor can overcome the barriers caused by the lack of time and required knowledge for personalized instruction. Appropriate use of open educational resources viewed as the behavioral and environmental factors can resolve the concern caused by the lack of continuous support including a supportive culture of openness for
reuse and reproduction and the growing availability of resources. Students enrolled in introductory statistics courses tend to have different prior knowledge and background for statistics learning. The personal factors influencing students' statistic learning include, but not limited to prior knowledge (Leppink, Broers, Imbos, van der Vleuten, & Berger, 2012), technical access (Neumann & Hood, 2009), competence (Boyle et al., 2014), motivation (Ejei, Weisani, Siadat, & Khezriazar, 2011; Lavasani, Weisani, & Ejei, 2011), and statistics learning anxiety (Lavasani, et al., 2011; Macher, Paechter, Papousek, & Ruggeri, 2012). Accordingly, a developmental model to support personalized instruction as well as to promote personalized learning was proposed. The purpose of this study was to evaluate if triadic reciprocal interaction among personal, behavioral, and environmental factors occurred in the developmental model, and thus promote personalized statistics learning in terms of improved achievement, increased motivation, and decreased statistics learning anxiety.

INDEX WORDS: Personalized Learning, Personalized Instruction, Introductory Statistics, Peer Modeling, Open Educational Resources
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DEDICATION

This dissertation is dedicated to my beloved family in Yilan, Taiwan, teachers, colleagues, and friends. Your love, encouragement, and support provided me the power to overcome each barrier in this journey.
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CHAPTER 1
INTRODUCTION

The classrooms in higher education are heterogeneous. Most classrooms in college, for example, are composed of students with different experiences as well as different achievement levels (Ferguson, 2001). Consequently, individual students may gain different levels of success and satisfaction in their classes (Carroll, 1975; Keefe & Jenkins, 2008). Teachers tend to contextualize their teaching practices, which aim to accommodate individual student needs, in order to maximize capabilities of students, minimize differences, and effectively enhance student learning (Keefe & Jenkins, 2008; Sands & Barker, 2004). Thus, personalization has played an important role among students and teachers in meeting their individual needs and has been considered necessary in higher education. College and graduate-level students enrolled in introductory statistics courses, such as Analysis of Variance (ANOVA) and applied correlation and regression, generally have different prior knowledge and backgrounds regarding these courses. Students enrolled in introductory statistics courses may experience various barriers due to gaps in existing knowledge and current skills. Therefore, personalization in teaching and learning is particularly important for these students who typically focus their attention only on content they deem essential.

Conceptual Framework of the Study

Every student is unique in the classroom. Individual differences among students can bring different ways of communication and interaction with the same objects or people. These differences can implicitly relate to the psychological states, including, but not limited to
affection, interest, and motivation, and influence one's decision-making and problem-solving processes. Dewey (1929) wrote that schools gradually helped children learn the meaning of given activities and then related these activities to themselves. However, the same activity may lead to various meanings among individual students, which can yield positive effects, negative effects or no effects at all. One learning solution cannot absolutely meet all learner needs. Therefore, the concept of personalization will be used to describe ways to effectively accommodate individual needs in learning and teaching.

**Personalized Learning and Instruction**

Personalization addresses the importance of individual needs and ways to effectively meet their needs. Personalization in education is conceptually classified into personalized learning and personalized instruction. Personalized learning refers to students’ unique ways of learning determined by their individual needs (Carolan & Guinn, 2007; Carroll, 1975; Johnson, Adams, & Cummins, 2012; Keefe & Jenkins, 2008; Miller, 2010). Personalized learning in the classroom allows for student flexibility as well as reduce the cognitive load in learning processes, and in turn, performance can be enhanced as well (Chen, 2007). Thus, personalized learning is viewed necessary to effectively support individual students per a diversity of needs and differences.

Instruction can be implemented in a personalized way to facilitate individual student learning. Personalized instruction refers to teaching practices that aim to meet individual student needs (Keefe & Jenkins, 2008). Although personalized instruction considers student aptitudes, diminishes the discrepancies and limitations, and improves student abilities to learn, it does not simply mean instructors teach everything in several different ways (Carolan & Guinn, 2007; Sands & Barker, 2004). Meaningful learning paths can be further determined through
personalized instruction which emphasizes a collective decision-making process and interaction among teachers and students (Anderson, 2007; Dolog, et al., 2008; Hamdan & Mattarima, 2012; Jenkins & Keefe, 2001; King-Shaver, 2008; Levy, 2008; Scigliano & Hipsky, 2010; Tobin & McInnes, 2008; Zajac, 2009). Thus, personalized instruction can specifically help individual students learn in a personalized way.

**Implementation of Personalization**

Individual differences and needs reflect a diversity of thoughts and behaviors among students. Personalization can be viewed necessary to explicitly minimize these differences and meet individual needs among learners. However, personalization also brings the concerns to teachers. There are three concerns which likely cause barriers for teachers to implement personalized instruction: 1) time, 2) continuous support, and 3) knowledge about personalized instruction (Lin & Kim, 2013). Effectively implementing peer-assisted learning and teaching through a modeling process is considered helpful to overcome the barriers in time and knowledge required for personalized instruction. In addition, appropriately using open educational resources can help resolve concern in the continuous support in implementing personalized instruction. Open resources which can be only used for the educational purpose are defined as open educational resources (UNESCO, 2002). Open educational resources have several advantages, including openness and multiple choice, which can respectively provide a supportive culture as well as the growing availability of resources.

**Modeling and triadic reciprocal interaction.** Modeling refers to the action that learners observe in other people or environments and pattern their behaviors, strategies, beliefs, thoughts, etc. Individual learners tend to acquire the knowledge or skills from models that they consider helpful and appropriate. Those models may come from various exemplars such teachers,
teaching assistants, and competent peers. Modeling can be used in a variety of contexts and help acquire knowledge and skills such as increasing the use of protective equipment in the workplace (Olson, Grosshuesch, Schmidt, Gray, & Wipfli, 2009), selecting effective learning strategy (McGivern, Levin, Ghatala, & Pressley, 1986), improving self-regulation skills in writing (Zimmerman & Kitsantas, 2002). Modeling effects can enhance the triadic reciprocal interaction caused by the factors of behaviors, environments and people, which are used to form a social learning environment (Bandura, 1986; Schunk, 2008).

Peer modeling specifically addresses the modeling process and interaction among peers. Peer modeling can be served as either a mastery or coping model (Schunk & Hanson, 1985, 1987; Schunk, Hanson, & Cox, 1987; Schunk & Zimmerman, 1995). Some modeling strategies such as verbal modeling, coping modeling, and cognitive modeling can also be applied in a peer modeling process (Schunk & Hanson, 1985; Schunk, et al., 1987; Schunk & Zimmerman, 1995).

**Peer-assisted learning and teaching.** A peer modeling process can facilitate skills development in motor, cognitive, social, and self-regulation skills, and thus improve student performance and achievement (Schunk & Hanson, 1985, 1987; Schunk, Hanson, & Cox, 1987; Schunk & Zimmerman, 1995). Consequently, a peer-assisted learning and teaching environment can be developed. The two primary advantages in such a peer-assisted learning and teaching environment are: 1) to stimulate cognitive development as peers work as teachers, and 2) to improve learners' persistence and orientation in motivation (Rohrbeck, Ginsburg-Block, Fantuzzo, & Miller, 2003). Thus, peer-assisted learning and teaching can be supported through a peer modeling process.

**Appropriate use of open educational resources.** Open educational resources are defined as resources used for educational purpose only and enabled by information and
communication technologies (UNESCO, 2002). The features of openness and multiple choices in open educational resources can overcome the barrier of continuous support in implementing personalized instruction. Openness provides a supportive culture and environment that users are not concerned about the violation of copyright laws for reusing and reproducing open educational resources (Caswell, Henson, Jensen, & Wiley, 2008; Clements & Pawlowski, 2012; Olcott Jr., 2012; Rogerson-Revell, 2007; Wiley & Gurrell, 2009). Multiple choices allow users to have alternative options in selecting resources and make learning adaptive (D'Antoni, 2009; Olcott Jr., 2012). Therefore, the appropriate ways to use open educational resources, which involve four levels of openness (Hilton III, Wiley, Stein, & Johnson, 2010), include reuse, redistribution, revision, and remix. These four ways can represent an effective approach to customize open educational resources as well as to promote personalized learning.

**Research Purposes**

The purpose of this study was to overcome the barriers that teachers implement personalized instruction and to support personalized learning through a peer modeling process and appropriate use of open educational resources in an introductory statistics course. The resulting effects can identify if there is any triadic reciprocal interaction among individual learning needs (personal factor), a peer modeling process (environmental factor), and appropriate use (behavioral factor) of open educational resources (environmental factor) to promote personalized learning in terms of improved mastery, increased motivation, and reduced statistics learning anxiety.

**Dissertation Overview**

This dissertation encompasses three ready to be published manuscripts. These three manuscripts report a series of studies conducted since August, 2013.
Chapter 2, *Personalizing Statistics Learning with Peer assistance in an Open Learning Environment*, delineates the theoretical foundation which develops the developmental model for personalized statistics learning and instruction. This paper started with a review of literature emphasizing personalization in education. Then, the paper described two solutions for the effective promotion of personalization: a peer modeling process and appropriate use of open educational resources. Based on triadic reciprocal interaction in social cognitive theory, this paper introduced the design of the developmental model for personalized statistics learning and instruction. Also, this paper discussed the application of open educational resources and their potential for personalized learning.

Chapter 3, *Personalized Statistics Learning in an Open Learning Environment through a Modeling Process*, reports the first evaluation study of the developmental model for personalized statistics learning and instruction. Extending the developmental model described in chapter 2, this chapter addressed triadic reciprocal interaction among individual learning needs, a modeling process in peer and non-peer settings, and the appropriate use of open educational resources. The purpose of this study was to develop an open learning environment to promote student personalized statistics learning through peer and non-peer modeling processes and appropriate use of open educational resources. The interrelationship among individual learning needs, peer and non-peer modeling processes, and appropriate use of open educational resources could be identified. Also, such effects on student achievement were investigated.

Chapter 4, *The Effect of Open Educational Resources on Motivation and Anxiety in Promoting Personalized Statistics Learning*, elaborated the second evaluation study validating the effectiveness of the proposed developmental model. In particular, student motivation and anxiety for statistics learning are perceived as two main determinants affecting student statistics
learning achievement (Ejei, Weisani, Siadat, & Khezriazar, 2011; Lavasani, Weisani, & Ejei, 2011; Macher, Paechter, Papousek, & Ruggeri, 2012). The purpose of the study specifically assessed how student motivation and statistics learning anxiety could relate to the use of open educational resources. Therefore, the relationship among student motivation, statistics learning anxiety, and their use of open educational resources could be identified.

Finally, Chapter 5 summarized the relevant key ideas among three manuscripts. Future research delineated the effectiveness and modified factors influencing the developmental model. Also, this chapter concluded with implications as well as suggestions for future studies.

**Research Questions**

Implementing a peer modeling process and appropriately using open educational resources were proposed to effectively resolve the three concerns in implementing personalized instruction. Furthermore, the triadic reciprocal interaction among the factors of people, behaviors, and environments essential for social learning environment can be enhanced and used to promote personalized statistics learning. However, several questions still remain unanswered. There is a need for a better understanding of how individual learning needs can relate to a peer modeling process and the use of open educational resources, and thus support personalized statistics learning. In particular, the promotion of personalized statistics learning can achieve three anticipated outcomes: an improvement of mastery, an increase of motivation, and a decrease of learning anxiety toward introductory statistics. Therefore, the following questions are used to guide this research study:

1. What is the effect of technical access and prior knowledge on achievement while implementing peer modeling in an open learning environment?
2. What is the effect of competence, motivation, and statistics learning anxiety on achievement while implementing peer modeling in an open learning environment?

3. What factors among learning needs, peer and non-peer modeling processes, and the appropriate use of open educational resources can effectively promote personalized statistics learning?

4. What is the overall relationship among learning needs, peer and non-peer modeling processes, and the appropriate use of open educational resources?

5. What are the effects of learning needs, peer and non-peer modeling processes, and the appropriate use of open educational resources on achievement in promoting personalized statistics learning?

6. What is the relationship between student motivation for statistics learning and the appropriate use of open educational resources?

7. What is the relationship between student statistics learning anxiety and the appropriate use of open educational resources?
References


CHAPTER 2
PERSONALIZING STATISTICS LEARNING WITH PEER ASSISTANCE IN AN OPEN LEARNING ENVIRONMENT

1 Lin, Y. and Branch, R. Submitted to *Educational Technology and Research Development*, 11/28/2014
Abstract

Personalization in education, which plays an important role in supporting individual student learning, is often classified as personalized learning and personalized instruction. Personalized learning refers to a student's unique way of learning as determined by their needs (Carolan & Guinn, 2007; Carroll, 1975; Johnson, Adams, & Cummins, 2012; Keefe & Jenkins, 2008; Miller, 2010). Teachers tend to increase their teaching effectiveness by addressing individual student needs through personalized instruction. However, three constraints, time, continuous support, and the required knowledge for personalized instruction, often prevent teachers from implementing it (Authors, 2013). The purpose of this study was to propose the developmental model of personalized learning and instruction, Peer-assistance-to-Personalization (P2P), and to identify the relationship among individual learning needs, a peer modeling process, and student achievement in an open learning environment. The resulting effects in the P2P model can examine the triadic reciprocal interaction to promote personalized learning. Thus, individual students can achieve mastery, improve motivation, and decrease their statistics learning anxiety.

Keywords: Personalized Learning, Personalized Instruction, Introductory Statistics, Peer Modeling, Open Educational Resources, Statistics Learning Anxiety
Personalizing Statistics Learning with Peer assistance in an Open Learning Environment

Students in higher education have various needs that represent a diversity of thoughts and may not be simply met by a single learning solution. Ferguson (2001) claims that most college classrooms are composed of students with different experiences as well as a variety of achievement levels that often challenge learning in a group setting. One of the effective strategies for such situations where students think and act differently tend to emphasize the way to personalize student experiences. Personalization allows individual students with different interests and preferences to gain optimal levels of success and satisfaction in their classes (Carroll, 1975; Keefe & Jenkins, 2008). Teachers contextualize their teaching methods in order to accommodate student needs so as to maximize their capabilities, minimize differences, and effectively enhance their learning (Keefe & Jenkins, 2008; Sands & Barker, 2004). However, the constraints of time, continuous support, and the required knowledge often prevent teachers from implementing personalized instruction (Authors, 2013). Accordingly, effective ways to personalize instruction, especially for complex subjects such as statistics, should provide opportunities for sufficient time, continuous support, and the required knowledge construction, and thus promote personalized learning.

The purpose of this study was to propose the developmental model of personalized learning and instruction, Peer-assistance-to-Personalization (P2P), and to identify the relationship among individual learning needs, a peer modeling process, and student achievement in an open learning environment. The resulting effects can also examine the triadic reciprocal interaction in the P2P model and help individual students effectively achieve mastery, increase motivation, and decrease their statistics learning anxiety.
Personalization in Education

Every student is unique in the classroom. Individual differences among students mean a variety of communication forms and interactions with other people within various learning environments. Individual differences can implicitly relate to the psychological states, including, but not limited to affection, interest, and motivation, and thus influence a student's decision-making and problem-solving processes. Dewey (1929) wrote that schools gradually helped children learn the meaning of given activities and then related these activities to themselves. However, the same activity may lead to various meanings which can yield positive, negative, or no effects at all. A single learning solution cannot meet all learner needs. Personalization addresses the importance of individual needs and ways to satisfy these needs. The developmental model derived in this study is formed from the two basic concepts of personalized learning and personalized instruction.

Personalized Learning

Individual students have their own ways of learning. Personalized learning refers to the unique ways of learning determined by individual student needs (Carolan & Guinn, 2007; Carroll, 1975; Johnson, et al., 2012; Keefe & Jenkins, 2008; Miller, 2010). Students bring their own interests and preferences to class and gain different levels of success and satisfaction (Carroll, 1975; Keefe & Jenkins, 2008). Personalized learning in the classroom allows for student flexibility. Students are able to set their own goals and achieve them at their own pace (Smith & Throne, 2009). Students can participate in class autonomously; for example, students can choose to work individually, in pairs or in small groups. Flexibility enables students to adopt alternative learning paths if the existing one cannot meet their needs (Chen, 2007). Flexibility can also reduce the cognitive load in a learning process, and in turn, performance can be
enhanced (Berghel, 1997; Borchers, Herlocker, Konstan, & Reidl, 1998; Chen, 2007). Thus, personalized learning is viewed as necessary to effectively support individual students with a diversity of needs and differences.

**Personalized Instruction**

Instruction can be implemented in a personalized way to facilitate individual student learning. Personalized instruction refers to teaching practices that aim to accommodate individual student needs (Keefe & Jenkins, 2008). Teachers can conduct an initial screening based on student prior experiences and academic achievement, and then decide which learning activities are relevant and useful (Dunn & Dunn, 1978; Fok & Ip, 2006; Klasnja-Milicevic, Vesin, Ivanovic, & Budimac, 2011). Although personalized instruction considers student aptitudes, diminishes their discrepancies and limitations, and improves their ability to learn, it does not simply mean that teachers teach everything in several different ways (Carolan & Guinn, 2007; Sands & Barker, 2004). Personalized and meaningful learning paths can be further determined through a collective decision-making process and interaction among teachers and students (Anderson, 2007; Dolog, et al., 2008; Hamdan & Mattarima, 2012; Jenkins & Keefe, 2001; King-Shaver, 2008; Levy, 2008; Scigliano & Hipsky, 2010; Tobin & McInnes, 2008; Zajac, 2009).

However, three constraints may likely cause barriers for teachers to implement personalized instruction: 1) lack of time, 2) lack of continuous support, and 3) lack of the required knowledge for personalized instruction (Authors, 2013). The time constraint on multiple instructional responsibilities may cause teachers to hesitate to implement personalized instruction into their classrooms (Carolan & Guinn, 2007). Personalized instruction can also be perceived as a burden if there is no continuous support which includes a supportive culture as well as the
constant availability of relevant resources (Carolan & Guinn, 2007; Miller, 2010). Teachers are not likely to accurately identify individual needs and guide them to relevant knowledge and skills if teachers do not have sufficient knowledge about personalized instruction.

**Implementation of Educational Personalization**

The implementation of educational personalization initially considers individual needs in learning and teaching. Peer-assisted learning and teaching and appropriate use of open educational resources are viewed as the two effective ways to resolve the three constraints that prevent teachers from implementing personalized instruction. Peer-assisted learning and teaching is formed through a peer modeling process in which students master their own learning by observing and interacting with peers. As peers work together to accomplish various learning tasks, they can provide individual feedback and comments to their peers. This can work as a way to overcome the barriers of time. Peer-assisted learning and teaching through a peer modeling process also considers individual attributes such as age, gender, and background. Such process can assist to construct new knowledge required for personalized instruction. Thus, extensive support provided by peers can help students maintain high learning engagement (Stenhoff, Benjamin, & Benjamin, 2007). Appropriate use of open educational resources can be viewed as necessary to continually support personalized instruction. Particularly, a growing availability of open educational resources facilitate the implementation of educational personalization. Accordingly, this paper proposed the developmental model of personalized learning and instruction, Peer-assistance-to-Personalization, which considers individual needs, a peer modeling process, and appropriate use of open educational resources (see Figure 2.1). The three elements in this developmental model align with the three factors that Bandura (1986) addressed in social cognitive theory: personal, behavioral, and environmental. Bandura (1986) emphasized
that the way people think, believe, and feel in the environment can influence how they behave. The interplay among these three factors can cause triadic reciprocal interaction in terms of human learning (Bandura, 1986). In particular, such interaction can be facilitated by observing and interacting with models and lead to the change of performance and achievement (Schunk, 2008).

Figure 2.1. Development Model of Peer-assistance-to-Personalization

The Peer-assistance-to-Personalization specifically addresses its application in the context of introductory statistics learning and uses a systematic approach that centers on effective instructional strategies for individual learning (Author, 2009; Gagne, Wager, Golas, & Keller, 2005). The personal factor indicates that individual needs in learning and teaching should be identified. Individual needs for personalized learning involve two levels: practical and psychological. Individual practical needs are shown by examining student technical access and prior knowledge about basic statistics. The psychological needs are identified by examining
student competence, motivation, and learning anxiety in statistics. The needs for personalized instruction mainly indicate the three constraints why teachers hesitate to implement personalized instruction: time, continuous support, and the required knowledge for personalized instruction. Behavior and environmental factors in this development model respectively emphasize the ways to effectively implement a peer modeling process and to appropriately use open educational resources.

**Individual Learning Needs**

Individual needs for personalized learning in the context of statistics learning are identified in five aspects: technical access, prior knowledge, competence, motivation, and learning anxiety in statistics. These needs represent the diverse and unique ways that students perceive and react toward the statistics learning environment.

**Technical access.** Technical access can determine how students apply tools and resources in dealing with learning tasks. The 24-hour access to laptops, for example, aids students to effectively develop their research and writing skills as they deal with problem-solving tasks (Lowther, Ross, & Morrison, 2003). Student achievement can be significantly improved if students have the full technical access (Lowther, et al., 2003).

**Prior knowledge.** Prior knowledge in a certain subject can influence new knowledge acquisition and transformation of cognitive skills. Learners tend to be more confident in acquiring knowledge if they have a higher level of prior knowledge (Lim, Reiser, & Olina, 2009). The auditory-only presentation can be viewed as a better way for learners with a high level of prior knowledge to master learning contents, while learners with a low level tend to prefer an audio-visual way (Leslie, Low, Jin, & Sweller, 2012). Additionally, various levels of
prior knowledge can decide the way to attain mastery of knowledge, and thus influence student learning achievement (Leslie, et al., 2012; Lim, et al., 2009).

**Competence.** Competence is the human capacity to effectively interact with the environment and further understand how the reciprocal effects between people and environment can be brought together (Deci & Moller, 2005). Competence is perceived as a by-product in learning (Deci & Moller, 2005) and gradually develops as students engage in learning activities that are considered fun and interesting. Student performance and achievement can relate to individual competence and lead to various ways to use cognitive tools (Liu & Bera, 2005). For example, students who have good performance and high achievement tend to feel competent and prefer using cognitive tools in productive ways such as content exploration. Conversely, students with lower performance may feel less competent and apply cognitive tools in recognizing hypotheses and assumptions (Liu & Bera, 2005). Thus, competence can be an important indicator about the way a student perceives his or her ability to construct new knowledge.

**Motivation.** As learners prefer learning in a certain way and engage in a given activity, their motivation is emerged and prompts them to behave. Motivation can be classified as intrinsic and extrinsic motivation, which respectively indicates learning behaviors as a result of interests and enjoyment (Deci, 1975; Weibel, Rost, & Osterloh, 2007), or the other desirable outcomes (Ryan & Deci, 2000). In particular, intrinsic motivation is considered vital to result in high engagement and positive learning achievement (Vansteenkiste, Lens, & Deci, 2006). The factors that influence how students are intrinsically motivated to behave include, but are not limited to interests (Ryan & Deci, 2009; Sansone, Smith, Thoman, & MacNamara, 2012; Schiefele, 2009), enjoyment (Lesser et al., 2013; Ryan & Deci, 2000, 2009), and perceived values or usefulness (Schunk, 2008; Wigfield & Eccles, 1992). Students tend to perform better if
they find the materials in class interesting (Gal & Ginsburg, 1994; Ryan & Deci, 2009). Students with higher interests tend to display a higher engagement level (Sansone, Fraughton, Zachary, Butner, & Heiner, 2011). Enjoyment and fun can also refer to an affective or emotional state that learners can feel in their own learning and lead to the emergence of intrinsic motivation (Ryan & Deci, 2009). Students can sustain their motivation in a learning process if they have a higher level of enjoyment. The values toward a learning activity and performance can be developed after students finish their learning tasks in a given situation. These values can include task-related and achievement-related values (Atkinson, 1957; Schunk, 2008; Wigfield & Eccles, 1992). Students generally complete learning tasks to achieve their goals. Different goals may result in different expectations and bring various perceptions in values and usefulness toward learning tasks (Schunk, 2008). Thus, goals such as pursuing the mastery of contents or finishing the coursework, can also affect student achievement-related values, and the way they motivate themselves and consequently behave.

**Learning anxiety in statistics.** Hanna, Shevlin, and Dempster (2008) indicated that undergraduate students in college perceived statistics as the least favorite subject. Some students tend to drop or are likely to postpone taking statistics courses. Around 80% of students in a statistics course may experience various levels of statistics learning anxiety (Hanna, et al., 2008). Statistics learning anxiety has been defined as a certain type of perception that makes students anxious, brings low motivation in learning statistics (Bell, 2003; Onwuegbuzie, 2000; Pan & Tang, 2004, 2005), and leads poor achievement (Macher, Paechter, Papousek, & Ruggeri, 2012). Several factors which likely cause statistics learning anxiety include gender (Bui & Alfaro, 2011; Hsiao & Chiang, 2011), ethnicity (Bui & Alfaro, 2011), self-perception (Onwuegbuzie, 2000; Pan & Tang, 2005), and age (Bell, 2003; Bui & Alfaro, 2011; Pan & Tang, 2004). Generally,
statistics learning anxiety can occur in six aspects: 1) anxiety in tests and exams, 2) interpretation anxiety, 3) worth of statistics, 4) fear of asking for help toward statistics, 5) fear of statistics teachers, and 6) computational self-concept anxiety (Hanna, et al., 2008). These six aspects of anxiety specifically elaborate how students feel about statistics learning and how statistics teachers can guide them with sufficient support.

**Peer Modeling Process**

Modeling refers to the action that learners observe in other people or environments and pattern their behaviors, strategies, beliefs, and thoughts. The changes in behaviors, cognition, emotion and affect, self-perceiving efficacy, and performance are made and improved by observing models (Bandura, 1965; Schunk, 2008; Wouters, Tabbers, & Paas, 2007). A modeling process can lead to triadic reciprocal interaction among three factors: personal, behavioral, and environmental (Bandura, 1986). Peer modeling refers to the interaction and modeling behaviors occurred among peers. Peer modeling can facilitate skills development in motor, cognitive, social, and self-regulation skills and improve student performance and achievement (Schunk & Hanson, 1985, 1987; Schunk, Hanson, & Cox, 1987; Schunk & Zimmerman, 1995). For example, teachers encourage peer modeling by providing high-quality feedback and comments in writing samples with students who need some improvement in their writing skills (Liu & Lin, 2007). Some attributes among peers such as age, gender, model competence, number of models, and background experiences can relate to peer modeling in ways that lead to behavior changes (Gog & Rummel, 2010; Schunk, 1987). Thus, peer-assisted learning and teaching can be formed through a peer modeling process. There are two primary advantages in a peer-assisted learning and teaching environment: 1) stimulating cognitive development among peers, and 2) improving persistence and orientation in learning motivation (Rohrbeck, Ginsburg-Block, Fantuzzo, &
Miller, 2003). Accordingly, a peer-assisted learning and teaching environment can enhance student achievement.

Some modeling types such as verbal modeling (Bandura, 1986), coping modeling (Schunk & Hanson, 1985), and mastery modeling (Schunk & Hanson, 1985) represent the different strategies applied in a peer modeling process such as discussion, demonstration, member check, and consultation with teachers or exemplary people. Verbal modeling allows learners to verbalize their thoughts and strategies to solve problems (Bandura, 1986). The strategy to represent verbal modeling is discussion. Coping modeling initially demonstrates fears and deficiencies to learners and lets them experience both failures and success in a problem-solving context (Schunk & Zimmerman, 1997; Zimmerman & Kitsantas, 2002). Learners can gradually improve their behaviors and performance in this process through demonstration and member check. Mastery modeling demonstrates that models provide perfect behaviors without any errors (Schunk & Hanson, 1985; Schunk & Zimmerman, 1997). Consultation with teachers or exemplary people can be perceived as a way to support mastery modeling.

**Appropriate Use of Open Educational Resources**

The Internet offers easy access to open resources such as Wikipedia, YouTube, and Flicker, which are mostly free. The educational use of open resources, defined as open educational resources (OERs), is enabled by information and communication technologies and adapted for noncommercial purposes (UNESCO, 2002). Approximately 50% of higher education institutions in the United States have used open educational resources, especially in online education (Allen & Seaman, 2012). Open educational resources have been applied in a variety of contexts (Clements & Pawlowski, 2012; Hockings, Breet, & Terentjevs, 2012; Lane & McAndrew, 2010; Olcott Jr., 2012), and broadly cover a variety of materials such as textbooks,
videos, and animations. (Clements & Pawlowski, 2012; D'Antoni, 2009; Lane & McAndrew, 2010). There are five salient advantages that open educational resources bring to education: 1) openness, 2) multiple choices, 3) shareability and reusability, 4) less duplication, and 5) preservation and dissemination.

Openness allows users to freely share, exchange, and reproduce open educational resources without violating copyright laws (Caswell, Henson, Jensen, & Wiley, 2008; Clements & Pawlowski, 2012; Olcott Jr., 2012; Rogerson-Revell, 2007; Wiley & Gurrell, 2009). Multiple choices enable learners to remediate or enrich their learning experiences with alternative options (D'Antoni, 2009; Olcott Jr., 2012). Shareability and reusability address the knowledge-sharing concept as users share their work with others (Caswell, et al., 2008; Hichang, MeiHui, & Siyoung, 2010; Olcott Jr., 2012; Rogerson-Revell, 2007). Reusability in open educational resources also leads to less duplication and makes indigenous open education resources well preserved and disseminated (Olcott Jr., 2012; Rogerson-Revell, 2007). These five advantages of open educational resources emerge in four different ways, which also represent the four levels of openness, to effectively use open educational resources: reuse, redistribution, revision, remix. (Hilton III, Wiley, Stein, & Johnson, 2010). Reuse indicates that users are allowed to reuse entire or partial open educational resources. Redistribution lets users legally share these resources with other users. In addition, users can be allowed to modify them in revision. Remix indicates that users can combine various resources together for new purposes. These four ways make open educational resources more adapted to some specific needs (Hilton III, et al., 2010) and can be applied to a personalized learning environment.
Research Questions

Identifying individual needs, implementing a peer modeling process, and appropriately using open educational resources can effectively promote personalized learning. Furthermore, the triadic reciprocal interaction among personal, behavioral, and environmental factors can be enhanced. However, several questions still remain unanswered. There is a need for a better understanding of how individual practical and psychological needs in learning can relate to a peer modeling process in an open learning environment, and thus promote personalized learning in terms of student achievement. Therefore, the following questions guided this research study:

1. What is the effect of technical access and prior knowledge on achievement while implementing peer modeling in an open learning environment?

2. What is the effect of competence, motivation, and statistics learning anxiety on achievement while implementing peer modeling in an open learning environment?

Methods

Participants

The participants in this study were students who were enrolled in introductory statistics courses at a university located in the southeastern United States. These participants came from different programs or departments. There were 113 participants in total. Eighty percent of participants were between 18 to 30 years old. Fourteen percent of participants were between 31 to 40. The remaining 6% were participants over 40. All participants in this study were likely pursuing an undergraduate or graduate degree at the time this study was being conducted. There was a various level of prior knowledge among students. The mean score of prior knowledge is 54.37 (SD= 19.63).
**Intervention**

There were two interventions in this study. The first intervention was that the students who were enrolled in introductory statistics courses were encouraged to work with peers to complete their homework. Some peer-assisted learning strategies such as member check, discussion, demonstration were promoted in class. Those strategies and their definitions were introduced in the first week of class. Member check was defined as the action that students checked the accuracy of answers after they completed homework without doing any further discussion yet. If students discussed any questions in their homework, modeling strategy used for homework completion should includ discussion. Students, on the one hand, likely discussed questions with peers in a peer modeling setting. On the other hand, discussion about homework might involve with instructors and teaching assistants in a non-peer modeling environment. Demonstration was defined as the action that students or non-peers such as instructors or teaching assistants showed a step-by-step calculation or presentation to use statistics software package to solve problems in homework. Consultation with instructors and teaching assistants mainly included the office hour sessions in which students asked questions about homework. Those strategies were also presented to students in the online assignment dropbox. Thus, students can accurately identify the peer and non-peer modeling strategies applied in every homework completion. The second intervention was the appropriate use of open educational resources. These open educational resources used in class were customized based on some specific purposes such as remediating student prior knowledge and working as supplements. The four ways to appropriately use open educational resources involves reuse, redistribution, revision, and remix. One of two researchers in this study helped select appropriate open educational resources from these 12 repository websites based on the weekly topic. The selected
resources were shared with the instructors to reuse or reproduce. For example, some simulations elaborating the concept of R Square were introduced to the entire class during the lecture and redistributed to students. These simulations provided an easy way for students to learn the abstract concept about R Square. In addition, the instructors revised couple of items in online assessment and combined them into homework. This can be perceived as a way to revise and remix open educational resources. Open educational resources provided by instructors were posted in the learning management system. So students can access these resources anytime and anywhere outside of the class. Students were likely to reuse these resources as they worked on their homework or prepared for exams. Students also looked for other open educational resources to clarify their unclear statistics concepts during the homework completion. In this way, these open educational resources were primarily reused and redistributed to other peers.

**Data Collection Procedures**

The data were collected during a 16-18 week period. There were three sessions to collect data. Individual needs examined by technical access, prior knowledge, competence, motivation, and learning anxiety in statistics were collected in the beginning of data collection. The ways that students worked collaboratively, and relevant learning strategies applied such as discussion, member check, and demonstration were collected as students submitted their homework through the entire semester. Individual scores in homework and examinations were collected at the end of the semester.

**Data Collection Tools**

*Learning characteristics survey.* This survey was used to assess student technical access, competence, motivation, and learning anxiety in statistics.
Technical access. The availability and access to hardware, statistics software packages, and Internet were investigated. For example, participants were asked if they have their own laptop or desktop to help them finish the homework.” There were 3 items in total.

Competence. The Perceived Competence Scale was used to identify student feelings of competence in a learning activity or in different contexts (Williams & Deci, 1996; Williams et al., 2004; Williams et al., 2006). There were 4 items in total with the reported internal consistency from 0.8 to 0.9 (Williams & Deci, 1996; Williams, Freedman, & Deci, 1998; Williams et al., 2006; Williams, McGregor, Zeldman, Freedman, & Deci, 2004).

Motivation. The Intrinsic Motivation Inventory (Ryan, 1982) was used to assess student perception about a given learning activity. Only the sub-scales in this inventory such as interest, enjoyment, perceived value, and usefulness were used in this study. There were 11 items in total with the reported internal consistency from 0.8 to 0.9 (McAuley, Duncan, & Tammen, 1989; Seybold, Braunbeck, & Randler, 2014).

Learning anxiety in statistics. The Statistical Anxiety Rating Scale (Cruise, Cash, & Bolton, 1985) was acknowledged as the most widely used instrument in examining statistics anxiety (Hanna, et al., 2008). Some items in the original scale have been revised and removed based on the context in this study. Twenty-two items in total were included and specified six aspects of anxiety: 1) worth of statistics, 2) interpretation anxiety, 3) test and class anxiety, 4) computational self-concept, 5) fear of asking for help, and 6) fear of statistics teachers. Reported internal consistency for the items was from 0.83 to 0.94 (Hanna, et al., 2008).

Prior knowledge test. Student prior knowledge was evaluated using the prior knowledge test. There were 10 items in total (Cronbach α=.65). These 10 items covered the six topics of
basic statistic: 1) distribution graph and normal distribution, 2) inference and probability, 3) correlation and regression, 4) two-way variables, 5) sampling and exploring data, 6) experiment.

**Cover-page information sheet.** Peer modeling process was examined using the cover-page information sheet. The average frequency that students worked collaboratively and relevant strategies they applied to complete homework such as member check, discussion, demonstration, and others specified by participants were calculated. There were 4 items in total.

**Homework and examinations.** Student achievement was measured using student scores on their homework and examinations. The possible scores for homework and examinations ranged from 0 to 100.

**Data Analysis**

The data were analyzed by using structural equation modeling in order to identify the direct and indirect effects among individual needs, a peer modeling process, and student achievement. Student mean scores in homework and examinations respectively worked as the outcome variables. Technical access, prior knowledge, and competence were observed variables. The three latent factors included peer modeling, motivation, and learning anxiety in statistics. The hypotheses are presented in Table 2.1. The path diagram for research questions 1 and 2 are separately outlined in Figure 2.2 and 2.3.

![Path Diagram for Research Question 1](image)

*Figure 2.2. Path Diagram for Research Question 1*
Table 2.1

*Research Questions and Hypotheses*

<table>
<thead>
<tr>
<th>Research Question</th>
<th>Hypotheses</th>
</tr>
</thead>
</table>
| 1. What is the effect of technical access and prior knowledge on achievement while implementing peer modeling in an open learning environment? | Hypothesis 1-1: Student achievement is directly influenced by student prior knowledge.  
Hypothesis 1-2: Student achievement is directly influenced by the technical access students have in learning introductory statistics.  
Hypothesis 1-3: Student achievement is directly influenced by the peer modeling students apply in introductory statistics courses. |
| 2. What is the effect of competence, motivation, and statistics learning anxiety on achievement while implementing peer modeling in an open learning environment? | Hypothesis 2-1: Student achievement is directly influenced by the peer modeling students apply in introductory statistics courses.  
Hypothesis 2-2: Student achievement is directly influenced by statistics learning anxiety.  
Hypothesis 2-3: Student achievement is indirectly influenced by statistics learning anxiety, as motivation has direct effects on student achievement.  
Hypothesis 2-4: Student achievement is directly influenced by motivation students have in introductory statistics courses.  
Hypothesis 2-5: Student achievement is directly influenced by competence students have in introductory statistics courses. |
Results

Descriptive statistics for all variables used in this study are presented in Table 2.2. A summary of the results for each hypothesis is reported below.

Table 2.2

Descriptive Statistics for all Variables Used in this Study

<table>
<thead>
<tr>
<th>Variables</th>
<th>M (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>homework score</td>
<td>92.64 (9.68)</td>
</tr>
<tr>
<td>exam score</td>
<td>88.98 (9.80)</td>
</tr>
<tr>
<td>technical access</td>
<td>2.65 (0.50)</td>
</tr>
<tr>
<td>prior knowledge</td>
<td>54.37 (19.63)</td>
</tr>
<tr>
<td>interest</td>
<td>3.44 (0.82)</td>
</tr>
<tr>
<td>enjoyment</td>
<td>3.09 (1.02)</td>
</tr>
<tr>
<td>usefulness</td>
<td>4.16 (0.88)</td>
</tr>
<tr>
<td>value</td>
<td>4.00 (0.89)</td>
</tr>
<tr>
<td>worth of statistics</td>
<td>1.93 (0.64)</td>
</tr>
<tr>
<td>interpretation anxiety</td>
<td>2.77 (0.85)</td>
</tr>
<tr>
<td>test and class anxiety</td>
<td>3.22 (1.14)</td>
</tr>
<tr>
<td>computational self-concept</td>
<td>2.24 (0.89)</td>
</tr>
<tr>
<td>fear of asking for help</td>
<td>2.38 (1.19)</td>
</tr>
<tr>
<td>fear of statistics teachers</td>
<td>2.59 (1.09)</td>
</tr>
<tr>
<td>competence</td>
<td>3.90 (0.79)</td>
</tr>
<tr>
<td>collaborative work</td>
<td>0.34 (0.38)</td>
</tr>
<tr>
<td>member check</td>
<td>0.23 (0.36)</td>
</tr>
<tr>
<td>discussion</td>
<td>0.34 (0.37)</td>
</tr>
<tr>
<td>demonstration</td>
<td>0.29 (0.37)</td>
</tr>
<tr>
<td>other strategies</td>
<td>0.27 (0.36)</td>
</tr>
</tbody>
</table>

Research Question 1

What is the effect of technical access and prior knowledge on achievement while implementing peer modeling in an open learning environment? Table 2.3 lists the relevant index values. Chi-Square Test values in homework and examinations were all larger than 63 ($p < .05$), and denoted that there was not a proper fit. Root Mean Square Error of Approximation (RMSEA) estimate values for both homework and examinations were larger than .01 and indicated a poor fit. Comparative Fit Index (CFI) values in homework and examinations were
less than 0.9 and implied a slightly bad fit. Both Standardized Root Mean Square Residual (SRMR) values in homework and examinations were larger than .08 and indicated a slightly poor fit.

Table 2.3

**Index Values for Research Question 1**

<table>
<thead>
<tr>
<th>Index</th>
<th>Homework</th>
<th>Exam</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chi-Square Test of Model Fit</td>
<td>$X^2=68.32^{**}$</td>
<td>$X^2=65.691^{**}$</td>
</tr>
<tr>
<td>Root Mean Square Error of Approximation (RMSEA)</td>
<td>0.152**</td>
<td>0.147**</td>
</tr>
<tr>
<td>Comparative Fit Index (CFI)</td>
<td>0.734</td>
<td>0.770</td>
</tr>
<tr>
<td>Standardized Root Mean Square Residual (SRMR)</td>
<td>0.109</td>
<td>0.103</td>
</tr>
</tbody>
</table>

* $p<.05$, ** $p<.01$

Model results for homework and examinations were respectively outlined in Figure 2.4 and Figure 2.5. The findings revealed that prior knowledge and technical access likely caused significant changes of achievement in examinations. Peer modeling did not significantly and directly influence student achievement. However, as indicated by the factor loadings, the applied strategies can significantly influence a peer modeling process in homework and examinations (See Table 2.4). There was no indirect effect in this model.

*Figure 2.4. Model Results for Homework*
Hypothesis 1-1. The findings indicated that student prior knowledge significantly influenced their achievement in examinations ($p<.01$), but not in homework ($p=.173$).

Hypothesis 1-2. The findings indicated that technical access brought about some effects on student achievement in examinations ($p<.01$), not in homework ($p=.141$).

Hypothesis 1-3. This hypothesis was rejected. Although peer modeling did not significantly influence student achievement in homework ($p=.116$) and examinations ($p=.418$), the strategies used such as collaborative work, member check, discussion, and some other relevant strategies brought about some significant effects on a peer modeling process.

Research Question 2

What is the effect of competence, motivation, and statistics learning anxiety on achievement while implementing peer modeling in an open learning environment? Table 2.5 lists the relevant index values. The Chi-Square Test values were larger than 100 ($p < .0000$). This
model did not have a good fit with the data. RMSEA estimate values were larger than .01 and indicated an improper fit. CFI values were less than 0.9 and also implied a poor fit. Both SRMR values in homework and exams were larger than .08 and indicated a bad fit.

Table 2.5

*Index Values for Research Question 2*

<table>
<thead>
<tr>
<th>Index</th>
<th>Homework</th>
<th>Exam</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chi-Square Test of Model Fit</td>
<td>$X^2=342.635^{**}$</td>
<td>$X^2=355.713^{**}$</td>
</tr>
<tr>
<td>RMSEA</td>
<td>0.132**</td>
<td>0.136**</td>
</tr>
<tr>
<td>CFI</td>
<td>0.691</td>
<td>0.681</td>
</tr>
<tr>
<td>SRMR</td>
<td>0.127</td>
<td>0.128</td>
</tr>
</tbody>
</table>

* p<.05, ** p<.01

The model results for homework and examinations were respectively outlined in Figure 2.6 and Figure 2.7. Findings revealed that motivation directly and significantly influenced student achievement in homework, not in examinations. In contrast, learning anxiety in statistics had a direct and significant effect on student examination scores. Learning anxiety in statistics had some direct and significant effects on motivation in both homework and examinations. Peer modeling did not significantly and directly influence student achievement. The factor loadings for the three latent factors: peer modeling, motivation, and learning anxiety in statistics are outlined in Table 2.6. The only indirect effect from learning anxiety in statistics through motivation had significant influence on achievement in homework, rather than in examinations (see Table 2.7).

*Figure 2.6. Model Results for Homework*
Figure 2.7. Model Results for Exam

Table 2.6

Factor Loading for Latent Factors

<table>
<thead>
<tr>
<th>Latent Factor</th>
<th>Homework</th>
<th>Exam</th>
</tr>
</thead>
<tbody>
<tr>
<td>Peer Modeling</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Collaborative Work</td>
<td>0.365**</td>
<td>0.359**</td>
</tr>
<tr>
<td>Member Check</td>
<td>0.241**</td>
<td>0.244**</td>
</tr>
<tr>
<td>Discussion</td>
<td>0.247**</td>
<td>0.250**</td>
</tr>
<tr>
<td>Demonstration</td>
<td>0.003</td>
<td>0.009</td>
</tr>
<tr>
<td>Other</td>
<td>-0.134**</td>
<td>-0.139**</td>
</tr>
<tr>
<td>Motivation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Interest</td>
<td>0.583**</td>
<td>0.583**</td>
</tr>
<tr>
<td>Enjoyment</td>
<td>0.690**</td>
<td>0.680**</td>
</tr>
<tr>
<td>Perceived Value</td>
<td>0.427**</td>
<td>0.430**</td>
</tr>
<tr>
<td>Perceived Usefulness</td>
<td>0.313**</td>
<td>0.319**</td>
</tr>
<tr>
<td>Statistics Learning Anxiety</td>
<td></td>
<td></td>
</tr>
<tr>
<td>test and class anxiety</td>
<td>0.724**</td>
<td>0.724**</td>
</tr>
<tr>
<td>interpretation anxiety</td>
<td>0.491**</td>
<td>0.483**</td>
</tr>
<tr>
<td>fear of asking for help</td>
<td>0.535**</td>
<td>0.521**</td>
</tr>
<tr>
<td>worth of statistics</td>
<td>0.446</td>
<td>0.457**</td>
</tr>
<tr>
<td>fear of statistics teachers</td>
<td>0.624**</td>
<td>0.609**</td>
</tr>
<tr>
<td>computational self-concept</td>
<td>0.725**</td>
<td>0.725**</td>
</tr>
</tbody>
</table>

* p<.05, ** p<.01

Table 2.7

Indirect Effect from Learning Anxiety in Statistics to Achievement

<table>
<thead>
<tr>
<th></th>
<th>Homework</th>
<th>Exam</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Effect</td>
<td>-0.416</td>
<td>-3.638**</td>
</tr>
<tr>
<td>Total Indirect Effect</td>
<td>-2.245*</td>
<td>-0.869</td>
</tr>
<tr>
<td>from learning anxiety in statistics through motivation</td>
<td>-2.245*</td>
<td>-0.869</td>
</tr>
</tbody>
</table>
Hypothesis 2-1. This hypothesis was rejected. Student achievement in homework ($p=.281$) and examinations ($p=.511$) was not directly influenced by the peer modeling process. However, the strategies including collaborative work, member check, discussion, and some other relevant strategies significantly influenced the peer modeling process.

Hypothesis 2-2. Student statistics learning anxiety was directly and negatively related with their achievement in examinations ($p=.047$), rather than homework ($p=.185$). As students had higher learning anxiety in statistics, they were likely to have a lower achievement in examinations.

Hypothesis 2-3. Student learning anxiety in statistics might bring some negative effects which significantly and indirectly affected their homework scores ($p=.01$), as motivation worked as a mediator between learning anxiety in statistics and student achievement. Thus, low motivation caused by the high learning anxiety might lead to low achievement in homework.

Hypothesis 2-4. According to the results, student motivation significantly and directly affected the achievement in homework ($p<.01$), not in examinations ($p=.272$).

Hypothesis 2-5. Student competence did not have significant effects on achievement in homework ($p=.656$) or examinations ($p=.71$). Thus, this hypothesis was rejected.

Discussion

The findings indicated that the entire model underlying the assumption of the Peer-assistance-to-Personalization did not have a proper fit with the data. Some direct and indirect effects among the observed variables and the latent factors supported or rejected the hypotheses in this study. Technical access, prior knowledge, and learning anxiety in statistics could significantly affect student examination scores. Motivation could have the significant effects on
student achievement in homework. Two suggestions are made to elaborate the results of the hypotheses, including 1) student needs addressed in different contexts, 2) effective strategies used in a peer modeling process.

**Student Needs Addressed in Different Contexts**

Contextualized student needs should be emphasized to effectively improve student achievement. Student needs in this study brought different effects on student achievement in homework and examinations, as students applied peer modeling strategies in an open learning environment. The needs examined by technical access and prior knowledge significantly influenced student achievement in examinations, not in homework. The need examined by motivation, directly and significantly affected student scores in homework. In contrast, learning anxiety in statistics directly and significantly influenced student scores in examinations. Further, learning anxiety brought some negative effects on motivation and thus indirectly influenced student achievement in homework. Contextualized student needs determine how the relevant support can be provided in an effective way. Accordingly, a personalized way of learning and teaching can be facilitated.

**Effective Strategies Used in a Peer Modeling Process**

Although peer modeling did not significantly influence student achievement in both homework and examinations, some strategies were proved to bring significant effects on a peer modeling process and included collaborative work, member check, discussion, inquiry of other senior students or tutors, and consultation with some experts in using software packages. These strategies should be appropriately applied to facilitate a peer modeling process. Thus, a peer modeling process can sufficiently provide peers with personalized support and effectively resolve the barriers in implementing personalized instruction.
Implications

There are two main implications in this study. First, the contextualized student needs are perceived as necessary for teachers to implement personalized instruction. Motivation in this study, for example, significantly affected student achievement in homework, not in examinations. Conversely, learning anxiety in statistics brought significant effects in examinations, rather than in homework. Thus, context can play an important role in affecting student achievement. The second implication is that a peer modeling process can be employed in applying effective strategies for peers to deal with learning tasks together. Therefore, these strategies can support the implementation of personalization in a peer-assisted learning and teaching environment.

Limitations

The main limitation in this study is the lack of multi-method data collection. Only self-report data, and homework and examination scores were collected in this study. Those results may simply provide some exploration of data and identify their relationship with the assumptions of the developmental model. There were no actual observations or other ways of data collection such as interviews in this study. The lack of multi-method data collection may cause some limitations in interpreting the findings. Multiple sources of data can be helpful to investigate some specific issues in the study.

Future Study

There is not a proper fit between the assumptions of the developmental model and the data. Therefore, model modification is suggested by adding or removing some paths in the developmental model to decrease the variation between the theoretical assumptions and real
practices in the study. Particularly, model modification may be helpful to detect if a peer modeling process can bring some indirect effects on student achievement.

**Conclusions**

Personalization in education plays an important role in supporting individual learners. However, the three constraints of time, continuous support, and the required knowledge for personalized instruction often prevent teachers from implementing it. A peer modeling process can overcome the barriers in time and the required knowledge for personalized instruction. The appropriate use of open educational resources can lessen the concern in the lack of continuous support. Students who are enrolled in an introductory statistics course represent a diverse group in reference to their prior knowledge and background. Contextualized student needs can specifically support the implementation of personalization considering individual needs and various contexts. Effective strategies used in a peer modeling process can effectively provide personal support to facilitate peer-assisted learning and teaching. Accordingly, the triadic reciprocal interaction among personal, behavioral, and environmental factors can be enhanced and promote personalized learning.
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Blue Ridge Summit, PA: Rowman & Littlefield Education.


CHAPTER 3

PERSONALIZED STATISTICS LEARNING IN AN OPEN LEARNING ENVIRONMENT

THROUGH A MODELING PROCESS ²

² Lin, Y. and Lu, Z. To be submitted to Computers in Human Behavior.
Abstract

Introductory statistics courses are commonly a requirement for undergraduate and graduate students learning research methodology. Students enrolled in such courses are likely to have different levels of prior knowledge and backgrounds, which tend to cause them to experience various barriers to successfully achieve the mastery of statistics. Educational personalization, which has been conceptually classified into personalized learning and personalized instruction, is an effective way to solve this problem. However, there are three barriers that may prevent teachers from implementing personalized instruction: 1) lack of time, 2) lack of continuous support, and 3) lack of required knowledge for personalized instruction. Accordingly, a developmental model was proposed, which aimed to overcome these three barriers that prevent teachers from implementing personalized instruction as well as to promote student personalized statistics learning through peer and non-peer modeling processes and the appropriate use of open educational resources. The interrelationship among individual learning needs, peer and non-peer modeling processes, and appropriate use of open educational resources was identified to examine if triadic reciprocal interaction occurred to promote personalized learning in terms of improved achievement, increased motivation, and decreased anxiety toward learning introductory statistics.

Keywords: Personalized Learning, Personalized Instruction, Introductory Statistics, Peer Modeling, Open Educational Resources
Personalized Statistics Learning in an Open Learning Environment through a Modeling Process

**Introduction**

Statistics is perceived as a complex subject in college or graduate schools. Some students in college view statistics courses unfavorable and easily drop them if these courses are not required for their program of study (Hanna, Shevlin, & Dempster, 2008; Hsu, Wang, & Chiu, 2009). Students enrolled in introductory statistics courses generally have different prior knowledge for basic statistics and come from different backgrounds. Accordingly, both undergraduate and graduate students may experience various barriers in statistics courses. Personalization can resolve the issue of heterogeneity in higher education and accommodate diverse learning needs (Essalmi, Ayed, Jemni, & Graf, 2010). Furthermore, student's learning performance can be enhanced (Reichelt, Kämmerer, Niegemann, & Zander, 2014).

Personalization in education can be conceptually classified into personalized learning and personalized instruction.

Personalized learning refers to the idea that individual ways of learning are determined by interests and preferences (Essalmi, et al., 2010; Ku, Harter, Liu, Thompson, & Cheng, 2007), and thus bring different levels of success and satisfaction (Carroll, 1975; Ferguson, 2001; Keefe & Jenkins, 2008). Personalized instruction refers to a customized way of teaching that takes into account individual learning needs (Keefe & Jenkins, 2008; Sands & Barker, 2004). However, there are three barriers that may prevent teachers from implementing personalized instruction: 1) lack of time, 2) lack of continuous support, and 3) lack of the required knowledge for personalized instruction (Lin & Kim, 2013). Much human learning occurs in a social learning environment involving personal, behavioral, and environmental factors (Bandura, 1986) (see Figure 3.1). Personalization Model in Figure 3.2 was a developmental model used to overcome...
the three barriers to implement personalized instruction as well as to promote personalized learning. This developmental model aligned with three factors of social learning environment. Individual learning needs are classified as the personal factor in the developmental model. A modeling process consisting of peer and non-peer interactions, which determines the development of social learning environment (Bandura, 1986; Schunk, 2008), serves as the environmental factor in the developmental model. A peer modeling process, in particular, can overcome the barriers caused by the lack of time and the required knowledge for personalized instruction. The availability of open educational resources is classified as the environmental factor. The appropriate ways to reuse or reproduce open educational resources, classified as the behavioral factor in the developmental model, can continually support personalized instruction because of openness and multiple choices features in open educational resources.

Figure 3.1. Social Learning Environment (Bandura, 1986)
Figure 3.2. Personalization Model

The purpose of this study was not only to overcome three barriers to implement personalized instruction but also to promote personalized statistics learning through the triadic reciprocal interaction caused by individual learning needs, a modeling process, and appropriate use of open educational resources. Individual students, thus, can achieve mastery of, increase their motivation in, and decrease their anxiety in the context of statistics learning.

**Personalization Model in Statistics Learning**

The Personalization Model supports both personalized learning and instruction by including three factors in a social learning environment: 1) identification of individual needs in teaching and learning as the personal factor, 2) implementation of a modeling process involving peer and non-peer interactions as the environmental factor, and 3) the availability of and appropriate use of open educational resources respectively as the behavioral and environmental factors. A modeling process emphasizing peer interaction and the appropriate use of open educational resources can resolve the three barriers in implementing personalized instruction.
The triadic reciprocal interaction (Bandura, 1986) caused by the factor of people, behavior, and environment can be used to promote personalized learning.

**Component 1: individual needs in teaching and learning**

The personal factor in the Personalization Model addresses individual needs that can represent diverse perceptions toward teaching and learning environments. Teachers may hesitate to implement personalized instruction if there is a lack of time, ongoing support, and the required knowledge for personalized instruction, which can be referred as individual needs in teaching. Students who enroll in an introductory statistics course generally have learning needs on two levels: practical and psychological. Student needs on a practical level can be identified by examining the availability of technical access in an introductory statistics course (Neumann & Hood, 2009) and the level of prior knowledge for basic statistics (Leppink, Broers, Imbos, van der Vleuten, & Berger, 2012). Student competence (Boyle et al., 2014), motivation (Ejei, Weisani, Siadat, & Khezriazar, 2011; Lavasani, Weisani, & Ejei, 2011), and statistics learning anxiety (Lavasani, et al., 2011; Macher, Paechter, Papousek, & Ruggeri, 2012) can determine their psychological needs for statistics learning.

**Technical access.** The availability of technical access can determine the way students perceive their skills and knowledge acquisition in a certain subject. Student technical access in an introductory statistics course includes the availability in hardware such as laptops and desktops, statistics software packages, and Internet access. Students who have unlimited access to laptops, for example, are more able to independently examine authentic issues, compared with students who have limited technical access (Lowther, Ross, & Morrison, 2003). Thus, students in the former group can further improve their research and writing skills. Students with full
technical access have more significant improvements in achievement than students who do not (Lowther, et al., 2003).

**Prior knowledge.** Prior knowledge plays an important role in determining the way students acquire knowledge, transfer cognitive skills, and decide the way they achieve the mastery of learning. Different levels of prior knowledge among students in class bring diversity and influence the ways students process information. Students with a high level of prior knowledge, for example, are generally more confident in acquiring new knowledge, and thus spend less time on an achievement test (Lim, Reiser, & Olina, 2009) and tend to prefer auditory-only presentation in class. Conversely, students with a low level of prior knowledge are likely to process information in an audio-visual format (Leslie, Low, Jin, & Sweller, 2012). Thus, different levels of prior knowledge may influence student cognitive skills and bring different levels of achievement (Leslie, et al., 2012; Lim, et al., 2009).

**Competence.** The interaction between people and the environment brings different levels of capacity in how students perceive and feel about themselves. Such individual capacity can be referred to as individual competence and strengthened in being engaged in a given activity (Deci & Moller, 2005). Competence decides the way that students solve a problem. Students tend to quickly explore content if they have more competence in using multiple cognitive tools than students who feel less competent and use cognitive tools to identify only their hypotheses and assumptions (Liu & Bera, 2005). Liu and Bera (2005) also indicate that students who have high achievement tend to be more competent to productively use cognitive tools.

**Motivation.** Motivation is the tendency that prompts students to behave in a certain way. Student motivation persist as students are engaged in a given learning activity. Motivation can be conceptually classified into intrinsic and extrinsic motivation (Deci, 1975; Ryan & Deci, 2000).
Intrinsic motivation prompts the behaviors caused by interest or enjoyment. Extrinsic motivation, in contrast, emerges as a result of the desired outcomes such as reward or punishment. Intrinsic motivation bring positive learning outcomes (Schunk, 2008). The factors affecting the way that students intrinsically motivate themselves include, but are not limited to interests (Ryan & Deci, 2009; Sansone, Smith, Thoman, & MacNamara, 2012; Schiefele, 2009), enjoyment (Lesser et al., 2013; Ryan & Deci, 2000, 2009), perceived values and usefulness (Schunk, 2008; Wigfield & Eccles, 1992). Students can be more engaged and positive toward their learning environment if they have more interests in a certain subject. Further, students are likely aware of the way to regulate their own learning experience (Sansone, Fraughton, Zachary, Butner, & Heiner, 2011). Enjoyment makes students sustain their learning motivation. Values and usefulness toward a given learning task can be influenced by the goals students set up and their perceptions in a class (Atkinson, 1957; Schunk, 2008; Wigfield & Eccles, 1992). These four factors of motivation can determine the way that students intrinsically motivate themselves in class and influence their achievement (Vansteenkiste, Lens, & Deci, 2006).

**Statistics learning anxiety.** Statistics has been perceived as a complex subject for undergraduate and graduate students. Students tend to drop statistics courses if they are not required for their program of study (Hanna, et al., 2008; Hsu, et al., 2009). Statistics learning anxiety is defined as a type of emotion or behavior in which students perceive statistics (Bell, 2003; Onwuegbuzie, 2000; Pan & Tang, 2004, 2005). Such anxiety in statistics learning can even result in low motivation and engagement. The factors likely causing statistics learning anxiety include gender (Bui & Alfaro, 2011; Hsiao & Chiang, 2011), ethnicity (Bui & Alfaro, 2011), self-perception (Onwuegbuzie, 2000; Pan & Tang, 2005), and age (Bell, 2003; Bui & Alfaro, 2011; Pan & Tang, 2004). Statistics learning anxiety can be classified into six types: 1) anxiety
in tests and exams, 2) interpretation anxiety, 3) worth of statistics, 4) fear of asking for help toward statistics, 5) fear of statistics teachers, and 6) computational self-concept anxiety (Hanna, et al., 2008). Some students may feel highly anxious about statistics as they prepare for exams or tests. The anxiety in tests and exams can even occur as students walk into the room to take a statistics exam (Vigil-Colet, Lorenzo-Seva, & Condon, 2008). Interpretation anxiety indicates that students may feel anxious to interpret the statistical data and formulas used in academic papers or professional reports (Vigil-Colet, et al., 2008). Worth of statistics refers to the ways and values that students perceive statistics. Thus, some students may feel that statistics has low relevance to their chosen field of study if they have low worth of statistics. The fear of asking for help toward statistics can cause students to feel anxious about this subject. Also, the fear of statistics instructors can cause statistics learning anxiety. Statistics learning anxiety is likely related to the individual perceptions about mathematical computation and ability. Thus, some students may be anxious about statistics and attribute their poor performance to their low ability and achievement in prior mathematics courses. Statistics learning anxiety can cause low achievement (Macher, et al., 2012) or performance (Hsu, et al., 2009) and can be improved by applying appropriate instructional strategies (Chiou, Wang, & Lee, 2014).

**Component 2: peer and non-peer modeling processes**

People tend to observe other people who are successful and pattern their actions, strategies, beliefs, and thoughts in order to improve their individual behaviors, cognition, emotion and affect, self-perceiving efficacy, and performance (Bandura, 1965; Schunk, 2008; Wouters, Tabbers, & Paas, 2007). This observational process can be perceived as a modeling process that may occur in peer and non-peer settings. Peer modeling refers to a learning process facilitated through observation and interaction among peers to enhance learning achievement
A peer modeling process can resolve the barriers caused by the lack of time and the required knowledge for personalized instruction. The time spent on some instructional responsibilities such as providing feedback and commenting can be more efficiently used as peers work together to deal with learning tasks. Therefore, learning engagement can be better maintained and sustained in this way (Stenhoff, Benjamin, & Benjamin, 2007). Also, a peer modeling process considering individual attributes such as age, gender, and background can work as an efficient way to construct new knowledge and skills required for personalized instruction. A non-peer modeling process mainly includes the interaction and observation among non-peers such as students and teachers or students and teaching assistants. Students who observe models likely have better performance and achievement than students who do not observe any models (Braaksma, Rijlaarsdam, & Bergh, 2002; Braaksma, Rijlaarsdam, Bergh, & Hout-Wolters, 2006; Zimmerman & Kitsantas, 2002). Several modeling methods can be viewed as learning strategies and have been applied in peer and non-peer settings. These modeling methods include, but are not limited to coping modeling (Schunk & Hanson, 1985), mastery modeling (Schunk & Hanson, 1985), verbal modeling (Bandura, 1986), and cognitive modeling (Bandura, 1986). Coping modeling is used as a way to gradually and successfully deal with learning tasks in a problem-solving context as learners initially experience fears and failure together (Schunk & Zimmerman, 1997; Zimmerman & Kitsantas, 2002). Mastery modeling, in contrast, is defined as a modeling method in which learners observe a perfect model without any errors (Schunk & Hanson, 1985; Schunk & Zimmerman, 1997). Verbal modeling indicates that knowledge and skills can be acquired in a verbal way. Thus, the learning strategies which cannot be directly observed can be promoted and can lead to cognitive modeling (Bandura, 1986). These modeling methods applied
in peer and non-peer modeling settings can form peer-assisted and non-peer-assisted ways of learning and instruction.

**Component 3: appropriate use of open educational resources**

The Internet makes open resources more accessible to users. Open resources which can be used for educational purposes are defined as open educational resources (UNESCO, 2002). Open educational resources have brought several significant advantages in education, including openness, multiple choices, and shareability and reusability. Openness allows users to use open educational resources without the violation of copyright laws (Caswell, Henson, Jensen, & Wiley, 2008; Clements & Pawlowski, 2012; Olcott Jr., 2012; Rogerson-Revell, 2007; Wiley & Gurrell, 2009). Students can have multiple choices in selecting open educational resources and make learning more adaptive. Students are also provided alternative options to enrich or remediate individual ways of learning in a traditional learning environment (D'Antoni, 2009; Olcott Jr., 2012). Shareability and reusability in open educational resources permit users to freely share and reuse them (Caswell, et al., 2008; Rogerson-Revell, 2007). Although openness and multiple choices in open educational resources can resolve the constraint caused by the lack of continuous support to implement personalized instruction, the use of open educational resources may not bring significant effects on student achievement (Dikshit, Garg, & Panda, 2013; Hilton, Gaudet, Clark, Robinson, & Wiley, 2013; Lovett, Meyer, & Thille, 2008). Three design strategies are proposed in order to promote personalized learning as well as to effectively improve student achievement: 1) identifying individual learning needs, 2) verifying purposes and contexts for personalized learning, and 3) implementing appropriate strategies.

**Identifying individual learning needs.** Individual learning needs represent individual differences in the classroom. Such needs should be identified prior to the customization of open
educational resources. This inventory of learning needs not only specifically supports individual ways of learning but also makes the use of open educational resources more adaptive and effective for individual students.

**Verifying purposes and contexts for personalized learning.** Personalized learning does not simply isolate or group students based on their needs or backgrounds. The specified contexts or purposes, in contrast, can precisely determine further implementation for individual students. The use of multiple cognitive tools in an ill-structured context, for example, prompts students to consider a wide range of alternatives to individually engage in a meaningful way of learning (Ge & Land, 2004; Liu & Bera, 2005). Students in an introductory statistics course have different levels of prior knowledge. Open educational resources can be used for remediation or enrichment purposes (D'Antoni, 2009; Olcott Jr., 2012). Customization of open educational resources for remediation can help students bridge the gap between prior knowledge and the skills required for a course. Open educational resources can also work as supplements to enrich individual student learning.

**Implementing appropriate strategies.** The appropriate strategies to customize open educational resources can support individual ways of learning based on individual learning needs or verified contexts and purposes, and thus promote personalized learning. The four levels of openness determine the ways to customize open educational resources: reuse, redistribution, revision, remix (Hilton III, Wiley, Stein, & Johnson, 2010). Users can use partial or all of open educational resources if they are only allowed to reuse them. Redistribution refers to the share of open educational resources with users. Users can modify open educational resources if they are allowed to revise them. Remix allows users to mix open educational resources with existing resources for new purposes. These four levels of openness inform adaption and flexibility in
open educational resources (Hilton III, et al., 2010) and assist learners to contextualize their ways of learning (Wang, Moore, Wedman, & Shyu, 2003).

Research Questions and Structural Equation Models

The triadic reciprocal interaction caused by personal, behavioral, and environmental factors develops a social learning environment in which much human learning occurs (Bandura, 1986). Individual learning needs, implementation of a modeling process in peer and non-peer settings, and the appropriate use of open educational resources can inform these three factors and can be used to promote personalized learning through their interrelationship. However, several questions still remain unanswered. There is a need for a better understanding of how individual learning needs, a modeling process in peer and non-peer settings, and the appropriate use of open educational resources can relate to each other, and thus foster personalized statistics learning. The promotion of personalized statistics learning can be evaluated by three elements: student achievement, student motivation for statistics learning, and statistics learning anxiety. Therefore, the following questions were used to guide this research study:

1. What factors among learning needs, peer and non-peer modeling processes, and the appropriate use of open educational resources can effectively promote personalized statistics learning?

2. What is the overall relationship among learning needs, peer and non-peer modeling processes, and the appropriate use of open educational resources?

3. What are the effects of learning needs, peer and non-peer modeling processes, and the appropriate use of open educational resources on achievement in promoting personalized statistics learning?
Research Question 1

An exploratory factor analysis was used to identify the number of factor(s) and to specify the dimensionality of factor(s) in order to discover the nature of the construct which influenced a set of responses. The number of factors could be identified by using Eigenvalue analysis. The maximum likelihood estimation method and GEOMIN factor rotation could help interpret factor loadings in the variables attributed to factors.

Research Question 2

A confirmatory factor analysis was used to examine the overall relationship among factors which were identified in Research Question 1. The developmental model built underlying the theoretical framework could be evaluated and could determine the dimensionality and its construct.

Research Question 3

Structural equation modeling was used to identify direct and indirect effects among factors. The proposed path diagram is listed in figure 3.3. Data was analyzed in this way to examine how student achievement can be directly and indirectly influenced by individual learning needs, peer and non-peer modeling processes, and the use of open educational resources. Student scores in homework and on exams worked as dependent variables. The factors were determined by the findings made in Research Question 1. In addition, the use of qualitative data collected from open-ended questions can provide some further findings for the use of open educational resources in introductory statistics classes.
Figure 3.3. Path Diagram for Research Question 3

Method

Participants

Participants in this study were students who enrolled in introductory statistics courses at a university located in the southeastern United States. Some participants might complete partial surveys or provide the same answers for all items within a survey. The two researchers in this study recoded data and simultaneously checked if any participants answered in such an unusual
Thus, 27 out of 135 participants were screened out. There were 108 participants in total. Eighty percent of the participants were between 18 to 30 years old. Fourteen percent of the participants were between 31 to 40. The remaining 6% were over 40. All participants in this study were likely pursuing an undergraduate or graduate degree at the time this study was being conducted. The level of prior knowledge ($M=54.54$, $SD=19.45$) was various among students.

**Intervention**

There were two interventions in this study. The first intervention was to encourage students to work with peers as they completed their homework. The peer and non-peer modeling strategies such as member check, discussion, demonstration, and consultation with instructors and teaching assistants were promoted in class. Those strategies and their definitions were introduced in the first week of class. Member check was defined as the action that students checked the accuracy of answers after they completed homework without doing any further discussion yet. If students discussed any questions in their homework, modeling strategy used for homework completion should include discussion. Students, on the one hand, likely discussed questions with peers in a peer modeling setting. On the other hand, students might discuss homework with instructors and teaching assistants in a non-peer modeling environment.

Demonstration was defined as the action that students or non-peers such as instructors or teaching assistants showed a step-by-step calculation or presentation of using statistics software package to solve problems in homework. Consultation with instructors and teaching assistants mainly included the office hour sessions in which students asked questions about homework. Those strategies were also presented to students in the online assignment instruction. Thus, students can accurately identify the peer and non-peer modeling strategies applied in every homework completion. The second intervention was that all students were provided access to
open educational resources throughout the courses. These resources were selected and collected from 12 repository websites of open educational resources (see Table 3.1). Ten out of 12 websites had an interdisciplinary collection and included a variety of materials such as textbooks, animation, games, and syllabus for free reuse or reproduction. The remaining two websites were primarily used for statistics teaching and learning. Open educational resources used in class were customized based on some specific purposes such as remediating student prior knowledge and working as supplements. The four ways to appropriately use open educational resources involves reuse, redistribution, revision, and remix. One of two researchers in this study helped select appropriate open educational resources from these 12 repository websites based on the weekly topic. The selected resources were shared with the instructors to reuse or reproduce. For example, some simulations elaborating the concept of R Square were introduced to the entire class during the lecture and redistributed to students. These simulations provided an easy way for students to learn the abstract concept about R Square. In addition, the instructors revised couple of items in online assessment and combined them into homework. This can be perceived as a way to revise and remix open educational resources. Open educational resources provided by instructors were uploaded to the learning management system. So students could access these resources anytime and anywhere outside of the class. Students were likely to reuse these resources as they worked on their homework or prepared for exams. Students also looked for other open educational resources to clarify their unclear statistics concepts during the homework completion. In this way, these open educational resources were primarily reused and redistributed to other peers.
### Table 3.1

**List of Repository for Open Educational Resources**

<table>
<thead>
<tr>
<th>Repository of Open Educational Resources</th>
<th>Collection</th>
</tr>
</thead>
<tbody>
<tr>
<td>Connexions (<a href="http://cnx.org/">http://cnx.org/</a>)</td>
<td>More than 17,000 learning objects or modules and over 1000 collections (textbooks, journal articles, etc.) are used.</td>
</tr>
<tr>
<td>CAUSEweb.org (<a href="https://www.causeweb.org/resources/">https://www.causeweb.org/resources/</a>)</td>
<td>The support in 4 areas are mainly provided: resources, professional development, outreach, research</td>
</tr>
<tr>
<td>Multimedia Educational Resource for Learning and Online Teaching (MERLOT) (<a href="http://www.merlot.org/merlot/index.htm">http://www.merlot.org/merlot/index.htm</a>)</td>
<td>There is a free and open peer-review process for the entire collection.</td>
</tr>
<tr>
<td>Khan Academy (<a href="https://www.khanacademy.org/">https://www.khanacademy.org/</a>)</td>
<td>Khan Academy provides the collection of videos which can be freely used by students and teachers.</td>
</tr>
<tr>
<td>The Sofa Open Content Initiative (<a href="http://sofia.fhda.edu/gallery/statistics/index.htm">http://sofia.fhda.edu/gallery/statistics/index.htm</a>)</td>
<td>The resources are created by a Learning Technology &amp; Innovations program at a community college in California.</td>
</tr>
<tr>
<td>Saylor.org (<a href="http://www.saylor.org/">http://www.saylor.org/</a>)</td>
<td>More than 300 courses are free and available.</td>
</tr>
<tr>
<td>Statistics Online Computational Resource (SOCR) (<a href="http://www.socr.ucla.edu/">http://www.socr.ucla.edu/</a>)</td>
<td>Those resources are mainly related to statistics and broadly cover games, experiment, wiki, hands-on activities, etc.</td>
</tr>
<tr>
<td>Open Learn (<a href="http://www.open.edu/openlearn/">http://www.open.edu/openlearn/</a>)</td>
<td>More than 650 courses are free and available.</td>
</tr>
<tr>
<td>Online Statistics Education: An Interactive Multimedia Course of Study (<a href="http://www.oercommons.org/courses/online-statistics-an-interactive-multimedia-course-of-study/view">http://www.oercommons.org/courses/online-statistics-an-interactive-multimedia-course-of-study/view</a>)</td>
<td>This website has a collection for learning and teaching introductory statistics and includes material such as textbook and video presentations.</td>
</tr>
<tr>
<td>Curriki (<a href="http://www.curriki.org/welcome/">http://www.curriki.org/welcome/</a>)</td>
<td>More than 50,000 resources are free and available.</td>
</tr>
<tr>
<td>HippoCampus.org (<a href="http://www.hippocampus.org/HippoCampus/">http://www.hippocampus.org/HippoCampus/</a>)</td>
<td>There are a variety of multimedia contents such as videos, animations, and simulations, which are available for K-12 and higher education.</td>
</tr>
<tr>
<td>OpenCourseWare Consortium (<a href="http://www.ocwconsortium.org/about-ocw/">http://www.ocwconsortium.org/about-ocw/</a>)</td>
<td>The resources for the use in the course such as syllabus and textbook are available. Also, the website has incorporation with other universities to develop and publish these resources.</td>
</tr>
</tbody>
</table>
Data Collection Procedures

Data was collected in a 16-18 week period. There were three stages for data collection. Individual learning needs were identified by examining student prior knowledge, technical access, competence, motivation, and learning anxiety in statistics in the beginning of semester. The way to work individually or collaboratively for homework completion was collected. Relevant peer and non-peer modeling strategies applied such as member check, discussion, demonstration, consultation with teachers or teaching assistants, and others were also collected through the semester. The use of open educational resources was collected at the end of semester. Student scores in homework and exams were collected in the end of the semester and served as their achievement in class.

Data Collection Tools and Measures

Learning Characteristics Survey. This survey was used to identifying individual learning needs by examining student technical access, competence, motivation, and learning anxiety in statistics in introductory statistics courses.

Technical access. The availability and access to hardware, statistics software packages, and Internet access were investigated to identify student technical access in an introductory statistics course.

Competence. Perceived Competence Scale was used to identify student feelings of competence in a learning activity. There were four items in total with a 5-point Likert scale used—(1) strongly disagree to (5) strongly agree. Reported internal consistency for the perceived competence items was 0.8 in various studies (Williams & Deci, 1996; Williams, Freedman, & Deci, 1998).
Motivation. Intrinsic Motivation Inventory (Ryan, 1982) was used to identify students' perceptions of the target activity known as statistics learning in this study. Only the sub-scales in this inventory such as interest, enjoyment, perceived value, and usefulness, were used in this study. There were 11 items in total. A 5-point Likert scale was used in rating each item- (1) strongly disagree to (5) strongly agree. Reported internal consistency for the items was 0.8. Validity has been accessed and got strong support in the former study (McAuley, Duncan, & Tammen, 1989).

Statistics learning anxiety. Statistical Anxiety Rating Scale (Cruise, Cash, & Bolton, 1985) was acknowledged as the most widely used instrument in examining statistics anxiety (Hanna, et al., 2008). Some items in the original scale have been revised and removed because of the context in this study. There were a total of 22 items which specified statistics learning anxiety in six: 1) worth of statistics, 2) interpretation anxiety, 3) test and class anxiety, 4) computational self-concept, 5) fear of asking for help, and 6) fear of statistics teachers. A 5-point Likert scale was used in rating each item. Reported internal consistency for the items was from 0.83 to 0.94 (Hanna, et al., 2008).

Prior knowledge test. Student prior knowledge was evaluated in six topics of basic statistics: 1) distribution graph and normal distribution, 2) inference and probability, 3) correlation and regression, 4) two-way variables, 5) sampling and exploring data, and 6) experiment. There were 10 items in total with the reliability of 0.65 in Cronbach’s alpha value.

Cover-page information sheet (Problem-solving Survey). This sheet was used on each homework completion. Students attached this sheet with each homework as they submitted their homework into their online assignment dropbox. Independent or collaborative ways to work and peer or non-peer modeling strategies applied on homework completion were measured by using
this sheet. Thus, peer modeling and non-peer modeling processes were examined. Generally, each student were likely to include multiple peer and non-peer modeling strategies used in homework completion.

**Peer modeling process.** A peer modeling process was measured to determine the extent that students worked collaboratively on homework and how students applied relevant strategies such as member check, discussion, demonstration, and others on their homework. A peer modeling process was attained by calculating the average times of collaborative work and of relevant strategies applied while completing homework.

**Non-peer modeling process.** A non-peer modeling process was measured to determine the extent that students worked independently on homework and how they applied relevant strategies such as discussion with non-peers, demonstration provided by non-peers, consultation with teachers and teaching assistants, and others. A non-peer modeling process was attained by calculating the average times of independent work and of relevant strategies applied while completing homework.

**Homework & exams.** Student achievement was measured using student mean scores on their homework and exams administered during the course. The possible scores for homework and exam likely ranged from 0 to 100.

**Satisfaction Survey.** This survey was mainly used to examine student satisfaction about the use of open educational resources. This survey was conducted on the last two weeks of course. Students who participated to this study were provided access in the learning management system to complete the survey. During these two weeks, each student can complete part of items and save them anytime. Then students can return to complete the remaining items and submit the survey in these two weeks. The use of open educational resources was measured by the four: 1)
reuse, 2) redistribution, 3) revision, and 4) remix. There were four items in total with a 5-point Likert scale used—(1) strongly disagree to (5) strongly agree. There were a total of four items with a reliability of 0.88 in Cronbach’s alpha value. The reliability for the remaining items relevant to the use of open educational resources involves three constructs: motivation, statistics learning anxiety, and the overall design and use of open educational resources. Motivation construct included 11 items with a reliability of .925 in Cronbach’s alpha value. The Cronbach's alpha value among the 5 items about the use of open educational resources to decrease statistics learning anxiety was .811. The construct about the overall design and use of open educational resources had a reliability of .925 in Cronbach’s alpha value for a total of 9 items. There were three open-ended questions in the Satisfaction Survey. These three open-ended questions mainly identified students' perceptions about the use of open educational resources and their importance for individual statistics learning.

Variables

The variables used in this research question are listed in Table 3.2. There are a total of 19 variables.

Table 3.2

<table>
<thead>
<tr>
<th>Instruments</th>
<th>Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>Learning Characteristics Survey</td>
<td>Technical Access</td>
</tr>
<tr>
<td></td>
<td>Competence</td>
</tr>
<tr>
<td></td>
<td>Interest</td>
</tr>
<tr>
<td></td>
<td>Enjoyment</td>
</tr>
<tr>
<td></td>
<td>Value</td>
</tr>
<tr>
<td></td>
<td>Usefulness</td>
</tr>
<tr>
<td></td>
<td>Worth of Statistics</td>
</tr>
<tr>
<td></td>
<td>Interpretation Anxiety</td>
</tr>
<tr>
<td></td>
<td>Test and Class Anxiety</td>
</tr>
<tr>
<td></td>
<td>Computational Self-concept</td>
</tr>
<tr>
<td></td>
<td>Fear of Asking for Help</td>
</tr>
</tbody>
</table>
Descriptive Statistics

Descriptive statistics including means and standard deviations of all variables used in the study are presented in Table 3.3.

Table 3.3

Mean and Standard Deviation for the Variables Used in the Study

<table>
<thead>
<tr>
<th>Variables</th>
<th>M (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>homework score</td>
<td>92.69 (9.77)</td>
</tr>
<tr>
<td>exam score</td>
<td>89.12 (9.91)</td>
</tr>
<tr>
<td>technical access</td>
<td>2.66 (0.50)</td>
</tr>
<tr>
<td>competence</td>
<td>3.94 (0.78)</td>
</tr>
<tr>
<td>prior knowledge</td>
<td>54.54 (19.45)</td>
</tr>
<tr>
<td>interest</td>
<td>3.44 (0.82)</td>
</tr>
<tr>
<td>enjoyment</td>
<td>3.14 (1.00)</td>
</tr>
<tr>
<td>usefulness</td>
<td>4.21 (0.77)</td>
</tr>
<tr>
<td>value</td>
<td>4.66 (0.79)</td>
</tr>
<tr>
<td>worth of statistics</td>
<td>1.93 (0.65)</td>
</tr>
<tr>
<td>interpretation anxiety</td>
<td>2.77 (0.87)</td>
</tr>
<tr>
<td>test and class anxiety</td>
<td>3.23 (1.15)</td>
</tr>
<tr>
<td>computational self-concept</td>
<td>2.26 (0.89)</td>
</tr>
<tr>
<td>fear of asking for help</td>
<td>2.36 (1.20)</td>
</tr>
<tr>
<td>fear of statistics teachers</td>
<td>2.59 (1.08)</td>
</tr>
<tr>
<td>peer modeling process</td>
<td>0.30 (0.19)</td>
</tr>
<tr>
<td>non-peer modeling process</td>
<td>0.36 (0.15)</td>
</tr>
<tr>
<td>reuse</td>
<td>3.58 (1.09)</td>
</tr>
<tr>
<td>redistribution</td>
<td>3.58 (0.98)</td>
</tr>
<tr>
<td>revision</td>
<td>3.38 (0.99)</td>
</tr>
<tr>
<td>remix</td>
<td>3.23 (1.07)</td>
</tr>
</tbody>
</table>
Research Question 1

Figure 3.4 indicates that up to five factors with the Eigenvalues exceeding 1 can be attained using Eigenvalue analysis. Table 3.4 presents the relevant index values for four and five factors. Chi-Square Test values for five factors did not achieve a significant level ($p > .05$) and denoted that there was a proper fit. In contrast, there was not a proper fit for the model with the four factors. Root Mean Square Error of Approximation (RMSEA) estimated values for two models respectively with four and five factors were less than .1 and indicated a perfect fit. Since Comparative Fit Index (CFI) values for both models with four and five factors were larger than .9, both models indicated a perfect fit between the assumption of developmental model and actual data practices. There was also a perfect fit because Standardized Root Mean Square Residual (SRMR) values for both models were less than .08. Although the relevant index values for five factors can present a proper fit between the assumption of developmental model and actual data practices, the findings examined by the four factors can be more interpretable than the five. Table 3.5 presents these four factors and the observed variables used to examine each factor. The observed variable, enjoyment, was not included in any factor based on results in an exploratory factor analysis.
Figure 3.4. Eigenvalue Analysis

Table 3.4

Index Values for Research Question 1

<table>
<thead>
<tr>
<th>Index</th>
<th>Four Factors</th>
<th>Five Factors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chi-Square Test of Model Fit</td>
<td>$X^2 = 156.79^{**}$</td>
<td>$X^2 = 102.06$</td>
</tr>
<tr>
<td>Root Mean Square Error of Approximation (RMSEA)</td>
<td>0.07</td>
<td>0.04</td>
</tr>
<tr>
<td>Comparative Fit Index (CFI)</td>
<td>0.94</td>
<td>0.98</td>
</tr>
<tr>
<td>Standardized Root Mean Square Residual (SRMR)</td>
<td>0.05</td>
<td>0.04</td>
</tr>
</tbody>
</table>

* $p < .05$, ** $p < .01$

Table 3.5

Four Factors and their Observed Variables

<table>
<thead>
<tr>
<th>Factor</th>
<th>Observed Variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>Motivation</td>
<td>prior knowledge</td>
</tr>
<tr>
<td></td>
<td>technical access</td>
</tr>
<tr>
<td></td>
<td>peer modeling process</td>
</tr>
<tr>
<td></td>
<td>interest</td>
</tr>
<tr>
<td></td>
<td>value</td>
</tr>
</tbody>
</table>
Learning Anxiety in Statistics
- usefulness
- worth of statistics
- competence
- test and class anxiety
- interpretation anxiety
- fear of asking for help

Negative Attitude toward Statistics
- competence
- worth of statistics
- fear of statistics teachers
- computational self-concept

Use of Open Educational Resources
- non-peer modeling process
- reuse
- redistribution
- revision
- remix

**Research Question 2**

A confirmatory factor analysis was applied to examine the overall relationship among the four factors identified in Research Question 1. The relevant index values are outlined in Table 3.6. Chi-Square Test value did not achieve a significant level \( p > .05 \) and denoted a proper fit. Root Mean Square Error of Approximation (RMSEA) estimate value was less than .1 and indicated a perfect fit. Comparative Fit Index (CFI) value was larger than .9 and implied a perfect fit. Standardized Root Mean Square Residual (SRMR) value was around .08 and indicated a proper fit. The model results and factor loadings are presented in Figure 3.5.

**Table 3.6**

<table>
<thead>
<tr>
<th>Index</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chi-Square Test of Model Fit</td>
<td>( X^2 = 171.76 )</td>
</tr>
<tr>
<td>Root Mean Square Error of Approximation (RMSEA)</td>
<td>0.04</td>
</tr>
<tr>
<td>Comparative Fit Index (CFI)</td>
<td>0.96</td>
</tr>
<tr>
<td>Standardized Root Mean Square Residual (SRMR)</td>
<td>0.08</td>
</tr>
</tbody>
</table>

\* \( p < .05 \), \** \( p < .01 \)
Figure 3.5. Model Results and Factor Loadings for Research Question 2
Research Question 3

Structural equation modeling was used to identify direct and indirect effects among factors and student achievement. Structural equation modeling (SEM) for homework and exams were separately analyzed. The relevant index values for student achievement in homework and exams are outlined in Table 3.7. Chi-Square Test values for homework and exams achieved a significant level ($p<.05$) and denoted a slightly improper fit. Root Mean Square Error of Approximation (RMSEA) estimate values for homework and exams were less than .1 and indicated a perfect fit. Comparative Fit Index (CFI) values for both homework and exams were larger than .9 and implied a perfect fit. Standardized Root Mean Square Residual (SRMR) values for both homework and exams were slightly larger than .08 and indicated a bad fit.

Table 3.7

Index Values for Research Question 3

<table>
<thead>
<tr>
<th>Index</th>
<th>Homework</th>
<th>Exam</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chi-Square Test of Model Fit</td>
<td>$X^2=172.16$</td>
<td>$X^2=183.60^*$</td>
</tr>
<tr>
<td>Root Mean Square Error of Approximation (RMSEA)</td>
<td>0.04</td>
<td>0.05</td>
</tr>
<tr>
<td>Comparative Fit Index (CFI)</td>
<td>0.96</td>
<td>0.95</td>
</tr>
<tr>
<td>Standardized Root Mean Square Residual (SRMR)</td>
<td>0.09</td>
<td>0.09</td>
</tr>
</tbody>
</table>

* $p<.05$, ** $p<.01$

Students tended to use open educational resources on homework completion, rather than on exam preparation. The eight advantages for using open educational resources in an introductory statistics course have included 1) clarification of abstract concept, 2) a variety of resources, 3) application of research methodology in the real world, 4) improvement individual skills used for statistics learning, 5) valuable learning experiences, 6) enhancement in individual
career, 7) enhancement in individual studies, and 8) a positive learning environment (see Table 3.8).

Table 3.8

Advantages for the Use of Open Educational Resources

<table>
<thead>
<tr>
<th>Advantage</th>
<th>Participant Response</th>
</tr>
</thead>
<tbody>
<tr>
<td>clarification of abstract concept</td>
<td>- visualize concept</td>
</tr>
<tr>
<td></td>
<td>- improve comprehension</td>
</tr>
<tr>
<td></td>
<td>- depict complicated concepts</td>
</tr>
<tr>
<td></td>
<td>- find answers of the questions before asking instructors</td>
</tr>
<tr>
<td></td>
<td>- fill the gap between what is known and what should be learnt</td>
</tr>
<tr>
<td>a variety of resources</td>
<td>- supplement statistics learning</td>
</tr>
<tr>
<td></td>
<td>- gain knowledge and information</td>
</tr>
<tr>
<td></td>
<td>- substitute outdated materials such as books</td>
</tr>
<tr>
<td></td>
<td>- provide additional support</td>
</tr>
<tr>
<td></td>
<td>- access to resources anytime and anywhere</td>
</tr>
<tr>
<td></td>
<td>- charge at no cost</td>
</tr>
<tr>
<td>application of research methodology in the real world</td>
<td>- provide a practical approach for people who don't regularly or frequently work with statistics to learn this subject</td>
</tr>
<tr>
<td></td>
<td>- understand the ways to apply this research methodology in the real world</td>
</tr>
<tr>
<td>improvement individual skills used for statistics learning</td>
<td>- complement individual analysis skill</td>
</tr>
<tr>
<td></td>
<td>- enhance problem-solving skill</td>
</tr>
<tr>
<td>valuable learning experiences</td>
<td>- provide study aid for people having difficulty in statistics learning</td>
</tr>
<tr>
<td></td>
<td>- meet needs for people who have different learning styles</td>
</tr>
<tr>
<td>enhancement in individual career</td>
<td>- help people find a job requiring statistics skills</td>
</tr>
<tr>
<td>enhancement in individual studies</td>
<td>- provide assistance in individual and dissertation studies</td>
</tr>
<tr>
<td>a positive learning environment</td>
<td>- provide humor</td>
</tr>
<tr>
<td></td>
<td>- attract student attention</td>
</tr>
<tr>
<td></td>
<td>- make student feel comfortable for statistics learning</td>
</tr>
<tr>
<td></td>
<td>- keep class interesting and engage students for statistics learning</td>
</tr>
<tr>
<td></td>
<td>- facilitate the learner's motivation</td>
</tr>
<tr>
<td></td>
<td>- make students less stressful about statistics learning</td>
</tr>
</tbody>
</table>
The model results for homework and exams are presented separately in Figure 3.6 and Figure 3.7. Accordingly, the only indirect effect from motivation through negative attitude toward statistics to student achievement was identified and listed in Table 3.9.

*Figure 3.6. Model Results in Homework for Research Question 3*
Figure 3.7 Model Results in Exam for Research Question 3
Table 3.9

*Indirect Effect from Motivation to Student Achievement*

<table>
<thead>
<tr>
<th></th>
<th>Homework</th>
<th>Exam</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Effect</td>
<td>1.76</td>
<td>3.39**</td>
</tr>
<tr>
<td>Total Indirect Effect</td>
<td>0.13</td>
<td>0.32</td>
</tr>
<tr>
<td>from Motivation, through Negative</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Attitude toward Statistics, to Student Achievement</td>
<td>0.13</td>
<td>0.32</td>
</tr>
</tbody>
</table>

* p<.05, ** p<.01

**Discussion and Implications**

**Discussion**

The four factors have been identified by an exploratory factor analysis and specified as motivation, negative attitude toward statistics, statistics learning anxiety, and the use of open educational resources. A confirmatory factor analysis was used to examine the relationship and dimensionality among these four factors. Direct and indirect effects of the four factors on student achievement were measured. Therefore, some suggestions are made in terms of the personal, behavioral, and environmental factors addressed in the developmental model and their effects on student achievement.

**Personal factor.** Personal factor refers to individual learning needs in introductory statistics courses. Motivation, negative attitude toward statistics, and statistics learning anxiety were examined and significantly influenced individual learning needs. Motivation can be positively measured by prior knowledge, technical access, interest, value, usefulness. Accordingly, student motivation for statistics learning can be decided by the level of prior knowledge, interest, value, and usefulness, and the availability of technical access. However, motivation can be negatively measured by a peer modeling process and worth of statistics. When
students rely highly on peer assistance and apply more relevant modeling strategies in completing homework, their motivation for introductory statistics learning is actually low. Also, as students perceive statistics learning as useless, their motivation is maintained on a low level.

Negative attitude toward statistics can be positively measured by worth of statistics, fear of statistics teachers, and computational self-concept. When students view statistics as useless, feel anxious about statistics teachers, and attribute their achievements to their prior math performances, these behaviors highly relate to a negative attitude toward statistics. There is a negative relationship between negative attitude toward statistics and low competence although such relationship did not achieve a significant level.

Statistics learning anxiety can be positively measured by test and class anxiety, interpretation anxiety, and fear of asking for help. Statistics learning anxiety can be caused when students take statistics tests, have to interpret quantitative findings in academic papers or professional reports, and feel anxious to ask for someone's help. However, statistics learning anxiety can be negatively measured by competence. The low competence is likely the cause of statistics learning anxiety.

Motivation can either negatively correlate with negative attitude toward statistics or statistics learning anxiety. Students' negative attitude toward statistics and statistics learning anxiety can be high if students have a low level of motivation. Students' negative attitude toward statistics can positively relate to their statistics learning anxiety. As students feel anxious about statistics learning, they tend to perceive statistics in a negative way. However, these interrelationships among motivation, negative attitude toward statistics, and statistics learning anxiety do not imply any causality. Student achievement on exams can be directly and significantly affected by motivation.
**Behavioral factor.** The appropriate use of open educational resources can be significantly measured by the four approaches used including reuse, redistribution, revision, and remix. Students are likely to redistribute open educational resources to other people as they reuse them. Users tend to remix open educational resources with other existing resources if these open resources are revised for various purposes. As indicated in the former studies (Dikshit, et al., 2013; Hilton, et al., 2013; Lovett, et al., 2008), the use of open educational resources did not cause any significant effects on student achievement in homework and exams. From the answers in the three open-ended questions within the Satisfaction Survey, the use of open educational resources mostly met student needs in access at no cost and in coursework to facilitate their understanding of abstract statistics concepts. There were few implicit differences among individual students who expressed that the use of open educational resources could effectively increase their motivation (e.g., the use of open educational resources made statistics class interesting) or decrease their statistics learning anxiety (e.g., feel less stressful toward statistics).

**Environmental factor.** A modeling process can be classified as peer modeling and non-peer modeling processes. When students have low motivation for introductory statistics learning, they tend to apply more peer modeling strategies and gain peer assistance to help them complete their homework. A non-peer modeling process can significantly affect students' use of open educational resources. Students may rely on the open educational resources provided by teachers or tend to look for other online resources when they work independently on their homework without any peer assistance. Thus, the use of open educational resources can be enhanced by a non-peer modeling process.
Implications

The four factors including motivation, negative attitude toward statistics, statistics learning anxiety, and use of open educational resources examine the relationship among individual learning needs, peer and non-peer modeling processes, and appropriate use of open educational resources. The interactions caused by these four factors also align with the triadic reciprocal interaction addressed in the developmental model. The interrelationships among these four factors is also perceived as a way to effectively identify individual learning needs and personalize learning experiences. Teachers, for example, may provide motivational support in their instruction as they note that students have a low level of prior knowledge. Motivation may play a vital role in terms of student achievement on exams, rather than in homework. Thus, contextualized motivational support may be provided to improve student achievement on exams.

Limitations and Future Study

There are four limitations in this study. The first limitation is the lack of multi methods to collect data. All the data were self-reported by students without any actual observations and interviews. Self-report data may cause some limitations in interpreting some specific findings in the study. Therefore, the three open-ended questions in the Satisfaction Survey are suggested to be used and to provide some findings about the insignificant effects that open educational resources brought to student motivation and statistics learning anxiety. Although these three open-ended questions may simply provide few details about the use of open educational resources, some concerns about the findings in this study can be resolved, at least partially.

The second limitation is the lack of iterative examinations. This study is an initial exploratory study examining the relationship among individual learning needs, peer and non-peer modeling processes, and the use of open educational resources to support personalized
instruction as well as to promote personalized statistics learning. The iterative examinations will be helpful to validate the assumptions made in the developmental model and evaluate triadic reciprocal interaction among the factors of people, behaviors, and environments.

The third limitation in this study is the supplemental, rather than mandatory, way to reuse most open educational resources. The advantage to reuse these resources in a supplemental way allows students to have choices to select the ones they need. However, such supplemental way to reuse open educational resources may cause the different level of intervention participants received in class. Some students may reuse all open educational resources, but some may barely use them.

The fourth limitation is the way to collect data about the use of open educational resources. Since the data about the use of open educational resources can include students’ use of open educational resources and their satisfaction with using them. Therefore, the use of open educational resources should be clearly defined. In this way, the use of open educational resources can be more precisely measured to answer our research questions. Additionally, the use of open educational resources should be collected in a weekly base, rather than in the end of semester. Thus, the change and trend to use open educational resources can be identified.

The data retrieved from the learning management system about student participation can, to some extents, help identify if open educational resources provided by instructors have been accessed in the future study. This can be perceived as another way to measure how open educational resources are reused by students. These data can include time that individual students spent on each open educational resources or the number of students accessing these open educational resources. Although the appropriate use of open educational resources is perceived as a way to continuously support teachers to implement personalized instruction, such use did
not cause any significant effects on student achievement, which may become another concern for teachers. Some empirical studies, in particular, have indicated that student achievement may not be enhanced by the use of open educational resources (Dikshit, et al., 2013; Hilton, et al., 2013; Lovett, et al., 2008). Therefore, the four ways to appropriately use open educational resources with increased motivation, decreased statistics learning anxiety, minimized negative attitude toward statistics, and improved student achievement will play a vital part in promoting personalized statistics learning in the future study. In addition, the data from 27 participants who have been screened out due to the partial or unusual completion is likely to convey some important information about student use of open educational resources. Although these data are not complete data and may not be able to provide sufficient information to answer research questions in this study, these data may allow us to measure student use of open educational resources by specifically looking at student answers in 3 open-ended questions of the Satisfaction Survey, and thus to identify if there is any trend in these data.

**Conclusion**

Statistics is usually perceived as a complex subject and tends to be a requirement for the program of study in college and graduate schools. Undergraduate and graduate students are most likely to drop statistics courses if they are not required to take them (Hanna, et al., 2008). The promotion of educational personalization takes into account motivation, statistics learning anxiety, negative attitude toward statistics, and the use of open educational resources. Peer and non-peer modeling processes involving various modeling strategies can influence motivation and the use of open educational resources. In this way, the triadic reciprocal interaction caused by motivation, statistics learning anxiety, negative attitude toward statistics, and the appropriate use of open educational resources can be used to overcome these three barriers that prevent teachers
from implementing personalized instruction and to effectively support personalized learning in introductory statistics courses.
References


CHAPTER 4

THE EFFECT OF OPEN EDUCATIONAL RESOURCES ON MOTIVATION AND
ANXIETY IN PROMOTING PERSONALIZED STATISTICS LEARNING

3 Lin, Y. Submitted to The International Review of Research in Open and Distributed Learning,
02/07/2015
Abstract

Personalization in education can be classified as personalized learning and personalized instruction, which respectively emphasize students' unique ways of learning and teachers' effective approaches to support individual learning. However, teachers may view personalized instruction as a burden if there is a lack of continuous support (Authors, 2013). Openness and multiple choices in open educational resources can overcome this barrier that prevents teachers from implementing personalized instruction. The appropriate ways to use open educational resources include reuse, redistribution, revision, and remix (Hilton III, Wiley, Stein, & Johnson, 2010). Open educational resources customized through these four approaches can promote implicit social interaction and form a social learning environment which can be determined by personal, behavioral, and environmental factors (Bandura, 1986; Schunk, 2008). Student motivation and statistics learning anxiety were perceived as the two main personal factors affecting student achievement (Ejei, Weisani, Siadat, & Khezriazar, 2011; Lavasani, Weisani, & Ejei, 2011; Macher, Paechter, Papousek, & Ruggeri, 2012). The availability of open educational resources and the appropriate ways to use them respectively worked as the environmental and behavioral factors. The purpose of this study was to examine the relationship among student motivation, statistics learning anxiety, and the appropriate use of open educational resources. In this way, the resulting effects can measure the occurrence of triadic reciprocal interaction to promote personalized statistics learning.

Keywords: Personalized Learning, Personalized Instruction, Introductory Statistics, Open Educational Resources, Motivation, Statistics Learning Anxiety
The Effect of Open Educational Resources on Motivation and Anxiety in Promoting Personalized Statistics Learning

Individual differences can determine students' preferred ways of learning and can likely influence how they interact with their peers, instructors, and learning environment. Individual differences may also occur because of students' psychological states such as motivation, learning anxiety, etc. and may result in various learning needs. Taking a statistics course as an example, students may experience different learning barriers due to their backgrounds or previous learning performances. Motivation and statistics learning anxiety have been perceived as the two main psychological factors affecting student achievement in statistics learning (Ejei, et al., 2011; Lavasani, et al., 2011; Macher, et al., 2012). A high level of statistics learning anxiety may bring low learning motivation (Bell, 2003; Onwuegbuzie, 2000; Pan & Tang, 2004, 2005). These two factors can also bring differences into the class and influence a variety of ways that teachers can implement instruction to effectively support individual students.

One learning solution cannot meet all learner needs. Teachers tend to customize the design and implementation of their curriculum in order to accommodate personal needs and minimize individual differences. Accordingly, educational personalization can be conceptually classified as personalized learning and instruction, and emphasizes effective ways to accommodate individual needs in learning and teaching. However, teachers may not implement personalized instruction if there is a lack of continuous support (Authors, 2013). Open educational resources including a supportive culture of openness and the growing availability of resources can overcome the lack of continuous support. The appropriate use of open educational resources, which includes reuse, redistribution, revision, and remix, can prompt an implicit social interaction among teachers, students, and users who customize them. Such social interaction
tends to form a social learning environment involving personal, behavioral, and environmental factors (Bandura, 1986; Schunk, 2008).

Although the appropriate use of open educational resources can overcome the barrier caused by a lack of continuous support, and thus form a social learning environment, there is relatively little understanding if such ways to use open educational resources can relate to motivation and anxiety for statistics learning, and hence promote personalized learning. The purpose of this study was to identify the interrelationship among student motivation, statistics learning anxiety, and the appropriate use of open educational resources, which informs the triadic reciprocal interaction addressed in a social learning environment.

**Personalized Learning**

Students have their unique ways of learning which represent individual differences and needs. Personalized learning is determined by individual needs as well as their own ways of learning (Carolan & Guinn, 2007; Carroll, 1975; Johnson, Adams, & Cummins, 2012; Keefe & Jenkins, 2008; Miller, 2010). Flexibility plays an important role in personalized learning to support individual students and reduce their cognitive load (Chen, 2007). Thus, individual goals and the learning pace can be decided by students (Smith & Throne, 2009). Consequently, meeting a variety of needs and effectively minimizing their differences are necessary in personalized learning.

**Personalized Instruction**

Teachers contextualize their teaching practices in order to meet individual learning needs. Personalized instruction refers to the way that teachers consider student diversity and effectively support individual ways of learning to minimize heterogeneity in the classroom (Keefe & Jenkins, 2008). Personalized instruction addresses both differentiation and meaningfulness
(Carolan & Guinn, 2007; Sands & Barker, 2004). Thus, a meaningful learning path can emerge and can be decided by a collective and interactive process among students and teachers, which can influence the implementation of personalized instruction (Anderson, 2007; Dolog, Simon, Nejdl, & Klobučar, 2008; Hamdan & Mattarima, 2012; Jenkins & Keefe, 2001; King-Shaver, 2008; Scigliano & Hipsky, 2010; Tobin & McInnes, 2008; Zajac, 2009).

**Constraint for personalized instruction.** Personalization in education is perceived as being necessary to accommodate individual learning needs by implementing personalized learning and instruction. However, teachers tend to perceive personalized instruction as a burden if there is a lack of continuous support (Carolan & Guinn, 2007; Authors, 2013; Miller, 2010). Such support fostering the implementation of personalized instruction includes a supportive culture as well as the availability of resources (Carolan & Guinn, 2007; Authors, 2013; Miller, 2010).

**Continuous support for personalized instruction.** Open educational resources are featured for their openness and multiple choices, which inform a supportive culture and a growing availability of resources. Openness allows users to use open educational resources without violating the copyright laws (Caswell, Henson, Jensen, & Wiley, 2008; Clements & Pawlowski, 2012; Olcott Jr., 2012; Rogerson-Revell, 2007; Wiley & Gurrell, 2009) and creates a supportive culture and environment for users to legally reuse these resources. A growing availability of open educational resources provide alternative options to users (D'Antoni, 2009; Olcott Jr., 2012). Thus, open educational resources can be customized for the remediation or enrichment purposes (D'Antoni, 2009; Olcott Jr., 2012). Openness and multiple choices are two salient features in open educational resources and can serve as continuous support for teachers to implement personalized instruction.
**Developmental Model for Personalized Statistics Learning**

The appropriate use of open educational resources which continuously supports personalized instruction can prompt an implicit social interaction among teachers, students, and other users who customize open educational resources. Teachers, for example, may reuse the same open textbooks that have been revised by other users for similar purposes. The chapters within a textbook can be reordered to meet instructional needs and redistributed to students. Thus, a social learning environment in which much human learning occurs (Schunk, 2008) can be formed and can involve personal, behavioral, and environmental factors within this social learning environment. Accordingly, a developmental model was proposed in the context of statistics learning and used to promote personalized learning (see Figure 4.1). This developmental model identifies individual learning needs as a personal factor, including student motivation and statistics learning anxiety which have been perceived as the two main psychological factors for statistics learning (Ejei, et al., 2011; Lavasani, et al., 2011; Macher, et al., 2012). The availability of open educational resources can work as an environmental factor, while the appropriate ways to use them can serve as a behavioral factor. The triadic reciprocal interaction among individual learning needs, the availability of open educational resources, and their appropriate use can promote personalized statistics learning in terms of increased learning motivation and decreased statistics learning anxiety.
Figure 4.1. Developmental Model for Personalized Statistics Learning

**Personal Factor**

**Motivation.** Motivation is the tendency that learners behave in a certain way to achieve their goals. As learners get interested in an activity in which no outer rewards are imposed, the desire to engage in this activity can be defined as intrinsic motivation (Deci, 1975). Extrinsic motivation, in contrast, indicates that learners do activities to gain outer rewards or to avoid punishments (Schunk, 2008). Thus, the basic distinction between intrinsic and extrinsic motivation refers to the idea that learners feel interested and enjoyable toward a given activity or that they simply do it for separate outcomes (Ryan & Deci, 2000). Numerous factors have been identified to affect learners' intrinsic or extrinsic motivation. Only the factors influencing students' intrinsic motivation are addressed in this study and include interest (Ryan & Deci, 2009; Sansone, Smith, Thoman, & MacNamara, 2012; Schiefele, 2009), enjoyment (Lesser et al.,...
As students find in-class materials interesting and enjoyable, they tend to perform better than students who perceive these materials less interesting (Gal & Ginsburg, 1994; Ryan & Deci, 2009). Enjoyment and fun are viewed as the two important indicators of intrinsic motivation and can relate to affective and motivational properties, an emotional state, and an individual learning trait (Lesser, et al., 2013). Therefore, play and active learning are considered two effective ways to intrinsically motivate students (Ryan & Deci, 2009) and engage them in learning activities which may not be enjoyable or fun (Ryan & Deci, 2000). Learning values can be classified as task-related and achievement-related values (Atkinson, 1957; Schunk, 2008; Wigfield & Eccles, 1992). Learners likely impose their own values toward learning tasks as they work on them. Achievement-related values, in contrast, represent how learners value their behaviors and performance after completing a given task. Value and usefulness emerge due to the different expectations in learning and learning goals (Schunk, 2008) and thus, influence student intrinsic motivation.

Statistics learning anxiety. Statistics learning anxiety has been referred to as a certain level of anxious feelings that students encounter as they learn statistics (Bell, 2003; Onwuegbuzie, 2000; Pan & Tang, 2004, 2005). More than 50% of students in a class may experience various levels of statistics learning anxiety (Hanna, Shevlin, & Dempster, 2008). Such anxious feelings toward statistics learning can also be perceived as a certain type of perception that causes low motivation (Bell, 2003; Onwuegbuzie, 2000; Pan & Tang, 2004, 2005) and leads to poor achievement (Macher, et al., 2012). Six factors have been identified as the cause of statistics learning anxiety: 1) worth of statistics, 2) interpretation anxiety, 3) test and
class anxiety, 4) computation self-concept, 5) fear of asking for help, and 6) fear of statistics teachers (Cruise, Cash, & Bolton, 1985; Hanna, et al., 2008). These six factors can also determine the extent to which students feel anxious about statistics learning.

Students may consider statistics worthless if they have a high level of statistics learning anxiety. Interpretation anxiety indicates that students have difficulty in interpreting quantitative-based findings as they read some scholarly reports or papers (Vigil-Colet, Lorenzo-Seva, & Condon, 2008). Statistics learning anxiety can occur if students have to take statistics tests and exams. Such anxiety may appear as students walk into the room to take a statistics exam (Vigil-Colet, et al., 2008). Statistics learning anxiety can also be caused by a perceived lack of knowledge in math. Thus, some students may feel anxious about statistics learning because of their low achievements or poor performances in prior math or similar classes. If students rarely ask for assistance or frequently fear their statistics teachers, their statistics learning anxiety can be moderately high.

**Environmental Factor**

Open resources used for educational purposes only are defined as open educational resources. Non-commercial use and adaption through information and communication technology are perceived as the two main features that open educational resources bring to higher education (UNESCO, 2002). Approximately fifty percent of institutions in U.S. higher education have widely used open educational resources, including online education (Allen & Seaman, 2012). Open educational resources have been applied in a variety of contexts, including, but are not limited to online courses (Tu, Sujo-Montes, Yen, Chan, & Blocher, 2012), foreign language learning (Hung, 2011; Jia, Chen, Ding, & Ruan, 2012; Kavaliauskienë, 2011; Wang & Yang, 2012), health science education (Windle, Wharrad, McCormick, Laverty, & Taylor,
open university (Conole & Weller, 2008; Gourley & Lane, 2009), open courseware (Caswell, et al., 2008; Keats, 2009), teacher professional development (Sapire & Reed, 2011; Thakrar, Zinn, & Wolfenden, 2009), and corporate training (Geith, Vignare, Bourquin, & Thiagarajan, 2010). Open educational resources can also be used for different purposes such as the use of open educational resources in a problem-based learning environment to enhance pedagogy and to improve the quality of learning activities (Gurell, Kuo, & Walker, 2010).

Open educational resources have brought several advantages to teaching and learning, including, but are not limited to 1) openness, 2) multiple choices, 3) shareability and reusability, and 4) less duplication. Because open educational resources can be freely shared, exchanged, and reproduced, users are not concerned about copyright issues and the violation of relevant laws (Caswell, et al., 2008; Clements & Pawlowski, 2012; Olcott Jr., 2012; Rogerson-Revell, 2007; Wiley & Gurrell, 2009). Openness also allows users to customize open educational resources without any extra cost (Caswell, et al., 2008; Friesen, 2009) based on some specific purposes such as course co-creation (Lane & McAndrew, 2010). Multiple choices in open educational resources assist students to have alternative options to further support their learning (Caswell, et al., 2008; Olcott Jr., 2012). Students, for example, can make an appropriate decision in selecting colleges to attend after they take courses in university-wide open courseware. Open courseware can also work as optional choices to remediate or enrich student learning experiences in a traditional learning environment (D'Antoni, 2009; Olcott Jr., 2012). Shareability and reusability can be emphasized as users reuse and reproduce open educational resources (Rogerson-Revell, 2007). Reusability also leads to less duplication (Olcott Jr., 2012; Rogerson-Revell, 2007). These advantages make a learning environment more adaptive with a high level of flexibility.
**Behavioral Factor**

Openness and multiple choices of open educational continuously support teachers' implementation of personalized instruction. The appropriate ways to use open educational resources, which serve as the behavioral factor in this developmental model, include the following: reuse, redistribution, revision, remix, which also inform the four levels of openness (Hilton III, et al., 2010). Reuse allows users to entirely or partially use open educational resources. Users can simply share these resources with other people by redistributing them. Open educational resources can be flexibly revised for some specific needs (Hilton III, et al., 2010). Combining a variety of open and non-open educational resources for new purposes has been referred to as remix.

**Research Questions**

Although the availability of open educational resources can continually support teachers to implement personalized instruction, several questions still remain unanswered. There is a need for a better understanding of how student motivation and statistics learning anxiety can relate to the appropriate use of open educational resources. The relationship among motivation, statistics learning anxiety, and the appropriate use of open educational resources can be evaluated and can determine if triadic reciprocal interaction occurs, and thus promotes personalized statistics learning. Therefore, the following questions were used to guide this research study:

1. What is the relationship between student motivation for statistics learning and the appropriate use of open educational resources?
2. What is the relationship between student statistics learning anxiety and the appropriate use of open educational resources?
Methods

Participants

Some participants might complete partial surveys or provide the same answers for all items within a survey. The two researchers in this study recoded data and simultaneously checked if any participants answered in such an unusual way. Thus, 27 out of 135 participants were screened out. A total of 108 participants in this study were undergraduate and graduate students enrolled in introductory statistics courses. These participants came from different programs or departments and had various levels of prior knowledge for introductory statistics. All participants in this study were over eighteen years old and were likely pursuing a post-secondary degree at the time they participated in the study.

Context

The variation in prior knowledge for introductory statistics was moderately large. Some participants might have taken one or two similar statistics courses before, but some might have never. All participants were provided access to the open educational resources throughout the course. These resources were collected and selected from 12 repository websites of open educational resources (see Table 4.1). Ten out of twelve websites had an interdisciplinary collection for free reuse or reproduction. Only two websites, Statistics Online Computational Resource (SOCR) and Online Statistics Education: An Interactive Multimedia Course of Study, were primarily used for statistics teaching and learning.
Table 4.1

*List of Repository for Open Educational Resources*

<table>
<thead>
<tr>
<th>Repository of open educational resources</th>
<th>Collection</th>
</tr>
</thead>
<tbody>
<tr>
<td>Connexions (<a href="http://cnx.org/">http://cnx.org/</a>)</td>
<td>More than 17,000 learning objects or modules and over 1000 collections (textbooks, journal articles, etc.) are used.</td>
</tr>
<tr>
<td>CAUSEweb.org (<a href="https://www.causeweb.org/resources/">https://www.causeweb.org/resources/</a>)</td>
<td>The support in 4 areas are mainly provided: resources, professional development, outreach, research</td>
</tr>
<tr>
<td>Multimedia Educational Resource for Learning and Online Teaching (MERLOT) (<a href="http://www.merlot.org/merlot/index.htm">http://www.merlot.org/merlot/index.htm</a> )</td>
<td>There is a free and open peer-review process for the entire collection.</td>
</tr>
<tr>
<td>Khan Academy (<a href="https://www.khanacademy.org/">https://www.khanacademy.org/</a>)</td>
<td>Khan Academy provides the collection of videos which can be freely used by students and teachers.</td>
</tr>
<tr>
<td>The Sofa Open Content Initiative (<a href="http://sofia.fhda.edu/gallery/statistics/index.html">http://sofia.fhda.edu/gallery/statistics/index.html</a>)</td>
<td>The resources are created by a Learning Technology &amp; Innovations program at a community college in California.</td>
</tr>
<tr>
<td>Saylor.org (<a href="http://www.saylor.org/">http://www.saylor.org/</a>)</td>
<td>More than 300 courses are free and available.</td>
</tr>
<tr>
<td>Statistics Online Computational Resource (SOCR) (<a href="http://www.socr.ucla.edu/">http://www.socr.ucla.edu/</a>)</td>
<td>Those resources are mainly related to statistics and broadly cover games, experiment, wiki, hands-on activities, etc.</td>
</tr>
<tr>
<td>Open Learn (<a href="http://www.open.edu/openlearn/">http://www.open.edu/openlearn/</a>)</td>
<td>More than 650 courses are free and available.</td>
</tr>
<tr>
<td>Online Statistics Education: An Interactive Multimedia Course of Study (<a href="http://www.oercommons.org/courses/online-statistics-an-interactive-multimedia-course-of-study/view">http://www.oercommons.org/courses/online-statistics-an-interactive-multimedia-course-of-study/view</a>)</td>
<td>This website has a collection for learning and teaching introductory statistics and includes material such as textbook and video presentations.</td>
</tr>
<tr>
<td>Curriki (<a href="http://www.curriki.org/welcome/">http://www.curriki.org/welcome/</a>)</td>
<td>More than 50,000 resources are free and available.</td>
</tr>
<tr>
<td>HippoCampus.org (<a href="http://www.hippocampus.org/HippoCampus/">http://www.hippocampus.org/HippoCampus/</a>)</td>
<td>There are a variety of multimedia contents such as videos, animations, and simulations, which are available for K-12 and higher education.</td>
</tr>
<tr>
<td>OpenCourseWare Consortium (<a href="http://www.ocwconsortium.org/about-ocw/">http://www.ocwconsortium.org/about-ocw/</a>)</td>
<td>The resources for the use in the course such as syllabus and textbook are available. Also, the website has incorporation with other universities to develop and publish these resources.</td>
</tr>
</tbody>
</table>
Intervention

Open educational resources mainly worked as supplements throughout the courses for enrichment purpose and were likely to be customized as remediation to bridge the gap between prior knowledge in introductory statistics and existing skills. The four ways to appropriately use open educational resources involves reuse, redistribution, revision, and remix. One of two researchers in this study helped select appropriate open educational resources from these 12 repository websites based on the weekly topic. The selected resources were shared with the instructors to reuse or reproduce. For example, some simulations elaborating the concept of R Square were introduced to the entire class during the lecture and redistributed to students. These simulations provided an easy way for students to learn the abstract concept about R Square. In addition, the instructors revised couple of items in online assessment and combined them into homework. This can be perceived as a way to revise and remix open educational resources. Instructors not only introduced open educational resources during lectures but also shared them with students. Open educational resources provided by instructors were posted in the learning management system. So students can access these resources anytime and anywhere outside of the class. Students were likely to reuse these resources as they worked on their homework or prepared for exams. Students also looked for other open educational resources to clarify their unclear statistics concepts during the homework completion. In this way, these open educational resources were primarily reused and redistributed to other peers.

Procedures

Data collection was conducted for 16 to 18 weeks. The learning characteristics survey was initially administered and used to examine student motivation and anxiety in statistics learning. Participants started using open educational resources in the course after completing the
learning characteristics survey. Each participant completed the satisfaction survey at the end of the data collection. This survey was used to identify the use of open educational resources in class. This survey was conducted on the last two weeks of course. Students who participated to this study were provided access in the learning management system to complete the survey. During these two weeks, each student can complete part of items and save them anytime. Then students can return to complete the remaining items and submit the survey in these two weeks.

**Measures**

*Motivation.* Intrinsic Motivation Inventory (Ryan, 1982) was used to examine participant perceptions about a target learning activity known as introductory statistics learning in this study. Only the sub-scales of interest, enjoyment, perceived value and usefulness were used because of the context in this study. Participants, for example, were asked their opinions about the statement, "I enjoy studying statistics or similar courses very much." There were 11 items in total, and a 5-point Likert scale was used in rating each item (1) strongly disagree to (5) strongly agree. The reported internal consistency for the items was 0.8, which was validated with strong support (McAuley, Duncan, & Tammen, 1989).

*Statistics learning anxiety.* Statistical Anxiety Rating Scale (Cruise, et al., 1985) is acknowledged as the most widely used instrument in examining statistics anxiety (Hanna, et al., 2008). For example, participants were asked their opinions about the statement, "Studying for an examination in a statistics course." Some of the items in the original scale were deleted due to the context of study. There were a total of 22 items which addressed statistics learning anxiety, and a 5-point Likert scale was used in rating each item. The first nine items had (1) no anxiety to (5) very much anxiety. The rest of the 13 items included (1) highly disagree to (5) highly agree
to rate statistics learning anxiety. Reported internal consistency for the items was from 0.83 to 0.94 (Hanna, et al., 2008).

**Use of open educational resources.** The use of open educational resources was measured by the four levels of customization: 1) reuse, 2) redistribution, 3) revision, and 4) remix. Participants were asked their perceptions for the use of open educational resources customized in these four ways. For example, participants were asked to evaluate their perception on this item "Open educational resources in the course such as answer sheets or open textbooks are revised." Four items on a 5-point Likert scale were used (1) strongly disagree to (5) strongly agree. The reliability of these 4 items was 0.88 of Cronbach’s alpha value. The reliability for the remaining items relevant to the use of open educational resources involves three constructs: motivation, statistics learning anxiety, and the overall design and use of open educational resources. Motivation construct included 11 items with a reliability of .925 in Cronbach’s alpha value. The Cronbach’s alpha value among the 5 items about the use of open educational resources to decrease statistics learning anxiety was .811. The construct about the overall design and use of open educational resources had a reliability of .925 in Cronbach’s alpha value for a total of 9 items. In addition, three open-ended questions were also used to identify the importance and value that students perceived in using open educational resources for individual statistics learning.

**Data Analysis**

The variables used in this study are listed in Table 4.2. There are a total of 14 variables. Exploratory factor analysis was applied to identify the number of factors and the nature of the construct which influenced a set of responses. The maximum likelihood estimation method and Geomin factor rotation helped interpret factor loadings within each factor and observed
variables. In this way, the dimensionality of factors could be initially specified. Confirmatory factor analysis was used then to examine the overall relationship among the factors identified in the exploratory factor analysis. Thus, the developmental model built underlying the theoretical assumption could be verified. Some answers from three open-ended questions can also provide some findings about students' use of open educational resources.

Table 4.2

*List of Instruments and Variables Used*

<table>
<thead>
<tr>
<th>Instruments</th>
<th>Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>Learning Characteristics Survey</td>
<td>Interest</td>
</tr>
<tr>
<td></td>
<td>Enjoyment</td>
</tr>
<tr>
<td></td>
<td>Value</td>
</tr>
<tr>
<td></td>
<td>Usefulness</td>
</tr>
<tr>
<td></td>
<td>Worth of Statistics</td>
</tr>
<tr>
<td></td>
<td>Interpretation Anxiety</td>
</tr>
<tr>
<td></td>
<td>Test and Class Anxiety</td>
</tr>
<tr>
<td></td>
<td>Computational Self-concept</td>
</tr>
<tr>
<td></td>
<td>Fear of Asking for Help</td>
</tr>
<tr>
<td></td>
<td>Fear of Statistics Teachers</td>
</tr>
<tr>
<td>Satisfaction Survey</td>
<td>Reuse</td>
</tr>
<tr>
<td></td>
<td>Redistribution</td>
</tr>
<tr>
<td></td>
<td>Revision</td>
</tr>
<tr>
<td></td>
<td>Remix</td>
</tr>
</tbody>
</table>

**Results**

Descriptive statistics including means and standard deviations of all variables are presented in Table 4.3.

Table 4.3

*Mean and Standard Deviation for the Variables Used in the Study*

<table>
<thead>
<tr>
<th>Variables</th>
<th>M (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>interest</td>
<td>3.44 (0.82)</td>
</tr>
<tr>
<td>enjoyment</td>
<td>3.14 (1.00)</td>
</tr>
<tr>
<td>usefulness</td>
<td>4.21 (0.77)</td>
</tr>
<tr>
<td>value</td>
<td>4.66 (0.79)</td>
</tr>
<tr>
<td>Factor</td>
<td>Eigenvalue</td>
</tr>
<tr>
<td>--------------------------------</td>
<td>------------</td>
</tr>
<tr>
<td>worth of statistics</td>
<td>1.93</td>
</tr>
<tr>
<td>interpretation anxiety</td>
<td>2.77</td>
</tr>
<tr>
<td>test and class anxiety</td>
<td>3.23</td>
</tr>
<tr>
<td>computational self-concept</td>
<td>2.26</td>
</tr>
<tr>
<td>fear of asking for help</td>
<td>2.36</td>
</tr>
<tr>
<td>fear of statistics teachers</td>
<td>2.59</td>
</tr>
<tr>
<td>reuse</td>
<td>3.58</td>
</tr>
<tr>
<td>redistribution</td>
<td>3.58</td>
</tr>
<tr>
<td>revision</td>
<td>3.38</td>
</tr>
<tr>
<td>remix</td>
<td>3.23</td>
</tr>
</tbody>
</table>

Figure 4.2 indicates that up to four factors with the Eigenvalues exceeding 1 can be attained in the explanatory factor analysis. Although the relevant index values for these four factors indicate a proper fit between the assumption of developmental model and actual data practices, the findings examined by the three factors are more interpretable than the four. Hence, Table 4.4 lists the three factors: motivation, statistics learning anxiety, and use of open educational resources, and their observed variables within each factor.
Table 4.4

Three Factors and their Observed Variables

<table>
<thead>
<tr>
<th>Factor</th>
<th>Observed variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>Motivation</td>
<td>interest</td>
</tr>
<tr>
<td></td>
<td>value</td>
</tr>
<tr>
<td></td>
<td>usefulness</td>
</tr>
<tr>
<td></td>
<td>worth of statistics</td>
</tr>
<tr>
<td>Statistics Learning Anxiety</td>
<td>test and class anxiety</td>
</tr>
<tr>
<td></td>
<td>interpretation anxiety</td>
</tr>
<tr>
<td></td>
<td>fear of asking for help</td>
</tr>
<tr>
<td></td>
<td>worth of statistics</td>
</tr>
<tr>
<td></td>
<td>fear of statistics teachers</td>
</tr>
<tr>
<td></td>
<td>computational self-concept</td>
</tr>
<tr>
<td>Use of Open Educational Resources</td>
<td>reuse</td>
</tr>
<tr>
<td></td>
<td>redistribution</td>
</tr>
<tr>
<td></td>
<td>revision</td>
</tr>
<tr>
<td></td>
<td>remix</td>
</tr>
</tbody>
</table>

The relevant index values in the confirmatory factor analysis are outlined in Table 4.5.

Chi-Square Test value did not achieve a significant level ($p>.05$) and denoted that there was a proper fit. The Root Mean Square Error of Approximation (RMSEA) estimate value was equal to or less than .05 and indicated a perfect fit. The Comparative Fit Index (CFI) value was more than .9 and implied a perfect fit. The Standardized Root Mean Square Residual (SRMR) value was less than .08 and indicated a great fit. Most index values indicate that there is a proper fit between the assumption of the developmental model and the data practices. The model results and factor loadings are presented in Figure 4.3. All factor loadings within each factor reach a significant level of .05 or .01, which means that all factors can be properly measured by these observed variables.
Table 4.5

**Index Values for Confirmatory Factor Analysis**

<table>
<thead>
<tr>
<th>Index</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chi-Square Test of Model Fit</td>
<td>$X^2 = 81.02$ ($p = .101$)</td>
</tr>
<tr>
<td>Root Mean Square Error of Approximation (RMSEA)</td>
<td>.05</td>
</tr>
<tr>
<td>Comparative Fit Index (CFI)</td>
<td>.98</td>
</tr>
<tr>
<td>Standardized Root Mean Square Residual (SRMR)</td>
<td>.07</td>
</tr>
</tbody>
</table>

* $p < .05$, ** $p < .01$

![Figure 4.3. Model Results and Factor Loadings](image-url)
**Research Question 1**

What is the relationship between student motivation for statistics learning and the appropriate use of open educational resources? The model results in Figure 4.3 show that there is a negative correlation between motivation and the use of open educational resources. However, such relationship neither denotes the causality nor causes any significant effects among motivation and the use of open educational resources. Remix and revision have a positive and significant correlation. Open educational resources were more likely to be remixed with other existing resources as these resources were revised to meet instructional needs. Among the four observed variables measuring student motivation of statistics learning, there are two pairs which have a positive relationship: 1) interest with enjoyment, and 2) value and perceived usefulness. The perceived usefulness has a negative relationship with student enjoyment for introductory statistics learning although such negative correlation does not cause any significant effects. The findings from the three open-ended questions indicated that students tended to use open educational resources on homework completion, rather than on exam preparation. The eight advantages in Table 4.6 for using open educational resources in an introductory statistics course have included 1) clarification of abstract concept, 2) a variety of resources, 3) application of research methodology in the real world, 4) improvement individual skills used for statistics learning, 5) valuable learning experiences, 6) enhancement in individual career, 7) enhancement in individual studies, and 8) a positive learning environment. Participants indicated that the use of open educational resources brought them humor, attract their attention, kept class interesting, and facilitate student motivation.
Table 4.6

*Advantages for the Use of Open Educational Resources*

<table>
<thead>
<tr>
<th>Advantage</th>
<th>Participant Response</th>
</tr>
</thead>
</table>
| clarification of abstract concept | - visualize concept  
- improve comprehension  
- depict complicated concepts  
- find answers of the questions before asking instructors  
- fill the gap between what is known and what should be learnt |
| a variety of resources | - supplement statistics learning  
- gain knowledge and information  
- substitute outdated materials such as books  
- provide addition support  
- access to resources anytime and anywhere  
- charge at no cost |
| application of research methodology in the real world | - provide a practical approach for people who don't regularly or frequently work with statistics to learn this subject  
- understand the ways to apply this research methodology in the real world |
| improvement individual skills used for statistics learning | - complement individual analysis skill  
- enhance problem-solving skill |
| valuable learning experiences | - provide study aid for people having difficulty in statistics learning  
- meet needs for people who have different learning styles |
| enhancement in individual career | - help people find a job requiring statistics skills |
| enhancement in individual studies | - provide assistance in individual and dissertation studies |
| a positive learning environment | - provide humor  
- attract student attention  
- make student feel comfortable for statistics learning  
- keep class interesting and engage students for statistics learning  
- facilitate the learner's motivation  
- make students less stressful about statistics learning |
Research Question 2

What is the relationship between student statistics learning anxiety and the appropriate use of open educational resources? The model results in Figure 4.3 show that there is a positive correlation between statistics learning anxiety and the use of open educational resources. However, such relationship neither denotes the causality nor causes any significant effects among statistics learning anxiety and the use of open educational resources. There is a positive and significant relationship between interpretation anxiety and test and exam anxiety. As students feel anxious about their statistics tests and exams, their anxiety in interpreting quantitative findings in academic papers or reports is also in a high level. As presented in Table 4.6, few participants also indicated that the use of open educational resources might make them less stressful about statistics learning.

Discussion

The entire developmental model shows a proper fit between the assumption of the developmental model and the data practices. In addition to identifying the factor loadings used to measure each latent factor, the relationship among the observed variables was also examined. Enjoyment negatively correlates with the fear of statistics teachers. Students' fear of statistics teachers relatively decreases as they enjoy their statistics courses. The worth of statistics significantly and negatively correlates with value and usefulness. Student value and perceived usefulness about statistics learning may be high if they do not perceive worthlessness of statistics.

The use of open educational resources neither significantly correlates with motivation nor with statistics learning anxiety. Although the appropriate use of open educational resources can work as an effective way to continuously support teachers in implementing personalized
instruction, such support did not cause a significant triadic reciprocal interaction with student motivation and statistics learning anxiety, let alone the promotion of personalized statistics learning. However, multiple students expressed that open educational resources can provide a positive learning environment which can provide humor, make statistics learning interesting, and attract student attention for statistics learning. Some students indicated that the use of open educational resources can make them feel less stressful and help them find answers before asking for help with instructors.

Therefore, the appropriate use of open educational resources involving reuse, redistribution, revision, and remix should not only provide students with motivational support but also effectively decrease statistics learning anxiety. The use of humorous cartoons is an example of effectively reducing student statistics learning anxiety (Pan & Tang, 2005). Teachers can look online for humorous cartoon examples in the repository of open educational resources and reuse them in class to decrease student statistics learning anxiety. Therefore, students in this way are more likely to perceive statistics courses as interesting, rather than boring.

**Implications**

This study addressed personal, behavioral, and environmental factors emphasized in social cognitive theory to examine the relationship among motivation, statistics learning anxiety, and the appropriate use of open educational resources. As indicated by the study findings, student motivation for statistics learning could be significantly measured by their interest, enjoyment, value, and usefulness toward introductory statistics courses. There are six factors that might significantly cause statistics learning anxiety: 1) worth of statistics, 2) test and class anxiety, 3) interpretation anxiety, 4) fear of statistics teachers, 5) fear of asking for help, and 6) computational self-concept. The appropriate use of open educational resources could be
significantly measured by the four approaches of customization involving reuse, redistribution, revision, and remix. The appropriate use of open educational resources can be perceived as an effective way to provide continuous support with teachers to implement personalized instruction. However, such use may not cause significant triadic reciprocal interaction with student motivation and statistics learning anxiety, and thus promote personalized statistics learning. Hence, the customization of open educational resources considers not only reuse, redistribution, revision, and remix but also motivational support and effective ways to decrease statistics learning anxiety. Consequently, personalization in education classified as personalized learning and personalized instructional can be effectively promoted.

**Limitations and Future Study**

There are four limitations in this study. The first limitation is the sample size of a total of 108 participants in this study. The sample size for studies using structural equation modeling to analyze data can be determined by the number of indicators and factors, the magnitude of factor loadings, and the path coefficients. There is still no rule-of-thumb to decide the value of sample size yet. The suggested sample size in literature can range from 30 to 450 (Wolf, Harrington, Clark, & Miller, 2013), 50 to 70 (Sideridis, Simos, Papanicolaou, & Fletcher, 2014) or at least start from 100 or 200 (A. Boomsma, 1982; Anne Boomsma, 1985). Although the results in this study indicated a proper fit between the assumption of the developmental model and the actual data, the entire model can usually be validated if there is a large sample size exceeding 200 participants. Thus, the developmental model underlying the theoretical assumption can also be substantially verified.

The second limitation is the lack of multi-method ways to collect data. All the data were self-reported by students who voluntarily participated in this study. There were no actual
observations and interviews in this study. Although self-reported data can help examine the overall construct underlying participants' responses, there are some limitations in interpreting some specific findings through such data. Therefore, actual observations and interviews can assist in explaining some specific questions pertaining to the construct of the model.

The third limitation in this study is the supplemental, rather than mandatory, way to reuse most open educational resources. The advantage to reuse these resources in a supplemental way allows students to have choices to select the ones they need. However, the supplemental way to reuse open educational resources may cause the different level of intervention participants received in class. Some students may reuse all open educational resources, but some may barely use them.

The fourth limitation is the way to collect data about the use of open educational resources. Since the data about the use of open educational resources can include students' use of open educational resources and their satisfaction with using them. Therefore, the use of open educational resources should be clearly defined. In this way, the use of open educational resources can be more precisely measured to answer our research questions. Additionally, the use of open educational resources should be collected in a weekly base, rather than in the end of semester. Thus, the change and trend to use open educational resources can be identified.

**Conclusion**

Personalization in education, which can be classified as personalized learning and personalized instruction, addresses individual ways of learning and effective teacher instruction to support each student. Teachers may not be able to implement personalized instruction if there is a lack of continuous support (Authors, 2013) which includes a supportive culture as well as the availability of resources (Carolan & Guinn, 2007; Miller, 2010). Openness and the growing
availability of open educational resources can be viewed as necessary to continuously support teachers' implementation of personalized instruction. The ways to appropriately use open educational resources include reuse, redistribution, revision, and remix. Open educational resources customized through these four ways can prompt an implicit social interaction and form a social learning environment where much human learning occurs (Bandura, 1986; Schunk, 2008). Thus, a developmental model that addressed personal, behavioral, and environmental factors and their triadic reciprocal interaction in a social learning environment (Bandura, 1986) was proposed and used to promote personalized statistics learning. Accordingly, student motivation and statistics learning anxiety served as the personal factor. Behavioral and environmental factors indicated the availability of open educational resources and appropriate ways to use them. The aim of this study was to examine the relationship among student motivation, statistics learning anxiety, and the appropriate use of open educational resources and to measure if any triadic reciprocal interaction occurred. Although the resulting effects did not cause any significant triadic reciprocal interaction in the developmental model, motivational support and effective ways to decrease statistics learning anxiety should be included in the customization process of open educational resources. Thus, personalization in education with an emphasis on personalized learning and instruction can be effectively promoted.
References


Authors. (2013). [Title omitted for blind review].


Keats, D. (2009). The road to free and open educational resources at the University of the Western Cape: A personal and institutional journey. *Open Learning, 24*(1), 47-55. doi: 10.1080/02680510802627829


CHAPTER 5

CONCLUSION

A peer modeling process can overcome the barriers caused by the lack of time and required knowledge for personalized instruction. The appropriate use of open educational resources can resolve the issue for the lack of continuous support. Accordingly, triadic reciprocal interaction addressing personal, behavioral, and personal factors in a social learning environment provided the theoretical framework and formed the developmental model used to promote personalized statistics learning as well as to support personalized instruction. The results of these studies are consistent with similar studies about implementing personalized instruction and promoting personalized statistics learning (Lin & Kim, 2013). The two main interventions used in this dissertation study were modeling strategies applied in peer and non-peer settings and the appropriate use of open educational resources.

Chapter 2 discussed ways a developmental model was used to promote personalized learning and to develop instruction. The developmental model was implemented in introductory statistics courses, and the effects of individual learning needs and a peer modeling process on student achievement were examined. The findings in this study indicated that the entire developmental model did not have a proper fit with the actual data practices. Technical access, prior knowledge, and statistics learning anxiety could significantly and directly affect student examination scores. Motivation could have significant and direct effects on student achievement in homework. Statistics learning anxiety significantly and indirectly affected student homework scores as motivation served as mediator. That is, low motivation caused by high learning anxiety
tends to lead low achievement in homework. However, a peer modeling process did not cause any significant effect on homework or exams.

Extending the developmental model proposed in Chapter 2, Chapter 3 identified the interrelationship among individual learning needs, peer and non-peer modeling processes, and the appropriate use of open educational resources. Chapter 3 served as the first evaluation study and indentified the factors significantly influencing the entire developmental model. Also, the relationship among each factor was investigated. The four factors identified were: motivation, learning anxiety in statistics, negative attitude toward statistics, and the use of open educational resources. In terms of triadic reciprocal interaction addressing the factors of people, behavior, and environment in a social learning environment, the use of open educational resources did not achieve a statistical significant level to influence student needs in motivation, learning anxiety in statistics, negative attitude toward statistics, and learning achievement in homework and exams. A peer modeling process could negatively relate to student motivation. Student motivation toward introductory statistics learning was actually low if they highly relied on peer assistance and applied relevant modeling strategies in completing homework. A non-peer modeling process could significantly decide student use of open educational resources. Students were more likely to use open educational resources provided by teachers or look for other online resources if they worked independently on their homework without any peer assistance. Thus, the use of open educational resources involving reuse, redistribution, revision, and remix can be enhanced.

Chapter 4 was the second evaluation study which specifically verified the developmental model by examining the relationship among student motivation, statistics learning anxiety, and the use of open educational resources. Motivation and statistics learning anxiety are perceived as the two main determinants affecting student statistics learning achievement (Ejei, Weisani, Siadat, & Khezriazar, 2011; Lavasani, Weisani, & Ejei, 2011; Macher, Paechter, Papousek, &
The entire model had a proper fit between the assumption of the developmental model and the actual data practices. Student motivation and their anxiety in statistics learning could significantly relate to each other. However, the appropriate use of open educational resources involving reuse, redistribution, revision, and remix did not significantly relate to student motivation and statistics learning anxiety. Thus, the triadic reciprocal interaction among student motivation, statistics learning anxiety, and the use of open educational resources was not significantly developed and used to promote personalized statistics learning.

The study demonstrated several important results for promoting personalized statistics learning and instruction in terms of individual learning needs, student achievement, and two interventions: a modeling process in peer and non-peer settings, and the appropriate use of open educational resources. Motivation and statistics learning anxiety classified as the personal factor had a negative correlation to each other. Student achievement was directly influenced by motivation and statistics learning anxiety. Although a peer modeling process which worked as the environmental factor did not cause any significant effect on student achievement, it could negatively relate to student motivation. The appropriate use of open educational resources did not bring any significant effects on student motivation and statistics learning. A non-peer modeling process and four ways to customize open educational resources could determine the use of open educational resources. More studies are necessary to specifically validate the developmental model and examine its effects in promoting personalized learning and instruction. Accordingly, the next section provides some implications and suggestions for future study.

**Implications and Suggestions**

The purpose of the study was to resolve the three concerns in implementing personalized instruction as well as to promote personalized statistics learning. The findings in a serious of studies indicated three implications and suggestions in consideration of individual learning.
needs, student achievement, and two interventions: modeling processes in peer and non-peer settings and the appropriate use of open educational resources.

**A Peer Modeling Process and Individual Learning Needs**

A peer modeling process did not cause significant and direct effects on student achievement as indicated in chapter 2, but negatively related to student motivation for statistics learning as indicated in Chapter 3. Such negative relationship between a peer modeling process and student motivation for statistics learning in Chapter 3 led positive and significant effects on student achievement of exam. A peer modeling process which includes a collaborative way to complete homework and peer modeling strategies applied such as discussion with peers becomes one of indicators to detect learners' tendency to engage in an introductory statistics course. If students highly rely on peer assistance in completing the homework, their motivation for statistics learning is actually low and may lead to the low achievement in exams. Therefore, the provision of motivational support with students who depend on a high level of peer assistance may essentially help them improve their achievement in exams.

**A Non-peer Modeling Process and Use of Open Educational Resources**

Although a non-peer modeling process can relate to the use of open educational resources involving reuse, redistribution, revision, and remix, such use was not able to cause significant effects on student achievement. A non-peer modeling process includes an independent way to complete homework and non-peer modeling strategies applied such as consulting with teachers and teacher assistants. The study findings indicated that open educational resources were simply customized and provided by teachers as supplements in class lectures, rather than reused or reproduced in homework or exam. If open educational resources can be reused, redistributed, revised, and remixed in the design and development of student assessment, the use of open
educational resources in this way may be able to bring some significant effects on student
achievement.

**Individual Learning Needs and the Use of Open Educational Resources**

The findings in Chapters 3 and 4 indicated that the use of open educational resources
involving reuse, redistribution, revision, and remix did not lead to significant effects on student
achievement, motivation, and anxiety for statistics learning. On one hand, such four ways to
customize open educational resources can overcome the teacher's barrier of continuous support
in implementing personalized instruction. On the other hand, use of open educational resources
does not relate to increased motivation and decreased statistics learning anxiety, which mainly
serve as two main psychological factors affecting student achievement in statistics learning (Ejei,
et al., 2011; Lavasani, et al., 2011; Macher, et al., 2012). The needs for motivational support in a
statistics class as well as for effective ways to reduce statistics learning anxiety should be
considered in the process to customize open educational resources. Thus, some significant effects
among the use of open educational resources, student motivation, and statistics learning anxiety
can be formed to cause the triadic reciprocal interaction, and thus promote personalized statistics
learning and instruction.

**Future Research Directions**

The findings should be considered as an initial step to validate a developmental model
underlying the assumption of social learning environment in the social cognitive theory to
promote personalized statistics learning as well as to overcome the three barriers that prevent
teachers from implementing personalized instruction. The further evaluation of the
developmental model is necessary. Thus, two suggestions are made for the future research
directions. First, all the introductory courses were delivered in a face-to-face context. The
findings indicated that the use of open educational resources in such context did not bring
significant effects on student achievement or significantly relate to student motivation or
statistics learning anxiety. Although students used open educational resources as supplements for
enriching or remediating their introductory statistics learning, the interaction between students
and teachers or among peers in a face-to-face context might lead to some limitations to the use of
open educational resources. Students may directly rely on the assistance provided by peers or
instructors in a face-to-face context rather than use these online resources to understand some
complex concepts. An online learning context in which students use synchronous and
asynchronous tools, rather than have the face-to-face interaction, to communicate with peers and
instructors may likely increase the use of open educational resources and possibly lead to some
changes on student achievement, motivation, and statistics learning anxiety. More studies should
be conducted to further examine the use of open educational resources in an online learning
context.

Second, a longitudinal study will be helpful to identify the effectiveness of the
developmental model. Although the entire study was conducted in a period of 16 to 18 weeks,
the intervention of peer modeling strategies used in this study might vary from courses. Students
in some courses were requested to complete homework assignments per week, but some might
complete less than 5 homework assignments per semester. Therefore, the peer modeling
strategies students applied, which informed a peer modeling process as they completed
homework, might have some variations. A longitudinal study not only examines the validity of
the developmental model but also the reliability in a long-term study and some changes brought
to individual students.

Continuous evaluation of the developmental model will not only contribute to the
advancement of personalized learning and instruction but also generate the principles to promote
personalization in education. Such principles should be also applied in different settings such as
K-12 or professional learning environments to identify their effectiveness in new contexts.

Therefore, the relationship among students needs examined by motivation and statistics learning anxiety, a modeling process informing problem-solving skills in peer and non-peer settings, and the use of open educational resources can be identified and used to validate the developmental model.
References


APPENDICS
December 5, 2013

Dear ROBERT Branch:

On 12/5/2013, the IRB reviewed the following submission:

<table>
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<th>Type of Review</th>
<th>Modification</th>
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<tr>
<td>Title of Study</td>
<td>Promoting Personalized Learning with Open Educational Resources</td>
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<tr>
<td>Investigator</td>
<td>ROBERT Branch</td>
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<tr>
<td>IRB ID</td>
<td>MOD000003538</td>
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<tr>
<td>Funding</td>
<td>None</td>
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<td>Grant ID</td>
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The IRB approved the protocol from 12/5/2013.

In conducting this study, you are required to follow the requirements listed in the Investigator Manual (HRP-103).

Sincerely,

Larry Nackerud, Ph.D.
University of Georgia
Institutional Review Board Chairperson
### Activity Details (Modification MOD00000358 closed (Approved))

**Author:** Christina Bowden (Office of the Vice President for Research)

**Logged For (IRB Submission):** JPSL

**Activity Date:** 12/5/2013 5:11 PM EST

**Documents:**
- Consent Form, JPSL
- Protocol, Promoting Personalized Statistics Learning through Modeling in an Open Learning Environment
- Recruitment Material, JPSL

### Activity Details (Modification MOD00000358 Opened)

**Author:** Yu-ju Lin (Institute for Interdisciplinary Research on Education & Human Dev.)

**Logged For (IRB Submission):** JPSL

**Activity Date:** 11/11/2013 1:50 PM EST

**Documents:**
APPENDIX B. INFORMED CONSENT FORM FOR RESEARCH STUDY

UNIVERSITY OF GEORGIA
CONSENT FORM
Promoting Personalized Statistics Learning through Modeling in an Open Learning Environment

Researcher’s Statement
We are asking you to take part in a research study. Before you decide to participate in this study, it is important that you understand why the research is being done and what it will involve. This form is designed to give you the information about the study so you can decide whether to be in the study or not. Please take the time to read the following information carefully. Please ask the researcher if there is anything that is not clear or if you need more information. When all your questions have been answered, you can decide if you want to be in the study or not. This process is called “informed consent.” A copy of this form will be given to you.

Principal Investigator: Rob Maribe Branch
Department of Career and Information Studies
(706) 542-9518

Purpose of the Study
This is a quasi-experimental study that will examine how graduate-level students, who benefit from an open and personalized learning environment, can achieve the mastery, improve motivation and decrease their anxiety toward introductory statistics. The purpose of this study is to develop an open learning environment to promote student personalized learning in an introductory statistics course. By reusing and reproducing open educational resources considering individual student needs, students, who play the role as peer-teachers, can learn how to plan and implement personalized instruction to help peer-students learn introductory statistics. Students who enroll in an introductory statistics course on graduate-level (either online or face-to-face courses) will be invited to this study.

Study Procedures
If you agree to participate, you will be asked to complete …
1) two thirty-minute surveys (learning characteristic survey and satisfaction survey, 60 minutes in total)
2) a prior-knowledge test (30 minutes)
3) a cover page information sheet (30 minutes)
4) allow scores in homework and in-class exam to be used in the study.

Risks and discomforts
We do not anticipate any risks from participating in this research. If you anticipate any risks or discomforts you may experience, you may ask questions now or call the Principal Investigator listed on the front page of this form.

Benefits
Participants who benefit from such an open and personalized learning environment could achieve mastery in, increase motivation in, and decrease their anxiety toward learning quantitative methodology. There are no expected benefits yet to society/humankind at this time.

Alternatives
None
Incentives for participation
The participant will not receive any incentive in the form of monetary or non-monetary for being in the study.

Audio/Video Recording
There is no audio/video recording in this study.

Privacy/Confidentiality
The data will be labeled with a direct identifier or an indirect identifier (code) that the research team can link to individually identifiable information but the results, when disseminated, will not be individually-identifiable. All survey results (e.g., learning characteristic survey, satisfaction survey) and scores (e.g., prior-knowledge test, homework and in-class exam) will be collected and stored in the course management system and laptops of principal and co-principal investigators. Those data will be stored for five years. The privacy and the confidentiality of the research data will be only used in the study and protected by the investigators carefully. Some data (e.g., scores in a prior-knowledge test, homework, and in-class exam) will include the information that identify participants directly (e.g., name, student ID). The participants’ names and contents about these data will be coded. The key to the code will be in an encrypted and/or password protected file. The coded data file will be maintained on a separate computer/server. Only principal and co-principal investigators have the access to all these data and determine the code which is assigned to each individual participant. Those data will be accessed and reviewed by the investigators only for research purposes. All data files will be stripped of individually identifiable information and the key to the code destroyed after data collection and analysis. The research data will not be released without your consent unless required by law or a court order. The data resulting from the participation will not be made available to other researchers in the future for research purposes not detailed here.

Taking part is voluntary
Your participation in this study is entirely voluntary. Your decision about participation will have no bearing on your grades or class standing. You can refuse to participate or stop participating at any time without penalty or loss of benefits to which you are otherwise entitled. If you decide to withdraw from the study, the information that can be identified as yours will be kept as part of the study and may continue to be analyzed, unless you make a written request to remove, return, or destroy the information.

If you have questions
The main researcher conducting this study is Yu-Ju Lin, a graduate student at the University of Georgia. Please ask any questions you have now. If you have questions later, you may contact Rob Maribe Branch at rbranch@uga.edu or at (706) 542-9518. If you have any questions or concerns regarding your rights as a research participant in this study, you may contact the Institutional Review Board (IRB) Chairperson at 706.542.3199 or irb@uga.edu.

Research Subject’s Consent to Participate in Research:
To voluntarily agree to take part in this study, you must sign on the line below. Your signature below indicates that you have read or had read to you this entire consent form, and have had all of your questions answered.

______Yu-Ju Lin
_________________________________________  ____________________  _____________
Name of Researcher    Signature    Date
<table>
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<th>Name of Participant</th>
<th>Signature</th>
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Please sign both copies, keep one and return one to the researcher.
APPENDIX C. PRIOR KNOWLEDGE TEST

1. Which statement is correct in describing the difference between observational and experimental study?
   A. Through an observational study, we can always find out the findings and draw a conclusion.
   B. In an experimental study, there may not be a treatment which is deliberately imposed on individuals.
   C. In an observational study, the data can be recorded by one investigator without attempting to influence the mechanism.
   D. In an experimental study, any influential factors can be controlled, which may introduce the bias in the study.

2. In a well-designed experiment, what is the relationship (1, 2) among the three variables (i.e., the effort in study, intelligence, good grade on a test) below?
   ![Diagram](image)
   A. Confound, Lurking
   B. Cause, Effect
   C. Lurking, Cause
   D. Cause, Confound

3. Which correctly describes the population and sample in a well-designed experiment?
   A. If the population is small, we still can assess the characteristics in the population.
   B. A sample refers to the group(s) of individuals we choose in the population.
   C. In order to identify the characteristic in the population, we can use statistics to measure the population.
   D. In order to identify the characteristic in the sample, we can use parameters to measure the sample.

4. Which statement accurately describes correlation in a well-designed experiment?
   A. By plotting two variables on a scatter plot, we describe the relationship by examining the direction and the strength, which correlation denotes.
   B. Positive or negative correlation between two variables definitely indicates that one variable causes another variable in a well-designed experiment.
   C. The correlation relationship among two variables can require two variables either quantitative or categorical.
   D. The strength of the relationship between the two variables can be seen by how much variation or scatter there is around the main form.
5. The racing record of men and women over time is outlined below. What findings can we obtain in terms of men’s and women’s racing time?

A. Compared with men, women’s racing time has sharply decreased by years.
B. Both group show a very strong negative linear relationship that would be apparent with the gender categorization.
C. Owing to the men’s complete data from early 1910 to 2000, the correlation between record of racing time and year for men is flatter than that for women.
D. There must be some measurement errors to measure men’s racing time, and these errors lead to the bias.

6. Which statement is correct about regression?

A. A regression line is a straight line that describes how an independent variable changes as a function of a dependent variable.
B. A regression line is frequently used to predict the value of a response variable for a given value of an explanatory variable.
C. The least-squares regression line may not always pass through the points defined by the average variables.
D. The distances from each point to the least-squares regression line is called residual variance.

7. There are two bags in each of which includes three red and white balls respectively. Now, two students are repeatedly drawing a ball from their bags and recording the red ball per draw. Then, both students return the ball back to the bag. Accordingly, the probability of the red ball is outlined below. Which statement is true about the probability of the red ball?
A. This result shown above is definitely not random, because we can predict the findings.
B. The draw made by the first student is independent from the second one. Also the draw that the first student makes each time is not relevant to other times.
C. There must be the measurement errors in the beginning of drawing, though the probability of red ball should be 0.5 in many repeated trials.
D. The probability of red ball is supposed to be 0.5, even though two students repeatedly draw the ball without putting it back to the bag.

8. You are tossing two dice. All the combinations of outcomes are shown below. Which statement is correct about the probability of the outcomes summing to 5 and 7?

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A. The probability of the outcomes summing to 5 is \( \frac{1}{9} \).
B. The probability of the outcomes summing to 7 is 1.
C. The probability of the outcomes summing to 5 is \( \frac{1}{18} \).
D. The probability of the outcomes summing to 7 is \( \frac{1}{12} \).

9. The bar graph below indicates the number of states and percent of states residents aged 65 and over. Which of the following statement is true about the distribution below?

A. The overall pattern is fairly not symmetrical because of two states apparently not belonging to the main trend.

B. Because there is a large enough data to show the number of states and percent of state residents aged 65 and over, the data will eventually turn out nice and symmetrical.

C. The reasons to cause the outliers are numerous, so we can not directly indicate that Alaska and Florida are outliers of the overall pattern of a distribution.

D. Alaska and Florida have unusual representation of the elderly in their population, which are considered outliers of the overall pattern of a distribution.

10. What will be the mean and median located, if the distribution of data is NOT normally distributed?

A. If the whole distribution is right skew, mean will be on the same position as median.

B. If the whole distribution is right skew, median will be on the left side of mean.

C. If the whole distribution is left skew, mean will be on the right side of median.

D. If the whole distribution is left skew, mean and median will be very close to each other.
APPENDIX D. LEARNING CHARACTERISTICS SURVEY

1. Your Student Number (last 4 digit):________

2. Your age

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<td>Over 50</td>
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<tr>
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<td>46~50</td>
<td>Over 50</td>
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Directions: People learn statistics in many different ways. This questionnaire has been designed to help identify your learning characteristic(s) of quantitative research methodology on practical and psychological levels. Read each statement in the following. Check the number of each item and best indicate your feelings about those statements. There are no right or wrong answers. Please give your immediate reaction to those statements.

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<td>5</td>
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<tr>
<td>Not at all true</td>
<td>Somewhat true</td>
<td>Very true</td>
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About the quantitative research methodology or similar courses,...

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<td>1. I enjoy studying quantitative research methodology or similar</td>
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<td>courses very much.</td>
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<tr>
<td>2. Studying quantitative research methodology or similar courses is</td>
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<td>fun.</td>
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<td>3. I thought studying quantitative research methodology or similar</td>
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<td>courses was boring.</td>
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<td>4. I do not have any attention in studying quantitative research</td>
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<td>methodology or similar courses.</td>
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<td>5. I would describe studying quantitative research methodology or</td>
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<td>similar courses as very interesting.</td>
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<td>6. I thought studying quantitative research methodology or similar</td>
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<td>courses is quite enjoyable.</td>
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<td>7. While I am studying quantitative research methodology or similar</td>
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<td>courses, I would think about how much I enjoy them.</td>
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<td>8. I believe studying quantitative research methodology or similar</td>
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<td>courses could be of some value to me.</td>
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<td>9. I would be willing to take more quantitative research methodology</td>
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<td>or similar courses because they have some values to me.</td>
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<td>10. I believe studying quantitative research methodology or similar</td>
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<td>courses could be beneficial to me.</td>
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<td>11. I think this is important to study quantitative research</td>
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<td>methodology or similar courses.</td>
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</table>
Based on my performance in the former quantitative research methodology or similar course, …

12. The final course grade in the former quantitative research methodology or similar course you have taken: (Please Specify)  ________________

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<tr>
<th>Item</th>
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<tr>
<td>13. I feel confident in my ability to manage my study in this course.</td>
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<td>14. I am capable of handling my study in this course.</td>
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<td>15. I am able to do my own study in this course.</td>
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<td>16. I feel able to meet the challenge of performing well in this course.</td>
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<td>17. do you have your own laptop or desktop to help you finish the coursework or assignments?</td>
<td>Yes ( )</td>
<td>No ( )</td>
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<td>18. do you have the statistics package (e.g., SPSS, SAS, R, etc.) in your own laptop or desktop to help you finish the coursework or assignments?</td>
<td>Yes ( )</td>
<td>No ( )</td>
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<td>19. do you have internet connection at your home?</td>
<td>Yes ( )</td>
<td>No ( )</td>
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<tr>
<td>No Anxiety</td>
<td>Very Much Anxiety</td>
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20. Studying for an examination in a statics course.  
21. Interpreting the meaning of a table in a journal article.  
22. Going to ask my statistics teacher for individual help with material I am having difficulty understanding.  
23. Reading a journal article that includes some statistical analyses.  
24. Trying to decide which analysis is appropriate for my research project.  
25. Doing an examination in a statistics course.  
26. Walking into the room to take a statistics test.  
27. Arranging to have a body of data put into the computer.  
28. Trying to understand the statistical analyses described in the abstract of a journal article.
<table>
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<tr>
<th>Item</th>
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<td>29. Since I am by nature a subjective person, so the objectivity of</td>
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<td>statistics is inappropriate for me.</td>
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<td>30. I wonder why I have to do all these things in statistics when</td>
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<td>in actual life I will never use them.</td>
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<td>31. Statistics is worthless to me since it is empirical and my area</td>
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<td>of specialization is abstract.</td>
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<td>32. Statistics takes more time than it is worth.</td>
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<td>33. I feel statistics is a waste.</td>
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<td>34. Since I have never enjoyed math, I do not see how I can enjoy</td>
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<td>statistics.</td>
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<td>35. I could enjoy statistics if it were not so mathematical.</td>
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<td>36. I wish the statistics requirement would be removed from my</td>
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<td>academic program.</td>
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<td>37. Statistics teachers speak a different language.</td>
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<td>38. Statisticians are more number oriented than they are people</td>
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<td>oriented.</td>
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<td>39. Statistics is not really bad. It is just too mathematical.</td>
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<td>40. I am never going to use statistics so why should I have to take</td>
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<td>it?</td>
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<td>41. I am too slow in my thinking to get through statistics.</td>
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Course Name (Fall/ Spring/ Summer, Year)

Homework/ In-class Activity #

Name:
Student ID:

- Collaboration with peers/ Individual study (choose one):
- Name(s) of peer(s) you work with:
- The way to solve a problem (choose what applies):
  1. member check
  2. discussion
  3. demonstration
  4. consultation with TA or instructor
  5. others (please specify):
- Search for supplemental resources (choose what applies):
  1. handouts
  2. textbooks/books
  3. online search
  4. others (please specify):
APPENDIX F. SATISFACTION SURVEY

<table>
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<tr>
<th></th>
<th>1 Strongly Disagree</th>
<th>2 Neutral</th>
<th>3 Strongly Agree</th>
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</table>

This survey is designed and used to identify your satisfaction about the use of open educational resources in this course (e.g., in lecture handouts or while you complete your homework or in-class tasks).

1. I enjoyed using open educational resources very much in this course.
2. Using open educational resources in this course was fun.
3. I thought using open educational resources in this course was boring.
4. Using open educational resources in this course did not hold my attention at all.
5. I would describe using open educational resources in this course as very interesting.
6. I thought using open educational resources in this course was quite enjoyable.
7. While I was using open educational resources in this course, I was thinking about how much I enjoyed it.
8. I believe using open educational resources in this course could be of some values to me.
9. I think that using open educational resources in this course is useful for ___
10. I think this is important to use open educational resources in this course because it can ___
11. I think using open educational resources in this course could help me to ___
12. I would be willing to use open educational resources in this course again because they have some values to me.
13. I believe using open educational resources in this course could be beneficial to me.
14. I think using open educational resources in this course is important.
15. I think using open educational resources in this course can help decrease my anxiety in interpreting the quantitative data.
16. I think using open educational resources in this course can help decrease my anxiety in statistics tests and courses.
17. I think using open educational resources in this course can help increase my confidence to understand and calculate statistics.
18. I think using open educational resources in this course can help increase my willingness to ask for help from other people (e.g., teacher, teacher assistants, peers).
19. I think using open educational resources in this course can change my perception about statistics teachers.
20. The overall design of using open educational resources in this course meet my needs in statistics learning.
21. The overall design of using open educational resources in this course helps me comprehend the abstract concept in the course.
22. The overall design of using open educational resources in this course helps me accurately understand the abstract concept in the course.
23. The overall design of using open educational resources in this course helps me clarify the abstract concept in the course.
24. The overall design of using open educational resources in this course is creative.
25. The use of open educational resources while I complete my homework or in-class tasks meets my needs in statistics learning.
26. The use of open educational resources while I complete my homework or in-class tasks helps me comprehend the abstract concept in the course.
27. The use of open educational resources while I complete my homework or in-class tasks helps me accurately understand the abstract concept in the course.
28. The use of open educational resources while I complete my homework or in-class tasks helps me clarify the abstract concept in the course.
29. Open educational resources in the course (e.g., in lecture handouts or while you complete your homework or in-class tasks) are reused\(^1\) by teachers or peer students.
30. Open educational resources in the course (e.g., in lecture handouts or while you complete your homework or in-class tasks) are redistributed\(^2\) by teachers or peer students.
31. Open educational resources in the course (e.g., in lecture handouts or while you complete your homework or in-class tasks) are revised\(^3\) by teachers or peer students.
32. Open educational resources in the course (e.g., in lecture handouts or while you complete your homework or in-class tasks) are remixed\(^4\) by teachers or peer students.

1. Reuse- People use all or part of the resources for their own purposes (e.g., watch an animation or simulation).
2. Redistribute- People can share the resources with others (e.g., links, tutorials, documents).
3. Revised- People can adapt, modify, translate, or change the form of resources (e.g., converse the word document into PDF format).
4. Remixed- People can take two or more existing resources and combine them to create a new resource (e.g., combine hyperlinks into lecture handouts or homework).